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Grey Wolf Optimizer based Resource Allocation and Optimization Algorithm in Cloud Computing Environment

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Abstract: The Internet of Things (IoT) operates as a decentralized network where various devices connect to the internet for communication. This intricate structure consists of multiple resources, gateways, and cluster heads. Effectively managing IoT resource allocation and scheduling tasks within this environment poses a significant challenge. The allocation and scheduling processes play a crucial role in establishing connections between IoT resources and gateways, ensuring optimized resource distribution at gateways. Given the potential for heavy traffic at individual gateways, manual resource allocation and scheduling are impractical, leading to increased overhead. To address this issue, our research proposes a hybrid approach aimed at optimizing resources and minimizing transmission costs. The approach leverages the Grey Wolf Optimizer (GWO) algorithm, inspired by the hunting behavior of grey wolves. Through experimentation on various benchmark functions, the hybrid GWO demonstrates satisfactory results, showcasing its potential for enhancing IoT resource management.

Keywords: *Resource Allocation, Optimization, Cloud Computing.*

1. Introduction

Present world just the starting period of transmission and global clarification. In this time span, community is forwarded one step ahead to the united or linked pattern. The network coverage becomes broaden and generated by IoT resources over interactive communication with people and other IoT resources are also expanded. So, the IoT can communicate with connected people and other internet devices any time anywhere and that seems to be emerging challenges [1]. The Quality of Service (QoS) is one of the challenges that has been attempted to achieved by the current generation of IoT. Bandwidth is assumed as a vital resource for IoT system and to improve the QoS, bandwidth management is needed. In the recent decade, IoT system has been prioritized due to huge request for multimedia services. Besides multimedia services many other services that are categorized by different features supplied in IoT system and these services need separate QoS methods [2][3]. The concept at the back of the IoT is to link everything to each other over the internet. By using the concept of IoT, there will be a lot of implementations in future and one of them is smart city [4][5]. Besides the smart city application, there are several fields where IoT will be applicable like in food, garments, domestic science, conveyance, pedagogy, amusement and many more. One of the familiar application of IoT is traffic control by keeping track of the traffic situation and based on that the most appropriate master plan has been decided to control the traffic [6][7]. The objective of any technology is to upgrade the human life so as IoT and several researchers have already contributed in IoT for various application to facilitate our society. The studies in [7] [8] are assumed as beginning of IoT. The studies [8][9] are linked with IoT for sensor design, smart grid and smart health system etc. As per information collected from source [10][11], number of internet devices connected in IoT environment is approximated to 16 billion by the end of 2021 as the importance of it is increasing and the IoT manufacturer will be able to achieve a market of $900 billion by the end of 2022 in America [10][11]. Even though, these digits are forecasting the future of IoT that will surely happen for market expansion and internet devices in time ahead. The improvement and enhancement of IoT focus on both the advancement of hardware and betterment capability of IoT systems. Several software approaches have been introduced for enhancing the capabilities of the IoT-based systems. For doing so, resource allocation in IoT environment has been identified as a challenge and known as IoT Resource Allocation Problem (IRAP). The solution of IRAP deals with the minimization of communication or transmission cost of IoT nodes. The performance of all relevant systems like Radio Frequency Identification (RFID) and wireless communication in 5th generation (5G) will expand as the solution of IRAP comes. The IoT system consists of two types of nodes, resource node and gateway. The resource node senses the circumstance and transmits information to others of the system. Another responsibility of the resource node is to thoroughly monitor the entire system therefore in IoT system that has huge number of resource nodes. A gateway works like a

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bridge for providing communication between resources and forwards the data to the various resource nodes too. But an IoT system does not have huge number of gateways like resources. So, in such scenario, it is a challenge to decide which group of resources should be linked to which gateway to minimize the communication cost. All the information sensed time to time by a resource should be passed by the same gateway for achieving the optimal solution. The load between resources cannot be considered as load between gateways. In some scenario, maximum load can be processed by single gateway. If such scenario occurs, then congestion will be created in communication between gateways [12][13]. Several evolutionary algorithms have been applying for resolving optimization problem since last decade. These evolutionary algorithms are motivated from nature or any visible occurrences, social behaviour of some animals or insects for optimizing the critical problems. These algorithms are mainly applicable for solving the problems whose solutions are in non-polynomial time. The relevant objective function can give good coverage to the evolutional algorithm for optimizing the problem timely [14]. In this paper we will deal with IRAP problem. This paper introduces a meta-heuristic algorithm based on Grey Wolf Optimizer (GWO). The GWO has been proposed in 2014 [15] motivated by the searching and hunting behaviour of grey wolves.

