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Metaheuristic Optimization-based Resource Allocation Technique for Cybertwin-driven 6G on IoE Environment

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***Abstract*—Rapid advancements of sixth generation (6G) network and Internet of Everything (IoE) supports numerous emerging services and application. Increasing mobile internet traffic and services, on the other hand, presented a number of challenges that could not be addressed with the current network design. The cybertwin is equipped with a variety of capabilities, including communication assistants, network data loggers, and digital asset owners, to address these difficulties. While spectrum resources are limited, effective resource management and sharing are essential in achieving these requirements. With this motivation, this paper presents a new Metaheuristic with Blockchain based Resource Allocation Technique(MWBA-RAT)for cybertwin driven 6G on IoE environment. The incorporation of the blockchain in 6G enables the network to monitor, manage and share resources effectively. The proposed MWBA-RAT technique designs a new Quasi Oppositional Search and Rescue Optimization (QO-SRO) algorithm for the optimal resource allocation process and this shows the novelty of the work. The QO-SRO algorithm involves the integration of Quasi Oppositional Based Learning (QOBL) concept with the traditional SRO algorithm to improve its convergence rate. A wide range of experiments are performed to highlight the enhanced outcomes of the MWBA-RAT technique.**

Keywords*—Resource allocation, Cybertwin, 6G networks, Metaheuristics, Internet of Everything, Blockchain

I. INTRODUCTION

The IoE(Internet of Everything) is described as the future of Internet and can attain smart interconnections of things, human, process and data [1, 2], using 5th generation mobile communication (5G) and AI technique for making network connection more valuable and relevant than before. End-to-end connections in IoE are replaced with a network infrastructure that supports data aggregation and processing, as well as fusion and service and distribution [3].The disruptive modification increases several issues for the network of IoE such as availability, mobility, scalability, security and so on.

For the cybertwin-based communication paradigm, cybertwin represents the end (human and objects) in virtual cyberspace located at the edge cloud. Three services, namely, communications assistant, digital asset and network behaviour logger may be provided by Cybertwin to meet various modern network design needs. If you're using the end-to-end communication approach, you need to connect your end device directly to the server that provides the service.6G-enabled communication networks have emerged as a viable technology for cybertwin. Digital twin technology is a virtual representation that mimics real-world products and processes, while cybertwin technology goes far further. It acts as a central point of contact and a repository for information about the Internet of Everything (IoE) applications running on the edge networks.

Fig. 1 illustrates the presented cybertwin based next generation network framework. In this novel framework, it has Edge Cloud, Core Cloud, Ends and the Cybertwin, the operations are outlined below. In contrast to current cloud networks, the Core Cloud is completely connected to each other via high-speed optical links. When Amazon AWS offers Cloud Computing (CC) as a specialized service, its underlying cloud foundation delivers a network service that includes communication, computation and caching resources. The Edge Cloud is located between the core cloud and the endpoints. Because it is closer, this cloud is able to respond to client requests more quickly. The edge clouds could therefore aid the core cloud in providing a higher QoS (Quality of Service) network environment. The proposed network framework provides the most important network function, namely, cybertwin. Located at the edge of the cloud, it is a digital representation of things and people in virtual cyberspace. The details of cybertwins will be explained in the next section. Using the Ends, user can keep track of all the devices and people connected to the network.

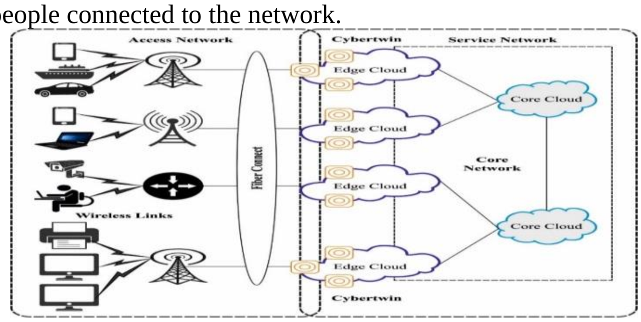

Fig. 1. Cybertwin based Network Architecture

In order to maximize system performance, Metaheuristic with Blockchain based Resource Allocation Technique(MWBA-RAT) model for the cybertwin driven 6G on IoE environment. It has guiding system that describes several processing techniques for various sorts of activities.

Later, MWBA-RAT built on blockchain and Cybertwin was developed to assure the system's dependability and safety. Finally, in order to assess the effectiveness of the Multi-dimensional Resource Allocation Technique, cost and efficiency models for various task processing techniques are developed. Opportunistic Spectrum Access (OSA) and auction processes have been proposed as ways to improve spectrum management. There are various drawbacks based on convergence, security, and high processing power notwithstanding the benefits. The Federal Communications Commission (FCC) has highlighted the vital role that the blockchain could play in 6G [4, 5, 6] as the future revolution in wireless communication. 6G and beyond networks might be highly scalable and provide effective answers to resource management and spectrum sharing if they were built on a communication network with the blockchain as its foundation[7,8].

This paper develops an effective metaheuristic with blockchain based resource allocation technique for cybertwin driven 6G on IoE environment (MWBA-RAT). Besides, the blockchain concept is involved in the 6G enabled network for monitoring, managing and sharing resources effectively. The proposed MWBA-RAT technique designs a new Quasi–Oppositional Search and Rescue Optimization (QO-SRO) algorithm for the optimal resource allocation process. In addition, the MWBA-RAT technique derives an objective function using different parameters to minimize the overall cost between the resources and gateways. Moreover, a graph clustering concept is introduced to boost the quality of the initial population and thereby enhancing the overall performance of the QO-SRO algorithm. To examine the enhanced outcomes of the MWBA-RAT method, an extensive set of experimental analysis is carried out.

