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Enhanced resource allocation in mobile edge computing using reinforcement learning based MOACO algorithm for IIOT

S. Vimal [a], Manju Khari [b], Nilanjan Dey [c], Rubén González Crespo [d,*], Y. Harold Robinson [e]

[a] Department of IT, National Engineering College, Kovilpatti, Tamil Nadu, India
[b] Department of CSE, Ambedkar Institute of Advanced Communication Technologies & Research, Delhi, India
[c] Department of IT, Techno International New Town (Formerly known as Techno India College of Technology), Rajarhat, Kolkata, India
[d] Faculty of Engineering, Deputy Director and Professor, Department of Computer Science, International University of La Rioja, Logroño, La Rioja, Spain
[e] School of Information Technology and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India

A R T I C L E I N F O

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A B S T R A C T

The Mobile networks deploy and offers a multiaspective approach for various resource allocation paradigms and the service based options in the computing segments with its implication in the Industrial Internet of Things (IIOT) and the virtual reality. The Mobile edge computing (MEC) paradigm runs the virtual source with the edge communication between data terminals and the execution in the core network with a high pressure load. The demand to meet all the customer requirements is a better way for planning the execution with the support of cognitive agent. The user data with its behavioral approach is clubbed together to fulfill the service type for IIOT. The swarm intelligence based and reinforcement learning techniques provide a neural caching for the memory within the task execution, the prediction provides the caching strategy and cache business that delay the execution. The factors affecting this delay are predicted with mobile edge computing resources and to assess the performance in the neighboring user equipment. The effectiveness builds a cognitive agent model to assess the resource allocation and the communication network is established to enhance the quality of service. The Reinforcement Learning techniques Multi Objective Ant Colony Optimization (MOACO) algorithms has been applied to deal with the accurate resource allocation between the end users in the way of creating the cost mapping tables creations and optimal allocation in MEC.

1. Introduction

The IoT based industry has enormous growth in urban planning with the foundation in the development of an industry for chips, Microcontroller kit, electronic gadgets and telecommunication systems forming a shape in the industrial segments. The attacks and vulnerable issues are the main concern in the IoT with the network breach. The vulnerability can be suspected with Intrusion Detection System that can encounter the anomalies with the reliable services of IoT applications. The various deep learning modelshave been proposed with the modeling scheme of learning and data from sensors form the structure of the setup. The Internet for sharing of communication and contents with a global communication established the objects connected and smart devices with the support of International Data Corporation (IDC) [1]. IoT paved the part of smart city with the support in optimization and enhancing the public services in a smarter way leading to smart transportation, smart parking, smart hospitalization and Urban development [2].

In Mobile edge computing based cloud setup IoT data gathering includes all data to be gathered from the remote server. The remote processing has been done in an emerging area with the bandwidth usage with the increased speed [3]. The fog computing and data processing have been done from the remote servers that increases the benefits of the data size and the low latency simulation in the filtered server data. The edge computing offers a very big offloading and the storage accuracy have been enriched with the privacy preservation in a smart way of IoT prediction [4].

In the Modern era people are getting connected to the real world through the online sector having an integrated circuit technology and wireless communication have been established with the signal acquisition and data preprocessing with the wireless communication capabilities. The IoT has been divided into three layers such as perception layer, network layer and application layer [5]. The Perception layer deals with the end devices and tail nodes [6]. The End devices monitor a progressive approach in elaborating the segment with the layer channel in the devices to support the RFID tags, Cameras and GPS devices. The sensors are being used by the parameters to form a environment in the sensing layer with the information from the

* Corresponding author.
E-mail addresses: svimalphd@gmail.com (S. Vimal), manjukhari@yahoo.co.in (M. Khari), neelanjandey@gmail.com (N. Dey), ruben.gonzalez@unir.net (R.G. Crespo), yhrobinphd@gmail.com (Y.H. Robinson).

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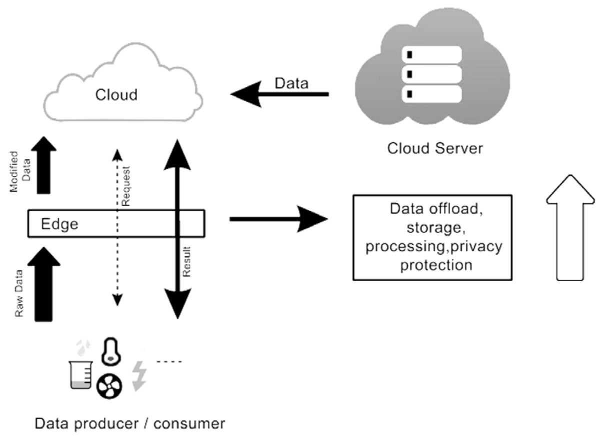

Fig. 1. Mobile edge computing paradigm.

physical world with analog-to-digital conversion [7]. The second phase of the IoT deals with the network layer which connects the sensing layer to the application layer that includes mobile communication and fixed communication using internet and private communication networks. The network layer includes various functionalities includes optical fiber communication, security access and satellite access [8]. The network layer deals with the applications in the application layer, Human Computer Interaction (HCI) are one of the biggest applications that retrieve the data from the valuable environment. The end devices include the IoT data retrieval from the environment with a information security and business domain. The security includes the analyses of data, compute, store and various technologies. The transmission of data communication is done between the end devices and sensors.