1.1. Grey Wolf Optimization (GWO)

Grey Wolf Optimization (GWO) is one of the metaheuristic algorithms influenced by social behaviours like leadership and hunting strategy of Grey Wolf population. The Grey wolves are considered to be represented at top level of food chain among the social candies. In the GWO algorithm three superior wolves have been chosen to guide the rest of wolves in the population for searching and hunting prey. These superior wolves are generally named as *α, β,* and *δ*. The wolf hunting approach is fulfilled by three consecutive approaches named as encircling, hunting and attacking prey [36].

- **Encircling steps:** This step gives the direction of how to encircling the prey. The numerical definition is shown by the equation 1 and 2.

$D = ||C * X_p(t) - X(t)||$
(1)

$X(t+1) = X_p(t) - A * D$
(2)

In Equation (1) and (2), $X_p(t)$ indicates the prey position and $X(t)$ is individual Grey wolf in population at t[th] iteration. The coefficient vectors A and C are computed by Equation (3) and (4).

$A = 2ar_1 - a$
(3)

$C = 2r_2$
(4)

In Equation (3) and (4), the variable r_1 and r_2 are random vector in [0,1], and the vector a is in [2,0] given by Equation (5).

$a = 2 - 2t/[Iter]_{max}$
(5)

Here in equation 5 the value of ‘a’ is linearly decreasing and it varies with the iterations

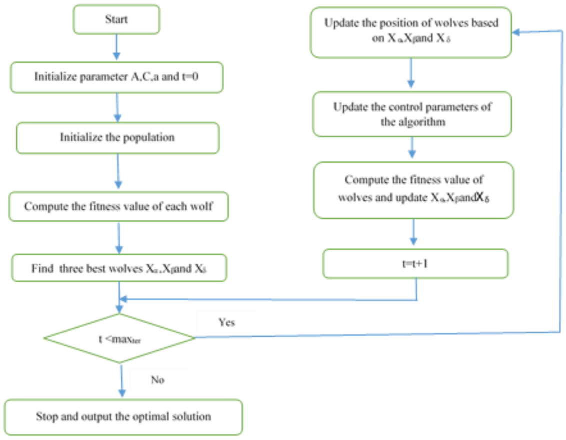

Fig. 1 Flow chart of GWO algorithm

- **Hunting:** We have already seen that α, β and δ wolves are superior they guide the others so it has been considered that these three wolves have good knowledge about the prey location. So the rest of wolves are compelled to chase the superior wolves. The mathematical formulation of hunting behaviour is represented by the list of equations from Equation (6 - 11).

$D_\alpha = ||C_1 X_\alpha - X(t)||$
(6)

$D_\beta = ||C_1 X_\beta - X(t)||$
(7)

$D_\delta = ||C_1 X_\delta - X(t)||$
(8)

$X_{i1}(t) = X_\alpha(t) - A_i 1 * D_\alpha(t)$
(9)

$X_{i2}(t) = X_\beta(t) - A_i 2 * D_\beta(t)$
(10)

$X_{i3}(t) = X_\delta(t) - A_i 3 * D_\delta(t)$
(11)

Here in Equation (6), (7) and (8), X_α, X_β and X_δ are the three superior wolves/solutions at tth iteration in Equation (9) to (11) and A1, A2 and A3 are computed by Equation (3). The average of three best wolves is represented by equation (12).

$X(t+1) = \frac{(X_{i1}(t) + X_{i2}(t) + X_{i3}(t))}{3}$

(12)

- **Attacking:** The hunting process will be continued until prey is not stopping and then wolves come into attacking mood. This behaviour is mathematically controlled by the variable a is decreased linearly with number of iterations. The exploration occurs during middle of total iteration and rest of iterations are defined for exploitation [37]. In attacking phase, wolves may adjust their position arbitrarily between the range varies from their current position to prey position.

The working flow of GWO algorithm has been represented by Fig. 1 The GWO algorithm starts by initializing the various parameters used throughout the process like A, C, a, t and population i.e set of wolves. After that, find out three best performing wolves by comparing the fitness values of entire population. Then check the termination condition if it doesn't meet, repeat the rest of steps. Position updating process of wolves will work based on the position of three best wolves also algorithm performs the updating of control parameters. Then again compute the fitness values of wolves and reselect the three best wolves. When termination condition satisfies, algorithm will stop and get the optimal solution as output. Even if, GWO is very straightforward process and useful for several operations, it permits inadequacy of population diversity, inequality among exploitation and exploration and immature convergence [38][39]. Moreover, the equation for updating position is appropriate to express exploitation stage but it is not acceptable to achieve at feasible solution. The pseudo code of GWO algorithm is given below.