II. Prior Resource Allocation Techniques on 6G Enabled IoE Environment

A. Resource Allocation

This section reviews the state of art resource allocation techniques for 6G enabled IoE environment. Mukherjee et al. [9] address the energy sharing problems by a IoT module with dynamic network or clustering for industrial 6G application. The study utilizes Artificial Intelligence(AI) for clustering the sensor nodes in the scheme for finding the primary nodes and predicting their position. When it comes to initial optimization, the study uses a Back Propagation Neural Network(BPNN) and a Convolutional Neural Network(CNN), both of which have been presented. Stackelberg games were used to develop an incentive mechanism for Resource Allocation (RA) based on vehicle satisfaction and total energy performance, by Wang et al. [10]. For reducing the delay and computation load of the Unmanned Aerial Vehicle (UAV), a distributed incentive method depending upon Alternating Direction Method of Multipliers (ADMM) aimed at optimizing the RA approach of every units. Li et al. [11] developed resource management between the Mobile Edge Computing(MEC) and IoT devices. As well, to search the Nash equilibrium, they introduced RA method acting behind every participant. Using this AI technique, auction participant acquires and accumulates experience by monitoring others behaviour and performing introspection that speed up the trading policies learning procedure of every agent in this opaque platform. In Hu et al. [12], This paper presents an Online Mobility-aware Offloading and Resource allocation(OMORA) approach based on Lyapunov optimization and Semi-definite Programming (SDP) optimization. This online solution enhances the offloading system without any prior knowledge of clients' mobility or the channel state. Mainak Adhikari et al.[24]The Deep Reinforcement Learning approach is used to distribute the incoming tasks from IoE apps based on dynamic requirements. On top of it, a Support Vector Machines (SVM) classification model is used to assess the data at the edge network and achieve high accuracy.

B. Resource Sharing

6G applications such IoT interdomain blockchain ecosystems, device to device interactions, and network slicing were discussed in detail by Xu et al. [13]. The Fully-Decoupled Radio Access Network(FD-RAN) was proposed by Yu et al. [14].There are two distinct types of base stations in an FD-RAN network: an Uplink Base Station (UBS) for transmitting information and a Downlink Base Station (DBS). Neurotransmission basics were first studied, and then the 6G design approach was proposed as a result. They introduced FD-RAN framework, elastic resource collaboration in FD RAN, and enhanced transport service layer architecture as a result of this principle. Jamil et al. [15] presented a conceptual method for establishing task off loading and RA framework for smart city platforms. First, they presented a new conceptual method, named convention module for RA and task offloading. Hao Xu et al[24].All of this might be accomplished with the help of blockchain technology. When it comes to 6G and other future networks, the blockchain has emerged as a key player because of its unique capabilities. In particular, the usage of the blockchain in 6G will enable the network to monitor and govern the use and sharing of resources more effectively. Q.Yu[26]. In this research, a multi-agent deep deterministic strategy gradient (MADDPG) is developed, which combines artificial intelligence into the edge computing architecture and maximizes processing efficiency by maximizing task hierarchical offloading and resource allocation.

C. AI-based control in IoE

Yang et al. [16] proposed an AI-enabled intelligent framework for 6G networks to understand knowledge discovery, intelligent service provisioning and automatic network adjustment, where the framework is separated as data mining , intelligent sensing layer, smart application layer and intelligent control layer. Later, they review the applications of AI technique for 6G networks and extend for employing the AI technique to improve the network performances effectively and efficiently. Manogaran and Rawal [17] proposed an Effective RA using Open Network Provision(ONP) for delay-controlled communications in the IoE platform. RA is enabled by describing a profit function that should be attained to

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control resource exploitation. The placement of lesser density fog nodes would adhere to the available resource and supports service reliability by raising seamlessness in transition. The nodes dual feature is used at RA, thus cost less communication delays. IoE terminals and fog node benefits are integrated for ensuring suitable non delay tolerant seamless service providing to the encompassed user from the desirable platform or framework.

D.Contribution

The main research contributions of this proposed systems are summarized as follows.

- To presents a new Metaheuristic with Blockchain based Resource Allocation Technique (MWBA-RAT) for cybertwin driven 6G on IoE environment.
- To monitor and sharing of resources effectively in 6G enabled IoE environments.
- To designs a new Quasi Oppositional Search and Rescue Optimization (QO-SRO) algorithm for the optimal resource allocation process.
- The QO-SRO algorithm involves the integration of Quasi Oppositional Based Learning (QOBL) concept with the traditional SRO algorithm to improve its convergence rate.
- To minimize the overall communication cost between the resources and gateways by using MWBA-RAT.

III. The Proposed MWBA-RAT Technique

A. Problem Formulation

The limitations of the existing systems can be formulated as follows. Generally, two kinds of nodes exist in the IoE network. The former one is the resource node which is offered to the service instances. The latter node is the gateway nodes which are linked to the resources. The gateways can link various portions of the IoE networks. The gateways enable the control of the traffic to several resources. The communication cost between the gateway and resources are fixed. The main issue is that the resources are distributed among the gateways and thereby results in minimum communication cost. Another view of this problem is the type of gateway link to one another.A major goal is to determine the pattern for resource allocation which has minimum communication cost.