The traditional IoT has the senor analysis of the data in the cloud based server with the process of identifying the key areas in the approach with the similar scalability issues and with the support of the network it has a refined data in the scalability issues in the refined condition having a separate module of the implementation with the draft of assuming the condition in the prescribed section and the technique to be assumed of the performance enhancement in the assumed transcription.

The technique of the IoT has to process the information with the offered needs in the environment with the multi interface needs in the process of adding the WSN networks to as simulate the control in the cellular base station. The WSN has the need based approach in the edge server having a cellular network in the fringed sector any time with the control plane offering a data based control in the needs of the network. The data sent to the network in the WSN has the edge monitoring has to be accomplished with the cellular network coverage in the prescribed assumptions [9]. The edge server is one of the opted cellular base stations in the network which consists of the connections of the IoT device with the data volatility as shown in Fig. 1.

The Edge computing supports the traditional cloud computing and fog computing with a desire to focus on the recent articles that investigate various fog computing with different IoT applications [10]. The IoT challenges are resolved using the edge connecting devices and hence the data segment may be achieved during the various IoT applications in the future research directions in the IoT metrics. The more paradigm shift will be done in an analysis in the future of IoT with various segments in the metrics for evaluating the future research analysis on the issues spread over in the deliverables of the fog based IoT mentors.

The most major problem is the creation of the adaptive mechanism in IIOT with MEC in resource allocation. The cognitive agent is an intelligent mechanism that supports the alternative sources for the resources in IoT with two terminologies that high performance should be guaranteed with the energy should be reserved with the strategy with the resource allocation. The examinable performance can be monitored with the response time, transmission time or security level. The prestored mapping is a cost effective approach to mitigate the energy optimization in the input task and the accurate energy prediction is retained within the approachable survey of contents. The mapping has the available computer node based on the data types and the data headers.

Reinforcement Learning (RL) is one of the predominant approaches which predict the optimal control to enhance the performance with the support of the connected devices.

The energy supply is assumed to be of in the hardware controls, network availability with its usage, congestion, jamming and spoofing in the network. The edge computing is also performed with the predefined devices based on the available feedback criteria are the two major criteria analysis engaged in the analysis of the secular environment and the feature based edge computing is also a developing paradigm [11]. The RL mechanism outlines the impact on the extended smart work in the quality of feedback mechanism (QoF). The QoF establishes the feedback mechanism with the dynamic cost mapping table and the computation cost is associated with the input mask that has been determined with the estimation of the user side in the performance for the value of the work in the AI intelligence. The Low Cost system design set up enables the mapping process in an elaborate way to access the RL algorithm for the process of setting up the table with the values in the current state. The current state has been monitored based on the quality of feedback derived from RL. The low cost establishes a state path allocation that establishes a network in allocating the resources with the associated values.

The dynamic RL based mechanism is the efficient resource allocation, since the network operator allocates the necessary resources based on the traffic changes. Besides it is a big process and cannot estimate the optimization in establishing the resource where it cannot be estimated with the single management process or single entity. The network may offer multiple entities sharing the resources in multiple paradigms; this dynamic process includes a very high computational cost. In such cases MOACO may support the optimal solution in considering the future real-world scenario.

Hence, the cognitive agent is designed to dynamically design a decision based on the task allocated within the surrounding actions, task and current state. The proposed RL based resource allocation in IoT is done with the data capture from dynamic heterogeneous data sources. The proposed approach for resource utilization has the ability to address the range of RL in terms of energy efficiency and throughput maximization than other mechanisms. The dynamic RL is also the best option for the device to device communication for the LTE network in terms of channel allocation approach too.

The main contributions of the work includes,

1. The paper impacts a novel approach to provide a RL solution to the resource allocation using IIoT. The dynamic programming along with the MOACO algorithm proposes a strategic allocation in the dynamic environment to address the challenge in the performance enhancement.

2. The mapping tables are used with the QoF for analyzing the effective performance and the optimal resource allocation in the periodical set up. The feedback, action and reward are used to outline the value function in RL with the level of QoF rewards and the action point monitoring in the communication networks.