Algorithm1. Grey Wolf Optimizer Algorithm (GWO)

Input: Population (N), t=0 and Max_{iter}

Output: The global optimal solution

1. Begin
2. Compute the value of A, C and a by using equation (3)-(5) respectively and fitness values for each individual's wolf
3. for t=1 to Max_{iter}
4. Select X_α, X_β, X_γ
5. for i=1 to N
6. Randomly initialize r_1 and r_2
7. Calculate X_{i1}, X_{i2} and Xi3 by using equation (9)-(11)
8. Calculate $X_{i(t+1)}$ by using equation (12)
9. Update the control parameter A, C and a
10. Calculate the fitness value each wolf
11. Update population
12. End for
13. End for
14. Return optimal solution
15. End
16. End

1.2. Challenges of GWO

Almost all optimization techniques follow two phases namely exploration and exploitation. Exploration is a technique of investigating the search area. At the very beginning of algorithm means at the earlier beginning iterations, the process searches the entire search area to find out the more feasible solutions and permits the individual wolf to prevent local optima. Deliberately, exploration decreases and exploitation increases, therefore the algorithm approaches towards the optimum solution. So to point out the proper equality between exploration and exploitation is urgently important factor for enhancing the performance of the algorithm [57]. Hence some modifications have been performed to achieve the better result.

1.2.1. Modification of GWO

The important parameter $'a'$ is applied to compute value of A and used to govern exploration and exploitation phases. We have already noted that a ϵ [2,0] i.e. linearly decreasing. As the algorithm progresses to the termination stages, exploration stage gradually slides toward the exploitation stage with the value of $'a'$ that declined linearly. Therefore, a is an important factor for this algorithm and so, the value of a has been updated non-linearly within the range [2,0] to get the better performance. The mathematical representation of 'a' has been modified by the Equation (13).

$$a = 2 - 2^t / max_{iter}^k$$
(13)

In Equation (13), t denotes the current iteration and $[max]_{iter}$ is maximum iterations and k is constant. The value of k ϵ [0,1] is used to prioritized the phases would be on exploitation and therefore performance of the searching process may deteriorate. When the $|k|$ >1, the entire searching area is surveyed and then gradually the algorithm enters into exploitation stage. The k value is decided by experimental approach. Authors in [57] have applied the non-leaner devaluation of parameter for performing better way still there is scope for additional enhancement. The search area has been exploited by applying the reduced number of iterations. So, R. Ahmadi et al have applied a mapping technique to perform a searching process locally near the best solution. The technique converts the position of best Grey to updated position and if the fitness value of new position outperforms then only Grey Wolf position will change to new position. The updated position is computed as follows

[57].

$X_n = X_\infty + r(U - L)(z - 0.5)$
(14)

Here upper and lower boundaries are represented by U and L respectively. The variable r denotes the center and z indicates mapping parameter that changes for each iteration is represented by the Equation (15).

$z_{t+1} = 4 * z_t * (1 - z_t)$
(15)

1.2.2. Improved GWO

Like GWO algorithm, Improved GWO (IGWO) algorithm follows some steps to achieve the optimal solutions. Many authors have been working on the improvement of GWO algorithm. In article [40], authors said about the three measurements like ergodicity, regularity and faster speed and they proved that tent map outperforms these measures to logistic map. The complex arithmetic reasoning is used to optimize the algorithms having chaotic sequence and in this case tent map has some preconditions. Mathematically tend map is a linear mapping and as the functions of it look like tent so its name as tent mapping [41]. The authors of [42] have applied tent chaotic map that uses the randomness, ergodicity and regularity for search optimization. This article also shows that tent chaotic map can continue the diversity of population, defeat the algorithms that fall into local optima and it also enhances the searchability globally. So tent chaotic map is the current trend for applying to several algorithms and simultaneously results have been improved. Tent chaotic based image encryption scheme has been proposed by Li et al. and this encryption scheme applies the known methods for performance analysis and security. The fault security analysis proves this algorithm effectiveness and security scheme [43]. Another proposed algorithm named improved tent map particle swarm optimization algorithm (ITM-CPSO) that works out on the cost related issues of nonlinear congestion management, register the cost related issues of nonlinear congestion management and to lower the universal uploading and cost additionally decrease divergence of the timing pulse generator output pre-decided level [44]. A tent Chaos Firefly Algorithm (CFA) has been introduced for optimizing the time correspondence of relay and CFA has been evaluated to various systems and found outperform [45]. Chaotic map is included to fruit fly optimization algorithm to enhance the convergence speed and universal performance [46]. The mathematical representation of tent mapping model that produces the chaotic sequence for initializing the population is given by Equation (16)

$$y_{i+1} = \begin{cases} {y_i}/{\propto}, & 0 \le y < \propto \\ {(1 - y_i)}/{(1 - \propto)}, & \propto \le y \le 1 \end{cases}$$
(16)

The tent chaotic map can be produced theoretically by Bernoulli shift transformation [50].