B. Blockchain Structure

Blockchain performs a significant part in the ledger maintaining industry and cryptocurrency. Because of the community vitality, the technology gets interested by the infrastructure commissioners, policymakers and mobile operators. Blockchain is a distributed database controlled by a hash tree that is normally irreversible and tamper proof [18]. Also, the nature of its Consensus Mechanism (CM), chain link data structure, that guarantees an unambiguous ordering of transactions. Generally utilized CM contains Proof of Work(PoW), Proof of Satke(PoS), Practical Byzantine Fault Tolerance(PBFT) and the complete analysis of security and performance of consensuses. The blockchain is a standard tool to track transactions when the blockchain native transaction is effective in panoptic situations. The blockchain native assets and resources would inspire data revolution. This improvement would considerably increase the security and efficiency of the scheme. It allows the Blockchain as a Service (BaaS), Infrastructure as a Service (IaaS) based on feasibility and the framework could be ordered in a dispersed manner by permitting the framework transactions without additional centralized management. Then, this system incubates the BaaI that gives a solid tool chain for settlement among consumer, producer and trader as displayed in Fig. 2.

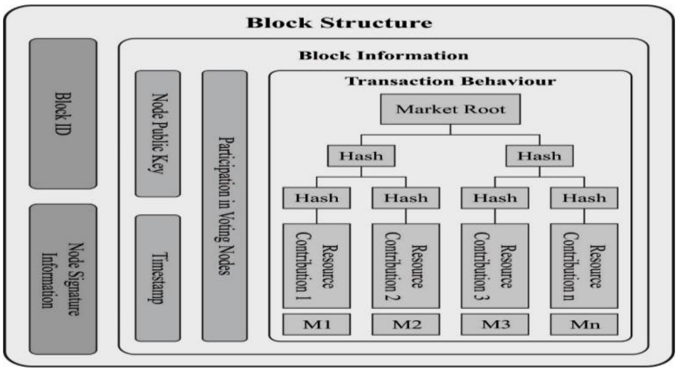

Fig. 2. Blockchain structure

C. Algorithmic Design of QO-SRO Technique

In the SRO technique, the human position equals the solution to the optimization problem, and the number of clues reaches the location that reflects the objective function for this solution.. A member of a team gathers clue data during the investigation. However, even though there are few clues left if you find ideal hints in a different location [19], they are used to improve the search process. Here, the left hints location is stored (matrix M), and the human position is preserved (matrix L) for future reference, in this technique (matrix X). Matrix M has the same dimensions as matrix X. They are ND matrices, where D is the dimension of the problem and N is the number of people. The clues matrix is a list of all the locations where clues have been obtained. Every time a human goes through a search phase, the matrix M and C are improved.:

$$C = \begin{Bmatrix} X \\ M \end{Bmatrix} = \begin{Bmatrix} X_{11} & \cdots & X_{1D} \\ \vdots & \ddots & \vdots \\ X_{N1} & \cdots & X_{ND} \\ M_{11} & \cdots & M_{1D} \\ \vdots & \ddots & \vdots \\ M_{N1} & \cdots & M_{ND} \end{Bmatrix}, \tag{1}$$

In which M and X denotes memory and human position matrix respectively and X_{N1} represents location of initial dimension for the N^{th} human. As well, M_{1D} represents position of D^{th} dimension for the initial memory. Assume the depiction provided in the early subsection and an arbitrary clue amongst attained clues, the searching direction could be determined by:

$$\mathrm{SD}_i = (X_i - C_k)\,, k \neq i, \tag{2}$$

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Here, X_i, C_k *and* SD_i denotes location of j^{th} human, the location of k^{th} clue and searching direction of j^{th} human, respectively. k signifies arbitrary integer number range between 1 and $2N$ and selected in a way $k \neq i$. It is essential for highlighting that human generally seek in this manner that each desired region is searched and few repetitive positions are ignored. Hence, the searching is to be created in such a manner where the motion of group members to each other is constrained. Hence, every dimension of X_j cannot be altered by motion in the direction of Eq. (2). To employ this limitation, the binomial crossover operator is employed. If the given clue is higher when compared to the clue interrelated to the existing location, a region near SD_j direction and the location of that searched clue then, the search procedure will undergo near the existing position beside the SD_i direction. At last, the succeeding equations are used for the social stage:

$$X'_{i,j} = \begin{cases} \begin{cases} C_{k,j} + \mathrm{r}1 \times (X_{i,j} - C_{k,j}), & if\ f(C_k) >, f(X_i) \\ X_{\mathrm{i},j} + \mathrm{r}1 \times (X_{i,j} - C_{k,j}), & otherwise \end{cases} & if\ r2 < \mathrm{SE or}\ j = j_{\mathrm{rand}}, \\ & otherwise, (\mathrm{J} = 1, \dots \mathrm{D}) \end{cases} \quad (3)$$

Here, $X'_{i,j}$ denotes the new position of j^{th} dimension of i^{th}human, $C_{k,j}$ indicates position of j^{th} dimension for the k^{th} attained clue, $f(C_k)$ and $f(X_i)$ signifies the values of objective function for the solution C_k and X_i, respectively; $r\mathrm{l}$ and $r2$ represents random number, j_{rand} denotes arbitrary number range of integer from 1to D. The $X'_{i,j}$ is diverse from $X_{i,j}$ and SE is a method variable that ranges from zero & one. Eq. (3) is used for attaining a new novel location of j^{th} human in each dimensions.