3. The QoS is enabled with the cognitive ability to provide a collaboration of the resource for the interaction of edge computing users and joint optimization between the caching resources. The network resources are assumed to be on the IIoT utilization with the concurrent resources.

The rest of the paper deal is organized as follows, In Section 2 Literature analysis has been addressed. Section 3 deal with the Proposed design model and Cognitive action based resource management, Section 4 deal with the Low cost system design using the table Value using

MOACO is discussed, Section 5 deal with the Dynamic Reinforcement Learning based Resource Allocation and task execution with efficient utilization. Section 6 deals with RL-MOACO edge computing resource allocation mechanism with metaheuristic algorithm to estimate the optimal solution. Section 7 showcase the experimental setup and result with concluding remarks are described in Section 8.

2. Related work

The RL mechanism provides a summarized view of mobile edge computing using the collaboration between mobile devices and an edge cloud is assumed for a cloud prediction with the amount of data transmitted in the cloud with the battery powered IoT devices and the general assumption has been applied for the networking devices to communicate effectively the energy consumption in the edge devices in the droplet framework for the energy management consideration. Faizal jaman et al. the reward strategy promotes the participating mobile devices to be communicated in the cloud service [12].

Moreover, Wei Lu et al. RL is assumed to be of in the IoT technologies to follow wide applications in smart home management and health care networks. The human activity recognition is assumed to be of the great attention in the resource allocation. The paper proposes a discriminant approach in the daily human activities to be done through the accelerometer issues with the sensor [13]. The ST transform is assumed to be of in the feature extraction and introduces a supervisor algorithm in the feature extraction in the supervised regularization for robust subspace learning methods is assumed to be of the more capable floating problems in the network assumption and the original subspace is assumed to have the featuristic analysis in the joint time frequency representation. The datasets has been proposed to be work with the three sets of comparisons in the schema.

Elmahdi Driouch et al. proposed that the simple heuristic algorithm has the scheduling and provides the resource sharing with the secondary link activation in dynamic resource sharing in communication networks using the RL technique [14]. The Primary user and secondary user use the same frequency bands within the networks. Proposed a graph theoretical model with network modeled as a weighted graph and the resource sharing is reduced to finding a sensitive vertex coloring in the constructed graph [15]. The resource sharing has some level of a resource server having the secondary transmissions and the best resource pairs are applied in terms of system sum rate. The transmission of primary users avoids interference with the level of transmitting power with the selection diversity [16]. The resource management is monitored with the transmission and the greedy approach is applied to the best resource effort allocation. Yang Song et al. proposed that the CR network has been studied with knapsack problem investigated for the resource allocation. The heuristic algorithm gives a better guarantee on supporting the resource allocation [17]. The limited frequency in the resource allocation has been used in the under utilization in the dynamic resource access techniques.

Yuxing Mao et al. presented that the handoff has a more frequent in case of multichannel access. The delay and data transmission occupies a relative degrades in the performance of the network [18]. The problem of minimizing the handoff is applies to the technique of establishing the holding time and throughput of the channels. Proposed that the use of wireless sensor and lack of resource transmission has been the key factor to estimate the quality of service. The unused resource from primary users and clusters has been engaged with the ratio in growth with the resource sharing strategy in primary users. The resource allocation has been followed with the primary band using ant colony optimization and the allocation is purely done with the Bertrand game and the multiple knapsack problem. Yao Wanga et al. presented that the resource allocation is a key problem with CR networks and used a graph based algorithms focus on the power control [19]. The resource allocation has a done with the novel joint resource power allocation control. The connection degree based algorithm has been called to support the function based on the system total utility having the new utility allocation in the QoS requirement of secondary users with the satisfied users.

Ibrahim Elgendy et al. proposed a mechanism for mobile user and IoT devices to provide a complex solution for the multimedia services enhancing the additional computations in the data communication. The devices are assumed to be the resource oriented and the limited computation power in the network communication [4]. The AES cryptographic technique has been applied to the shared resources in the efficient utilization in the cyber attacks. The joint consideration of the security enhances the time and energy consideration in the entire system to formulate a secured environment. The offloading algorithm is assumed to be of in the optimal computation with the decisions has been included in the MUs. The performance has been established with the execution and offloading schemes to be assumed of in the performance enhancement. The resource allocation has also been utilized in the data center for high speed big data [20].