$y_{i+1} = (2y_i) mod 1$
(17)

$y_i^j \epsilon [0,1]$ denotes a chaotic variable, $i = 1,2, \ldots n$ is statistical digit of chaotic variables, $j = 1,2, \ldots, n$ indicates the population size.

1.2.3. Gaussian Perturbation

The Grey Wolves use to encircle the prey during hunting time and this encircling event can be represented by the mathematical model given by $X(t+1) = X_p(t) - A.|C.X_p(t) - X(t)|$ Equation (9) – (11). The meaning of every term we have already defined at previous sections. So from this equation it is cleared that variable C plays a significant role in encircling the prey. The random vector C is represented by $C = 2r2$ where $r2$ is a random number so value of $C\epsilon[0, 2]$. The C assigns arbitrary weights for prey. These weights can expand i.e. (|C| >1) or cut down (|C| <1) in between distance of Grey wolves and prey. The optimization method of GWO incorporates the random search process and the intensity of C aids to prevent the algorithm happening into local optima [47]. The location of best wolf must have a decisive aspect in instructing the group to change the direction towards the leading solution. If the best wolf's position comes into the local optima, then the searching process will be halted and diversity of group will be cut down. The best wolf is always changeable and it is unpredictable while movement process of wolves happens. The random generation coefficient C has been changed to Gaussian perturbation for escaping from premature convergence and maintaining equality between global and local exploration capabilities. The Gaussian perturbation brings about some confusions/disorders to leader and that controls the diversity of the population. So the Equations (6)-(8) have been changed to the following by using Equation (18) and also modified Equations (9)-(11) by (19).

$C = Gaussian(\delta)$
(18)

$X(t+1) = X_p(t) - A.|Gaussian(\delta).X_p(t) - X(t)|$ (19)

1.2.4. Cosine Control Factor

The variable 'A' is called coefficient vector that makes equal the global and local search capabilities in GWO. In case of $|A| > 1$ indicates the global search process and $|A| > 1$ says the local searching operation of Grey wolves for attacking their prey. Initially the population i.e. Grey wolves are scattered into the integrated search place. Gradually by using the gained information, the individual Grey wolf moves towards the optimal solution through the optimization process. From the Equation (3) it is shown that value of vector 'A' depends on the variable 'a′ and additionally vector 'A' will affects the balance between exploration and development capacity of GWO.

The Grey wolves will be busy in searching and hunting process when a>1 and if value a>1 then Grey wolf will perform the hunting only. In GWO, the value of A is computing by attenuation factor 'a' and it is directly depends on the iterations. So it can be concluded that the convergence factor A varies linearly with deceasing order of iterations with the range from 2 to 0 but it has been seen that every single Grey wolf may not adjust linearly in searching process. Therefore, linear fall of convergent factor A can't follow existing optimization process perfectly. So, linear change attenuation factor a is replaced [48] by a′ given Equation (20).

$$a' = 2 * \cos\left(\pi/_2 * t/max_{iter}\right) \quad (20)$$

Besides these factor, another factor named as inertia weight is also a decisive parameter [49]. The value of inertial weight decides whether local searching or global searching is occurred. The algorithm will perform global search strongly that means search space will be expending if inertia weight is extensive on contract the algorithm prefers local search strongly that means search area is around the optimal solution and increasing the convergence speed if inertia weight is limited. A weight cosine control factor B(t) has been introduced [42] that incorporating the parameter a'. The weight cosine control factor B(t) varies synchronously with a' and that is applied for updating position of GWO to improve the global exploration capability. As the number of iterations increase, adjustment step length of the algorithm decreases, the global searching capabilities becomes smaller gradually and capability of local search becomes stronger moderately. The position of single Grey wolf is adjusted rather than moving to the origin while value of B(t) seems very limited. The B(t) is represented by Equation (21).

$$B(t) = cos\left(\frac{\pi}{2} * \frac{t}{[max]_{iter}}\right) \quad (21)$$

Therefore Equation (9) – (11) has been updated as Equation (22) given below.

$$X_1 = X_\alpha - B(t).A_1.|C_1 X_\alpha - X| \quad (22)$$

$$X_2 = X_\beta - B(t).A_2.|C_2 X_\beta - X| \quad (23)$$

$$X_3 = X_\delta - B(t).\mathrm{A}_3.|C_3 X_\delta - X| \quad (24)$$

Another set of improvements have been proposed in [36]. In GWO algorithm, α, β, and δ guide the other wolves to reach the optimal solution. This action points to involvement in locally optimal solution. Decreasing the population diversity is encountered as another aftereffect and that brings GWO to be considered into the local optimum. To resolve this side effect an Improved Grey Wolf Optimization (I-GWO) has been introduced [36]. For this improvement an updated search strategy including selecting and updating has been introduced. The I-GWO algorithm includes the three stages: initializing, movement and selecting and updating respectively.