In the subsequent stage, humans seek their current location using the same notion as in the social stage. In the separation step, each Xi dimension was modified. The $\mathrm{j^{th}}$ human's new location is obtained by:

$$X'_i = X_j + r3 \times (C_k - C_m)\,, i \neq k \neq m, \quad (4)$$

Whereas k & m represent random integer numbers varied from 1 & $2N$. To avoid motion beside other clues, k and m are chosen that $i \neq k \neq m$. $r3$ denotes an arbitrary amount using distribution range from zero and one. Each metaheuristic solution must be placed in the solution space, and if they are outside the allowed solution space, they must be redone. In case the human is far from the solution space. The following formulae are used to move the new location.

$$X'_{i,j} = \begin{cases} \dfrac{(X_{\mathrm{i},j} + X_j^{\max})}{2}, & if\ X'_{i,j} > x_j^{max}, \\ \dfrac{(X_{i,j} + X_j^{\min})}{2}, & if\ X'_{i,j} < x_j^{min}, \end{cases} \quad (j = 1, \dots, D) \quad (5)$$

Algorithm 1: Pseudocode of the SRO.

Begin:
Random parameter initialization and uniform population distribution $[X_j^{\min}, X_j^{\max}]$, $j = 1, \dots, \mathrm{D}$
Arrange the solutions in a reducing way and determine the optimal position (Xbest)
Utilize the initial half of the arranged solution for X and rest of them for M
Represent the algorithmic parameter (SE, MU) and set $\mathrm{USN_i} = 0$ where $i = 1, \dots, \mathrm{N}$
While termination condition is unsatisfied do
  For $i = 1$ to N do
    Social stage
$$\mathrm{C} = \begin{Bmatrix} X \\ M \end{Bmatrix}$$
      $\mathrm{SD}_j = (X_j - \mathrm{C}_k)$, k is arbitrarily chosen in such a way that $i \neq k$
      $j_{\mathrm{rand}} = \mathrm{rand\ int}\ [1, D]$
      $r1 = \mathrm{rand}\ [-1, 1]$
      For $j = 1$ to D do
$$X'_{i,j} = \left\{ \begin{cases} \mathrm{C_{k,j}} + \mathrm{r1} \times \mathrm{SD_{i,j}}, & if\ f(C_k) > f(X_i), \\ \mathrm{X_{i,j}} + \mathrm{r1} \times \mathrm{SD_{i,j}}, & otherwise \end{cases} \right.$$
$$X'_{i,j} = \begin{cases} \dfrac{(X_{i,j} + X_j^{\max})}{2}, & \text{if } X'_{i,j} > X_j^{\max} \\ \dfrac{(X_{i,j} + X_j^{\min})}{2}, & \text{if } X'_{i,j} < X_j^{\min} \end{cases}$$
      End For
$$M_n = \begin{cases} X_i, & \text{if } f(X'_i) > f(X_i), \\ M_n, & \text{otherwise} \end{cases}$$
$$X_i = \begin{cases} X'_i, \text{if } f(X'_i) > f(X_i) \\ X_i, \text{otherwise} \end{cases}$$
$$\mathrm{USN}_i = \begin{cases} \mathrm{USN}_i + 1, \text{if} f(X'_i) < f(X_i) \\ 0, \text{otherwise} \end{cases}$$
Individual stage
$$\mathrm{C} = \begin{Bmatrix} X \\ M \end{Bmatrix}$$
      $X'_i = X_i + \mathrm{rand}\ [0, 1] \times (\mathrm{C}_k - \mathrm{C}_m)$, k and m are randomly selected in such a way that $i \neq k \neq m$
      For $j = \mathrm{l}$ to D do
$$X'_{i,j} = \begin{cases} \dfrac{(X_{i,j} + X_j^{\max})}{2}, & \text{if } X'_{i,j} > X_j^{\max} \\ \dfrac{(X_{i,j} + X_j^{\min})}{2}, & \text{if } X'_{i,j} > X_j^{\min} \end{cases}$$
      End For
$$M_n = \begin{cases} X_i, & \text{if } f(X'_i) > f(X_i), \\ M_n, & \text{otherwise} \end{cases} n\ randomly\ selected$$
$$\mathrm{X}_i = \begin{cases} X_i \text{ if } f(X'_j) > f(X_i) \\ X_i \text{ otherwise} \end{cases}$$
$$\mathrm{USN}_i = \begin{cases} \mathrm{USN}_i + 1, & \text{if } f(X'_i) < f(X_i) \\ 0, & \text{otherwise} \end{cases}$$
      If $\mathrm{USN}_i > \mathrm{MU}$ do
        For $j = \mathrm{l}$ to D do
          $X_{i,j} = X_j^{\min} + \mathrm{rand}\ [0, 1] \times (X_j^{max} - X_j^{\min})$
        End for
$$\mathrm{USN}_i = 0$$
      End If
  End for
  Determine the present optimal position and update Xbest
End while
Return Xbest
End

Then, in every iteration, the group member would search based on the above mentioned two stages namely individual stage and social stage. After all phases, an objective function in location $X'_i(f(X'_i))$ are higher compared to prior one $(f\ (X_i))$, the early location (X_i) will be saved in the location of memory matrix (M) by Eq. (6) and this location will be adapted as a new novel location denoted by Eq. (7). Or else, this memory location is left and it is not upgraded and is given by,

$$M_n = \begin{cases} X_{\mathrm{i}}, & if\ f\ (X_i') >, f(X_i) \\ M_n, & \text{otherwise} \end{cases} \quad (6)$$

$$X_i = \begin{cases} X_{\mathrm{i}}', & if\ f\ (X_i') >, f(X_i) \\ X_i, & \text{otherwise,} \end{cases} \quad (7)$$