- Initializing Stage: The authors of [50] have used the following equation for randomly distributing N number of wolves in the given search space i.e $[l_i, u_j]$ is given below.

  $$X_{ij} = l_j + rand_j[0,1] * (u_j - l_j), i \in [1, N], j \in [1, D] \quad (25)$$

  A single wolf says i at iteration t is represented as

  $X_i(t) = X_{i1}, X_{i2}, X_{i3} \dots\dots, X_{iD}$ here D indicates problem dimension. The entire population is put in a matrix named as Pop having NXD dimension. The fitness value of a wolf says $X_i(t)$ is computed by Equation (25).

- Movement Stage: The authors of [50] have been inspired by the hunting behaviour of individual wolf to enhance the performance of GWO algorithm and that is also considered as an interesting social behaviour like group hunting of wolves [51]. The I-GWO includes an updated approach for movement of wolves to search the prey named as Dimension Learning-based Hunting (DLH). In DLH, each wolf is determined by its neighbours elected another wolf for the updated position of $X_i(t)$. So, the traditional GWO and DLH search approach produce different candidates. The traditional GWO has already been represented in the earlier section yet we represent the brief here.

- Traditional GWO: In normal GWO algorithm, best three wolves consider their names as α, β and δ have been chosen. Then attenuation factor a and coefficient A, C are computed by using Equation (5), (3), (4) respectively. After that, with respect to three best wolves X_α, X_β, and X_δ, prey encircling is computed by using Equations (6) – (11). And then updated position for wolf $X_i(t)$ say $X_{i-GWO}(t+1)$ has been calculated by Equation (12).

- Dimension Learning-Based Hunting (DLH) Search Strategy: As we have seen that in traditional GWO, updated position of individual is computed with the aid of α, β, and δ wolves of population. This strategy causes some problems like gradual convergence, premature diversity and wolves are tricked in the local optima. To address these issues, hunting strategy of individual wolf gained by its neighbors is acknowledged. So the dimension of updated position of $X_i(t)$ has been determined by following Equation (26) where individual wolf is determined by its several neighbors and wolf is chosen arbitrary from population.

$$X_{i-DLH,d}(t) = X_{(i,d)}(t) + rand(X_{(n,d)}(t) - X_{(r,d)}(t)) \quad (26)$$

The DLH searching approach has introduced another computation for updating position of wolf $X_i(t)$ known as $X_{i-DLH,d}(t)$. For calculating the $X_{i-DLH,d}(t+1)$ a radius $R_i(t)$ required to compute given by Equation (27) by applying Euclidean distance between present position of wolf of $X_i(t)$ and the candidate position $X_{i-GWO}(t+1)$.

$$R_i(t) = ||X_i(t) - X_{i-GWO}(t+1)|| \quad (27)$$

Then the neighbors of $X_i(t)$ named as $N_i(t)$ have been chosen by Equation (28) where $D_i(X_i(t), X_j(t))$ is the Euclidean distance between $X_i(t)$ and $X_j(t)$.

$$NL_i(t) = \{X_i(t) | D_i\left(X_i(t), X_j(t)\right) \leq R_i(t), X_j(t) \in pop\} \quad (28)$$

After constructing the neighbours of $X_i(t)$, Equation (28) is applied to achieve different neighbours learning like d^{th} dimension of $X_{i-DLH,d}(t+1)$ is computed by using the dth dimension of arbitrary neighbour where $X_{n,d}(t) \epsilon N_i(t)$ and an arbitrary wolf $X_{r,d}(t) \epsilon pop$.

- Selecting and Updating Phase: The objective of this phase is to select the preferable candidate by analyzing the fitness values of two candidates $X_{i-GWO}(t+1)$ and $X_{i-DLH,d}(t)$ by equation.

$$X_i(t+1) = \begin{cases} X_{i-GWO}(t+1), & if\ fitness(X_{i-GWO}(t+1) < fitness(X_{i-DLH}(t+1)) \\ X_{i-DLH}(t+1), & Otherwise \end{cases} \quad (29)$$

So to modify the position of $X_i(t+1)$, if $fitness(selecte_{candidate}) < fitness\left(X_i(t)\right)$ then $X_i(t) = select_{candidate}$ otherwise no updating is required in pop. After performing all these steps number of iterations will be incremented by one and these steps will be repeated until $iteration < max_{iteration}$.