M_n specifies the memory matrix's location of the n^{th} clue, which can be any integer number between 1 and N. As a result, the variety of ways and methods for finding a global best solution are enhanced by this type of memory boost. Everyone has a zero chance of getting into the United States Navy (US Navy). USN is fixed at zero for this individual if it discovers an optimal hint in the first or second stage of the search procedure, otherwise it would rise by one point and is given as zero.

$$\mathrm{USN}_i = \begin{cases} \mathrm{USN}_i + 1, & if\ f(X_i') <, f(X_j) \\ 0, & or\ else \end{cases} \quad (8)$$

The arbitrary location in the searching space is denoted by Eq. (9) and USN_i is fixed to zero:

$$X_{i,j} = X_j^{\min} + r4 \times (X_j^{\max} - X_j^{\min}) j = 1, \ldots, \mathrm{D}, (9)$$

where $r4$ denotes a random number and is different for all dimensions. Tizhoosh presented the concept of Oppositional Based Learning (OBL) which involves opposite numbers have maximum possibility of attaining a solution compared to arbitrary numbers. The integration of OBL technique results in enhanced performance and improved convergence rate. The QOBL technique makes use of quasi-opposite numbers effectually over the opposite numbers in the detection of global optimum result. Consider χ be a real number in I-dimension area. Assume the opposite and quasi-opposite numbers x^o and x^{qo} (of x) can be represented as follows:

$$x^0 = a + b - x \quad (10)$$

where $x \in \mathbb{R}$ and $x \in b]$.

$$x^{qo} = rand\left(\frac{a+b}{2}, x^0\right) \quad (11)$$

Consider $X(x_1, x_2, \ldots, x_n)$ as a point in n-dimension area. Consider the opposite point, $X^o(x_1^o, x_2^o, \ldots, x_n^0)$ and quasi opposite point, $X^{qo}(x_1^{qo}, x_2^{qo}, \ldots, x_n^{qo})$ and are represented as follows.

$$x_i^o = a_i + b_i - x_i \quad (12)$$

where $x_i \in \mathbb{R}$ and $x_i \in [a_i, b_i] \forall i \in 1,2, \ldots, n$.

$$x_i^{qo} = rand\left(\frac{a_i + b_i}{2}, x_i^o\right) \quad (13)$$

QOBL is applied to the SRO for initializing the population and generation jumping. It produces a set of optimal solutions for the initial population [20]. Algorithm 2 describes the QOBL pseudocode for the new population.

Algorithm 2: Pseudocode of QOBL

for $i = 1: Eco_{size}$
  for $j = 1: D$
    $X_{i,j}^o = lb_j + up_j - X_{i,j}$;
    $C_{i,j} = \frac{lb_j + up_j}{2}$;
    if $(X_{i,j} < C_{i,j})$
      $X_{i,j}^{qo} = C_{i,j} + (X_{i,j}^o - C_{i,j}) \times rand$;
    else
      $X_{i,j}^{qo} = X_{i,j}^o + (C_{i,j} - X_{i,j}^o) \times rand$;
    end
  end
end

D. Application of QO-SRO Technique for Resource Allocation

At this stage, the QO-SRO technique is employed for the optimum allocation of resources. In the 6G enabled IoE platform, it is considered that every resource node should interact with one another. Thus, for every solution to the resource allocation problem, the overall cost of network transmissions must be evaluated. It is considered that all resources should transmit a message to every resource. The overall cost of the messages is estimated and considered as the objective function. The overall cost is represented as T_c. The projected method attempts to reduce T_c, as estimated below,

$$T_c = \frac{\Sigma_{j=1}^{|V_g|}(d_j^r \times d^g)}{p} \quad (14)$$

where $|V_g|$ denotes the overall number of gateways, d_j^r indicates the overall cost of transmitting data among jth gateway and every resource related to it and d^g represents the overall cost of communications among gateways that is estimated by Eq. (15). Here, $(d_j^r \times d^g)$ denotes the optimal equation to calculate maximum value of the transmission cost (objective function). It is stated that the objective function value is assumed to be minimalized [21]. In other words, they must multiply d_j^r with d^g, since it is considered that every single gateway might transmit a message to every single resources. Hence, by multiplying these two values, they could estimate the overall transmission cost for every resource of a gateway. When they estimate this value for every gateway, they will have numerator part of T_c fraction.

$$d^g = \sum_{i=1}^{|V_g|} \sum_{\substack{j=1 \\ j \neq 1}}^{|V_g|} l_{ij} \quad (15)$$

where l_{ij} denotes the cost of transmission between gateways i and j. d_j^r is estimated by Eq. (16).

$$d_j^r = \sum_{k=1}^{|v_g^j|} \varepsilon_{jk} \quad (16)$$

whereas ε_{jk} indicates the cost of transmission among jth gateway and every resource linked to it. $|v_g^j|$ represents the number of linked resources to gateway j. For gateways containing resources higher than $\frac{|V_r|}{|V_g|}$, $p_i = 0$ increases the value of T_c. Eq. (17) estimates p.

$$P = 1 + \sum_{i=1}^{|V_g|} P_i \quad (17)$$

where $|V_g|$ is the total gateways and pi is the penalty of each gateway which is calculated using Eq. (18)

$$P_j = \begin{cases} 1 & if\, g_i^t \le \varepsilon \dfrac{|V_r|}{|V_g|} \\ 0 & if\, g_i^t > \varepsilon \dfrac{|V_r|}{|V_g|} \end{cases} \quad (18)$$

where g_i^t is the number of resources assigned to gateway i, $|V_r|$ is the number of resources and ε is the constant number.

E. Graph Clustering Process

The quality of the initial population plays a considerable role in the overall performance of the QO-SRO algorithm. Therefore, a graph clustering technique has been introduced for increasing the initial quality of the solution. By using the QO-SRO algorithm, the solution with maximum optimization ability can generate high quality and effective solutions. For illustration, consider a set of 3 gateways and 15 resources. Here, the gateways are scanned sequentially and in every round, the closer resource is allotted to the gateway. This process gets repeated until the exhaustion of all resources. The distance between the nodes is determined depending upon the communication cost. At every round, the closer resources can be treated for every individual node. The outcome of the technique gets varied based on the order of chosen gateways and various solutions are generated for the issue. The idea of graph clustering is that the penalty of the generated solutions is equivalent to 0 since it completely observes the load balancing.

Algorithm 3: Pseudo code of Graph Clustering

```
Input: Gateway and Resource Communication Cost Matrix
Output: Solution for chosen resources = { };
New= zero array in length |G| + |R|;
while (chosen Resources ≠ Resources) {
    for every Gateway like G_i {
        Determine R_j as a Resource with least cost for G_I ;
        allocate R_I to G_I;
    } }
set Gateway arbitrarily;
return new;
```

IV. Performance Validation

This section validates the performance of the proposed model against the existing state of art techniques in terms of different measures. Fig. 3 shows the convergence analysis of the MWBA-RAT technique in terms of system average cost. The experimental results reported that the MWBA-RAT technique has accomplished the maximum results with the minimal system average cost. It is also noted that the system average cost gets reduced with decrease in file size. For instance, under 5 iterations, the MWBA-RAT technique has obtained a reduced system average cost of 4.767, 4.777 and 4.906 on the file sizes of 500kb, 800kb and 1000kb respectively. In addition to this, under 8 iterations, the MWBA-RAT approach has gained a lesser system average cost of 4.311, 4.344 and 4.512 on the file sizes of 500kb, 800kb and 1000kb respectively.

A. Simulation Setup

We utilized an Intel i7 CPU @ 3.40 GHz machine with 16GB RAM and the Python platform to implement this task in the simulation setup. DRL-based approaches are implemented using GYM OpenAI, an open-source python package that is commonly utilized for this purpose. There are 100 IoE devices and 8 edge servers scattered evenly over the network. For the IoE device and the edge server, we set the clock frequency to four. Furthermore, we assumed a bandwidth of 5, a power of 5.

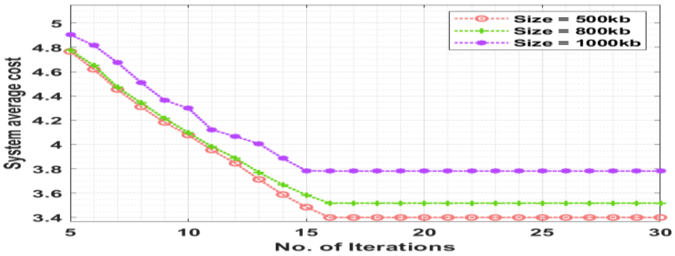

Fig. 3. Result analysis of MWBA-RAT model

TABLE I

COMPARATIVE ANALYSIS OF MWBA-RAT TECHNIQUE UNDER VARYING COMPUTATIONAL RESOURCES

System average cost				
Computational Resources	**MWBA-RAT**	**ECORA**	**TCCO**	**Local Computation**
1000	3.747	3.897	5.031	5.569
2000	3.705	3.875	4.546	5.569
3000	3.666	3.860	4.044	5.569
4000	3.624	3.747	3.747	5.569
5000	3.605	3.629	3.629	5.569
6000	3.605	3.620	3.620	5.569
7000	3.605	3.620	3.620	5.569
8000	3.605	3.620	3.620	5.569

To ensure the enhanced outcome of the MWBA-RAT technique, a detailed system average cost analysis is made under varying number of computational resources in Table 1. The experimental values reported that the MWBA-RAT technique has accomplished superior results with the minimum system average cost. For instance, with 1000 computational resources, the MWBA-RAT technique has obtained a least system average cost of 3.747 whereas the ECORA, TCCO and local computation techniques have attained a higher system average cost of 3.897, 5.031 and 5.569 respectively.

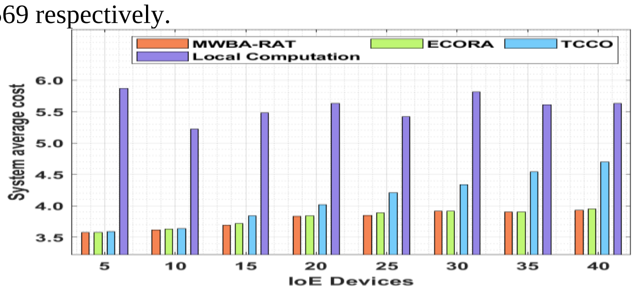

Fig. 4. System average cost analysis of MWBA-RAT model under IoE devices

To ensure the enhanced outcome of the MWBA-RAT technique, a detailed system average cost analysis is made under varying number of IoE devices in Fig. 4. The experimental values reported that the MWBA-RAT algorithm has accomplished superior results with the minimum system average cost. For instance, with 5 IoE devices, the MWBA-RAT technique has obtained a minimal system average cost of 3.578 whereas the ECORA, TCCO and local computation methods have attained a higher system average cost of 3.580, 3.590 and 5.870 respectively. In addition to this, with 40 IoE devices, the MWBA-RAT technique has obtained a least system average cost of 3.932 whereas the ECORA, TCCO and local computation methods have gained the system average cost of 3.950, 4.700 and 5.630 respectively. Eventually, a system average cost analysis of the BA-RAT manner with existing methods takes place in Table 2. From the attained outcomes, it is exhibited that the BA-RAT technique has gained effective outcome with the lower system average cost values under different required computation resources. For instance, under 500 required computation resources, a minimal system average cost of 2.63 is offered by the MWBA-RAT technique whereas the local computation, TCCO and ECORA techniques have obtained a higher system average cost of 2.78, 2.78 and 2.66 respectively.