Pseudo code for I-GWO algorithm

Algorithm: Improved Grey Wolf Optimizer Algorithm (I-GWO)

Input: Population size(N), Dimension(D), Max_{iter}

Output: The global optimal solution

1. Begin
2. Initializing parameters: A, C, a, t = 0 and calculate the fitness values for each individual
3. for t = 1 to Max_{iter}
4. Select X_α, X_β and X_δ
5. for i =1 to N
6. Calculate X_{i1}, X_{i2}, and X_{i3} by using Equation (9)-(11)
7. Calculate $X_{i-GWO}(t+1)$ by using Equation (12)
8. Compute $R_i(t)$ by Equation (27)
9. Compose the list of neighbours of $X_i(t)$ within radius $R_i(t)$ by using Equation (28)
10. for d = 1 to D
11. Update the position of $X_i(t)$ i.e. $X_{i-DLH,d}(t)$ by using Equation (26)
12. End for
13. Choose best ($X_{i-GWO}(t+1)$, $X_{i-DLH,d}(t)$) by using Equation (29)
14. Update population
15. End for
16. End for
17. Return optimal solution
18. End

2. Literature Review

Various research works are in progress and many have already been completed on visible resources for providing better services in both the IoT environment and other extensive environments. For these environment visible resources means the internet devices which have been chosen for executing services. There are several studies that attempted to find out the resource based services and made them available for users. However, in this section we have reviewed some articles related to Resource Allocation (RA). These reviewed articles may be categorized into two classes, one is based on deterministic algorithm and other based on heuristic and evolutionary algorithm. The deterministic algorithm based RA are obsolete and the algorithms based on second class are very popular and widely applicable in the recent decade. In the following sub-sections, we have represented each class of algorithm separately.

2.1. Methods Based on Deterministic Algorithms

Most of the researches that based on RA have the tendency to point out the NP-hard problem. The deterministic algorithms are considered as one of the solution of RA. These algorithms make up a branch of rules to allocate the resources. These rules must be steady with efficiency and efficacy. In these algorithms, if entire search space is scanned then more time is needed while few searches are the reason of inefficient resource allocation. Simple implementation is the primacy of these algorithms [16][17]. Some researchers have followed the thoroughgoing approaches to execute RA in the middleware layer. These thoroughgoing approaches mainly use the cluster architecture and that is not suitable for scatter architecture of IoT system. In this approach, steady and authentic association between resources are maintained. So, any effort has not been put for decreasing the volume of data dispatched on the network [18][19]. The researches have been going on various directions like service size, execution time of task, size of virtual machine etc. and for these purpose set of rules have been composed and these are known as rule-based approaches. The rules will assign the virtual memory capacity according to IoT services [20]. In [21], two deterministic algorithms have been introduced based on rule-based RA. The first algorithm computes the mean weightage of each source and according to mean value demanded service will be assigned. The second algorithm assigns the required resources randomly [21]. In [22], a new approach based on game theory has been proposed for device to device communication. This method implemented a response function for RA. This response function maximizes the fitness value of RA. Another game based approach has been introduced by Kim et al. and the objective function has been maximized the fitness value for handling RA in IoT [23]. This approach suffers from the computational complexity and the solution of RA problem never be represented by polynomial solution as it belongs to NP complete problem and without polynomial solution it would be tough. The problem size has been assumed as major restraint in articles discussed above. Therefore, new interest has been generated towards heuristic algorithms like genetic algorithm, cuckoo search algorithm, grey wolf optimizer etc.

2.2. Methods Based on Heuristic Algorithm

Besides deterministic based methods, heuristic algorithm is also applied to deal with RA problem. This approach becomes very population among the researchers recently. The objective of this algorithm is to find out the optimal solution without scanning the entire search space. These algorithms produce good result than deterministic algorithm in many cases by executing the complex implementation. The heuristic algorithms require less execution time as they need not to scan the entire search area. That has been assumed as a reason of its popularity. The heuristic method uses the Genetic Algorithm (GA), an evolutionary algorithm for solving RA problem. In GA based heuristic algorithm, individual RA model is designed by individual chromosome. The characteristic of scheduling is estimated by the fitness value of individual chromosome. The genetic operators help to progress of chromosomes and that creates the optimal model for RA [24]. The authors of [25] have proposed a new version of GA where individual chromosome consists of gateway and resource both. So that transmission cost between gateways has been reduced by solutions of RA [25]. A single particle constitutes a RA model in PSO-based heuristic where movement of particle creates an optimal solution [26]. Besides the above algorithms, in [27][28], Simulated Annealing, in [29], Tabo Search (TS) and Ant Colony Optimization (ACO) have been hugely applied to deal with RA problem. In the working of heuristic-based algorithm, arbitrary solutions are mapped to optimal solution through evolutionary process. Instead of using a single algorithm, two or more than two algorithms can work better for RA problem because one should be there to make up the delicacy of others. One of the studies used GA with ACO to find out the optimal solution for RA problem [30]. A group of authors have proposed an algorithm for searching the best solutions in optimal time by combining the search economics algorithm with k-means clustering algorithm to deal with IRAP problem [12]. In the current decade, the approaches based on deep learning are showing the new aspect to deal with RA problem as deep learning can properly handle the issues with expansive data [55][56]. A new RA technique has been introduced in [31] to reach the Service Level Agreements (SLA). Authors in [31] examined the proposed technique with respect to two benchmarks, one was capacity and other was enforcement period by using buffering, rate limiting and scheduling to create optimal solution for RA problem. Authors in [32] has considered all as resources and they represented their design by RA in IoT. They took an IoT-based healthcare system as case study and introduced a RA algorithm for that environment named as IoTR4HealthCare system. The IoTR4HealthCare system has been evaluated by two benchmarks one is cost and other is latency criteria [33]. Authors in [32] have designed a fuzzy classification based RA technique. Authors in [34] have enhanced a classification based Fuzzy Interference System (FIS) for jobs towards emergent and non-emergent. In this system, job has been forwarded to global CPU for allocating resources from cloud. The global CPU keeps track of all free and allocated resources and allocates the free resources to jobs according to need by considering transmission and computational cost. In [35], authors made an attempt to boost a RA method in the company of anti-jamming for IoT nodes. A Novel Automatic Control Allocation (ACA) model has been designed for supplying both elastic allocation and anti-jamming transmission. In this section we have tried to represent most of the work done for RA but seen only few are acceptable for IoT environment. This is the inspiration of our proposed work. Therefore, we attempt to design an algorithm that is modified for RA in IoT. The second issue that has been noted is unsuitable traversal of problem space. So, we try to apply a strong heuristic method based on GWO to improve the exploration process.