TABLE II

COMPARATIVE ANALYSIS OF MWBA-RAT TECHNIQUE UNDER VARYING REQUIRES COMPUTATION RESOURCES

System average cost				
Required computation resources	**Local computation**	**TCCO**	**ECORA**	**MWBA-RAT**
500	2.78	2.78	2.66	2.55
600	3.33	3.30	3.25	3.09
700	3.93	3.59	3.51	3.37
800	4.45	3.69	3.67	3.56
900	5.05	3.72	3.70	3.61
1000	5.57	4.14	3.82	3.50
1100	6.12	4.37	3.85	3.62
1200	6.75	4.76	3.90	3.71
1300	7.30	5.13	3.93	3.80
1400	7.79	5.52	4.06	3.90
1500	8.42	6.04	4.01	3.78
1600	8.94	6.38	4.24	3.67
1700	9.52	6.85	4.03	3.62
1800	10.04	7.40	4.27	4.01

At last, under 100 nodes, minimum power consumption of 0.878mW is attained by the MWBA-RAT technique whereas the conventional, TCCO and ECORA methods have obtained a maximum power consumption of 4.310mW, 3.830mW and 1.432mW respectively. From the above-mentioned results analysis, it is apparent that the MWBA-RAT technique is found to be an appropriate tool for resource allocation in the 6G IoE environment.

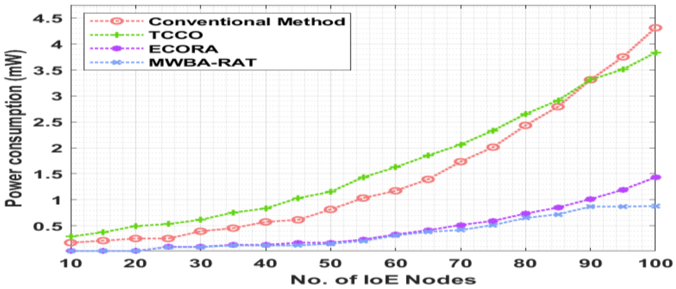

Fig. 5. Power utilization analysis of MWBA-RAT model

Finally, a power consumption analysis of the MWBA-RAT model with existing methods takes place in Fig. 5. From the obtained results, it is demonstrated that the MWBA-RAT technique has attained the effective outcome with lower power consumption values under different nodes. For instance, under 10 nodes, minimum power consumption of 0.012mW is attained (using Xilinx Power Estimator-XPE) by the MWBA-RAT technique whereas the conventional method, TCCO and ECORA techniques have obtained a higher power consumption of 0.173mW, 0.293mW and 0.013mW respectively.

V. CONCLUSION

This paper has developed an effective MWBA-RAT for cybertwin driven 6G on IoE environment. Besides, the blockchain concept is involved in the 6G enabled network for monitoring, managing and sharing resources effectively. The proposed MWBA-RAT technique designs a new QO-SRO algorithm for the optimal resource allocation process. In addition, the MWBA-RAT technique derives an objective function using different parameters to reduce the overall communication cost between the resources and gateways. MWBA-RAT offered minimal system average cost of 2.63 as well as minimum power consumption of 0.012mW than existing methods. Moreover, a graph clustering concept is introduced to boost the quality of the initial population and that enhances the overall performance of the QO-SRO algorithm. To validate the enhanced outcomes of the MWBA-RAT technique, an extensive set of experimental analysis is carried out. If prices and power consumption are lowered, the partial reconfiguration characteristic of a MWBA-RAT may play an important role in the development of sensor nodes in the future. Furthermore, power consumption and cost study on research nodes is required in order to adequately compare their capabilities and prospects with commercial nodes in 6G.

REFERENCES

[1] Yu, Q., Ren, J., Fu, Y., Li, Y. and Zhang, W., 2019. CybertWin: An origin of next generation network architecture. IEEE Wireless Communications, 26(6), pp.111-117.

[2] Abdelwahab, S., Hamdaoui, B., Guizani, M. and Rayes, A., 2014. Enabling smart cloud services through remote sensing: An internet of everything enabler. IEEE Internet of Things Journal, 1(3), pp.276-288.

[3] Mondal, A., Bhattacharjee, S. and Chakraborty, S., 2017, October. Viscous: An end to end protocol for ubiquitous

communication over internet of everything. In 2017 IEEE 42nd Conference on Local Computer Networks (LCN) (pp. 312-320). IEEE.

[4] Saad, W., Bennis, M. and Chen, M., 2019. A vision of 6G wireless systems: Applications, trends, technologies and open research problems. IEEE network, 34(3), pp.134-142.

[5] Tariq, F., Khandaker, M.R., Wong, K.K., Imran, M.A., Bennis, M. and Debbah, M., 2020. A speculative study on 6G. IEEE Wireless Communications, 27(4), pp.118-125.

[6] Dai, Y., Xu, D., Maharjan, S., Chen, Z., He, Q. and Zhang, Y., 2019. Blockchain and deep reinforcement learning empowered intelligent 5G beyond. IEEE Network, 33(3), pp.10-17.

[7] Amir Shabani, Behrouz Asgarian, Saeed Asil Gharebaghi, Miguel A. Salido, Adriana Giret, "A New Optimization Algorithm Based on Search and Rescue Operations", Mathematical Problems in Engineering, vol. 2019,https://doi.org/10.1155/2019/2482543

[8] Weiss, M.B., Werbach, K., Sicker, D.C. and Bastidas, C.E.C., 2019. On the application of blockchains to spectrum management. IEEE Transactions on Cognitive Communications and Networking, 5(2), pp.193-205.

[9] Mukherjee, A., Goswami, P., Khan, M.A., Manman, L., Yang, L. and Pillai, P., 2020. Energy Efficient Resource Allocation strategy in Massive IoT for Industrial 6G Applications. IEEE Internet of Things Journal.

[10] Wang, P., Xu, N., Sun, W., Wang, G. and Zhang, Y., 2021, March. Distributed Incentives and Digital Twin for Resource Allocation in air-assisted Internet of Vehicles. In 2021 IEEE Wireless Communications and Networking Conference (WCNC) (pp. 1-6). IEEE.

[11] Li, Q., Yao, H., Mai, T., Jiang, C. and Zhang, Y., 2019. Reinforcement-Learning-and Belief-Learning-Based Double Auction Mechanism for Edge Computing Resource Allocation. IEEE Internet of Things Journal, 7(7), pp.5976-5985.

[12] Hu, H., Wang, Q., Hu, R.Q. and Zhu, H., 2021. Mobility-Aware Offloading and Resource Allocation in an MEC-enabled IoT Network with Energy Harvesting. IEEE Internet of Things Journal.

[13] Xu, H., Klaine, P.V., Onireti, O., Cao, B., Imran, M. and Zhang, L., 2020. Blockchain-enabled resource management and sharing for 6G communications. Digital Communications and Networks, 6(3), pp.261-269.

[14] Yu, Q., Zhou, H., Chen, J., Li, Y., Jing, J., Zhao, J.J., Qian, B. and Wang, J., 2019. A fully-decoupled RAN architecture for 6G inspired by neurotransmission. Journal of Communications and Information Networks, 4(4), pp.15-23.

[15] Jamil, S.U., Khan, M.A. and ur Rehman, S., 2020, November. Intelligent Task Off-Loading and RA for 6G Smart City Environment. In 2020 IEEE 45th Conference on Local Computer Networks (LCN) (pp. 441-444). IEEE.

[16] Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J. and Wu, K., 2020. Artificial-Intelligence-Enabled Intelligent 6G Networks. IEEE Network, 34(6), pp.272-280.

[17] S. K. S. Tyagi and Q. Boyang, "An Intelligent Internet of Things aided Financial Crisis Prediction Model in FinTech," in IEEE Internet of Things Journal, doi: 10.1109/JIOT.2021.3088753.

[18] S. K. Sah Tyagi, Q. Boyang, A. Mukherjee and D. K. Jain, "Computing Resource Optimization of Big Data in Optical Cloud Radio Access Networked IIoT," in IEEE Transactions on Industrial Informatics, doi: 10.1109/TII.2021.3055818.

[19] A. Mukherjee, S. R. Pokhrel and K. K. Hiran, "An Intelligent and Optimal Resource Allocation Approach in Sensor Networks for Smart Agri-IoT," in IEEE Sensors Journal, doi: 10.1109/JSEN.2020.3020889.

[20] P. Goswami, A. Mukherjee, M. Maiti, S. K. S. Tyagi and L. Yang, "A Neural Network Based Optimal Resource Allocation Method for Secure IIoT Network," in IEEE Internet of Things Journal, doi: 10.1109/JIOT.2021.3084636.

[21] Sangaiah, A.K., Hosseinabadi, A.A.R., Shareh, M.B., Bozorgi Rad, S.Y., Zolfagharian, A. and Chilamkurti, N., 2020. IoT resource allocation and optimization based on heuristic algorithm. Sensors, 20(2), p.539.

[22] S. K. S. Tyagi and Q. Boyang, "An Intelligent Internet of Things aided Financial Crisis Prediction Model in FinTech," in IEEE Internet of Things Journal, doi: 10.1109/JIOT.2021.3088753.

[23] S. K. Sah Tyagi, Q. Boyang, A. Mukherjee and D. K. Jain, " Computing Resource Optimization Computing Resource Optimization Computing Resource Optimization of Big Data in Optical Cloud Radio Access Networked IIoT," in IEEE Transactions on Industrial Informatics, doi: 10.1109/TII.2021.3055818.

[24] Adhikari, Mainak & Munusamy, Ambigavathi & Kumar, Neeraj & Srirama, Satish. (2021). Cybertwin-driven Resource Provisioning for IoE Applications at 6G-enabled Edge Networks. IEEE Transactions on Industrial Informatics. PP. 1-1. 10.1109/TII.2021.3096672.

[25] Hao Xu, Paulo Valente Klaine, Oluwakayode Onireti, Bin Cao, Muhammad Imran, Lei Zhang, Blockchain-enabled resource management and sharing for 6G communications, Digital Communications and Networks,Vol.6, No.3, pp-261-269,2020.

[26] Q. Yu, J. Ren, H. Zhou, and W. Zhang, “A cybertwin based network architecture for 6g,” in 2020 2nd 6G Wireless Summit (6G SUMMIT). IEEE, 2020, pp. 1–5.