3. Method

Usually, it is supposed that all nodes must be in touch with each other in the fog or cloud computing environment. So, aggregate communication cost of entire network can be considered as one of the solutions of resource allocation problem. In network, a node can send the data to rest of the nodes. Therefore, Authors in [58] has considered the transmission cost of the message as fitness value and function for computing the transmission cost as fitness function. Here the name of fitness function has been named as total transmission cost denoted as Tc is given by Equation (30). The objective of the proposed algorithm is to minimize the fitness value.

3.1. Transmission Cost

$$T_c = \sum_{j=1}^{|g|} d_j^r d_g \quad (30)$$

Here, d_j^r is transmission cost between j^{th} gateway and all the IoT devices connected with it, g represents the total number of gateways and d_g is the transmission cost between gateways. The transmission cost between gateway and IoT devices is calculated by the following Equation (31).

$$d_j^r = \sum_{j=1}^{|r|} C_{jr} \quad (31)$$

C_{jr} is the communication cost of all resources connected to the j^{th} gateway which is computed by the following mathematical Equation.

$$C_{jr} = \sum_{i=1}^{|r|} (T_{ti} + T_{pi}) \quad (32)$$

T_{ti} is the transmission time, T_{pi} is the propagation time and T_{ti} can be estimated by the following equation given below

$$T_{ti} = bw_i / dr_i \quad (33)$$

Where bw_i is the bandwidth of i^{th} resource and dr_i indicates data rate of i^{th} resource.

$$d_g = \sum_{i=1}^{|g|} \sum_{j=1, i \neq j}^{|g|} CC_{ij} \quad (34)$$

CC_{ij} is the communication cost between i^{th} and j^{ih} gateways.

$$TT_c = \frac{T_c}{P} \quad (35)$$

TT_c is total transmission cost of the model. P is the penalty for each gateway.

3.2. Proposed Algorithm

In this paper we have designed an algorithm to allocate the resources so that we can optimize the transmission cost. The proposed algorithm has been based on the GWO. The steps of the proposed algorithm are given below:

Algorithm: Hybrid Grey Wolf Optimizer Algorithm (H-GWO)

Input: Population size(N), Dimension (D), Max_{iter}

Output: The global optimal solution

1. Begin
2. Initializing parameters: Max_{iter}, N, t=0, and population
3. Compute the value of AC and a by using Equation 3,14,16 respectively and fitness values for each individuals using Equation 35
4. Select X_α, X_β and X_δ
5. for i =1 to N
6. Calculate X_{i1}, X_{i2}, and X_{i3} by using Equation 22 to 24
7. Calculate $X_{i\text{-}GWO}(t+1)$ by using Equation 12
8. Compute $R_i(t)$ by Equation 30
9. Compose the list of neighbours of $X_i(t)$ within radius $R_i(t)$ by using Equation 31
10. for d = 1 to D
11. Update the position of $X_i(t)$ i.e. $X_{i\text{–}DLH,d}(t)$ by using Equation 26
12. End for
13. Choose best($X_{i\text{-}GWO}(t+1)$, $X_{i\text{–}DLH,d}(t)$) by using Equation 32
14. Update population
15. End for
16. End for
17. Return optimal solution
18. End

4. Result

In this section, we evaluate the efficiency of the proposed hybrid

GWO algorithm. The MATLAB and R software environment have been used to implement the proposed algorithm as computation time is not important factor for evaluation so we are going to represent the specification of computer. The earlier researchers neither used a familiar dataset nor common dataset for solving the RA problem in cloud. Therefore, we here designed the dataset for experiment. Regardless of dataset, RA issues should be deal before formation of network by the network administrator so this is not an instantaneous task. Therefore, network administrator has sufficient time to fix the issues for reaching the optimal solution by executing the proposed algorithm [52].

4.1. Data Set

We design the test date in small, medium and large size for evaluation. In the generated data set, the range of gateways is in between 4 to 100 and range of resources is 10 to 800. We generate total eight test data sets for analysing the proposed method. The details of sample of data sets given below:

Table 1. Description of Data Set

Data Set	Gateway Count	Resource Count
DS1	4	10
DS2	4	13
DS3	4	17
DS4	40	100
DS5	50	200
DS6	60	300
DS7	70	400
DS8	80	600

In the above table DS1, DS2 and DS3 are small scale, DS4, DS5 are medium size and DS6, DS7 and DS8 are assumed as large scale respectively. Indifferent of size, the communication cost between gateways is arbitrary digit ϵ [21, 40] and the communication cost between gateways and resources is another arbitrary number ϵ [1, 20]. The communication cost between gateways and resources is always considered as lower than the communication cost between gateways. Every test date consists of two matrices named Gateway and Resource for representing cost. Consider we have n number of gateways and m number of resources in test sample. Then in data set, we have matrix $[Gateway]_{nXn}$ of size nn for representing the cost between gateways and $[Resource]_{nXm}$ of size nm denotes the communication cost between gateways and resources. Here in Fig. 2, we present DS1.

$$Gateway_{4\times 4} = \begin{bmatrix} 0 & 25 & 35 & 21 \\ 25 & 0 & 24 & 36 \\ 35 & 24 & 0 & 27 \\ 21 & 36 & 27 & 0 \end{bmatrix}, Resource_{4\times 10} = \begin{matrix} 10 & 7 & 19 & 8 & 5 & 3 & 3 & 2 & 10 & 7 \\ 9 & 2 & 13 & 5 & 4 & 5 & 2 & 3 & 14 & 8 \\ 17 & 3 & 12 & 6 & 3 & 5 & 2 & 5 & 6 & 9 \\ 8 & 11 & 10 & 7 & 15 & 9 & 5 & 7 & 10 & 5 \end{matrix}$$

Fig. 2 Dataset DS1

5. Discussion

The proposed hybrid GWO algorithm has been evaluated on generated datasets. We tested GA [53], SEIRA [54] and WOA [52] algorithm on the same dataset for comparing the communication cost.

The Table 2 represents the comparison of the communication cost between resources and gateways with the foregoing methods [53] [54] [52] under the consideration that data is arbitrarily generated, resource allocation problem is assumed as Np-complete problem and no optimal solution is accessible. We have executed the proposed algorithm and the foregoing methods for 100 times for same data. The result of comparison specifies that hybrid GWO

Table 2. Comparative result analysis

DATA SET	GA [64]	SEIRA [63]	WOA [61]	H-GWO (Proposed)
DS1	672	672	672	672
DS2	809.5	809.5	809.5	809.4
DS3	919	919	919	919
DS4	1159	1150.7	1147	1147
DS5	1336.6	1332.3	1328	1328
DS6	1677	1660	1657	1656.7
DS7	2353	2309	2307.5	2307
D8	2928	2923	2917	2915.3

algorithm is satisfactory for dealing with RA problem. For small and medium size data set, we get the similar results as GA, SEIRA and WOA and sometimes we get the better result. For large data set we get up to the mark result in compare to the foregoing methods.

6. Conclusion & Future Work

In cloud computing environment, one of the significant issues is RA problem. Resource Allocation (RA) and scheduling deal with the fact of allocating optimal resources to task so that execution time would be decreased. Otherwise, if we allocate the resources randomly, that raises the energy wastage and result is global warming. So, scheduling and RA have important impact to the large scale system like cloud computing and we can’t pass over these issues. In this article an optimization algorithm has been proposed based on Grey Wolves Optimization with some achievable modifications for dealing with the RA problem. In this algorithm, individual wolf has been designed in combination of resources and gateways and represented as array. The proposed algorithm processes each wolf and calculates the fitness value based on the movement of wolves. We evaluate this algorithm on our data set and compare the result with the foregoing methods. The result analysis indicates that the proposed algorithm gives the noticeable output.

Declaration Statement

Data Availability Statements:

No standard dataset is available so own data set has been used. Data will be made available on reasonable request.

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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Author contributions

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Compliance with Ethical Standard

Research involving human participants and/or animals: No human or animal is involved in this research work.

Informed consent: This work is the extension of our previous research work.

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