Shubhangi K. Gawali et al. proposed that the Internet is assumed to be of in the emerging core technologies and the electronic devices communicate the several issues to address the challenges in frontier technologies The remote sensing is assumed to be about the control in the heterogeneous technologies and the IoT with the single technologies in the convergence of the prominent technologies in the Radio Frequency Identification with the networking in the WSN [21]. The real-time systems and the communication between devices with the IoT exposes the challenges on account of the device strategy and the device assumption in the rapid formation of the networks in the real-time communications [5]. The IIoT is exposed to various concerns in the IP versions having the research model in the single sensor. The IoT has a proposed solution towards the domains of the business people, sponsoring agents and the government sectors.

Songjun Ma et al. reported that the security in communication networks is a severe issue and needs to be encountered with various security approaches [22]. A Proposed solution for the greedy spectrum occupancy threat, in this threat the secondary user will act as a selfish node and occupy the network, utilize the spectrum fully [23]. The other users will be waiting in a queue for a higher time to access the spectrum; this may lead to a heavy traffic or congestion within the network. The queuing model proposed here describes the system framework with a greedy secondary user approach. The impacts of the system has been computed with the steady state performance and average occupancy time based on the number of users and channels, the decrease in occupancy time degrades the performance of the system. The steady state performance has been monitored with the wavelet based detection approach [24].

Abdelbaset Hamza et al. proposed that the communication networks have a group of SU that will compete for the use of channel having spectrum scarcity [25]. The PU will be leased used the spectrum in a least manner and it maximizes the network utilization in increasing the number of secondary users collaborating and reducing the interference between PU and SU. The energy efficient channel allocation has been allocated based on the maximum SINR algorithm for computing lower time complexity with a single parameter to estimate the SNR reduction factor. The performance will be evaluated by a finely tuned metaheuristic and a binary harmonic search algorithm [26]. Ruilong Deng et al. presented that the conflict of spectrum underutilization and scarcity in communication networks [27].

Yahong yang et al. proposed a multi objective task scheduling approach for the grid over the optical burst switching networks to estimate the computational resource and the network performance [28]. The requirement of the grid connected networks estimate a resource provider with the load balancing, scheduled optimization and the task completion time [7]. The ant colony optimization algorithm has been proposed with the multi-objective optical burst networks to identify the constraint in the resource enticed monitoring and the evolution of the network in the non dominated string in the convergence and diversity of the estimation in the single object optimization and the multi object optimization balanced control [29].

SS Chaudhari et al. proposed that the characteristics of the MANET with the support of limited resources using IoT to analyze the shared channel with the unbalanced load and the QoS service issuing in the routing of data in the resource estimation and the mobility of the data in the pre resource allocation [30]. The resource paradigm is assumed to be of the Cognitive agent (CA) focuses on the bandwidth and the estimation of the data on the pre-considered network in the focus of analyzing the cognitive agent [31]. The prediction of the resource in the data has been shared with the CA for resource prediction with the potential to solve the prediction in the CA. Whether it may be logical and thinking with the human is assumed to be of decision making in the human user alters with the user ability to hold the data in the CA with the mobile edge paradigm (MEC).

Mohammad Aazam et al. proposed that the technologies which are directly or indirectly connected to the IoT devices are assumed to be of the multimedia based IoT services in the establishment of the growing tendencies in the IoT with the social awareness in the SIoT paradigm [32]. The QoE Quality of Experience is measured in the dynamically allocated region to follow the incorporating QoE and the net promoter score is established within the mathematical model to frame the QoE parameter estimation in the CloudSim simulator in the regions using java and its impact with the proposed model [8].

Md SalikParwez et al. presented that the Wireless paradigm has the connectivity using the Internet of Things (IoT) with the next-generation wireless network in the predicted resources are being utilized with the virtualization to enhance the resource utilization with the support of sharing the content and the approach is elaborated with the use of Virtual networks and henceforth the mobile edge computing is assumed to be of the fast computing resource utilization platform in the cache resources [33]. The proposed model has the resource allocation in the adaptive environment for the wireless segments and hence the mobile virtual network operators are being utilized for the user allocation [34]. The virtual networks have the user with the allocated resources in the MVNO to perform a quality of service in the esteemed utilization of the resources. The resources uses the spectrum allocation in a predefined in a cache resources has the QoS requirements for maximizing the utility with the user ratings [35]. The simulations have been used with the numerical results and the proposed approach has the spectrum efficiency [36].

Qiuping Li et al. proposed that the Mobile edge computing is an innovative paradigm for the mobile devices that elaborately access the computational tasks with the mobile edge computing servers [37]. The wireless local area networks are used to enhance the most task execution through the wireless access points. The computation is performed with the offloading in the strategy and optimization in the multiple networks [38]. The ultimate aim is to optimize the system benefits with the aim of reducing the cost for the resource utilization in the system capability. The transmission power allocation and the bandwidth assignment are computed with the offloading strategy and the NP-hard problem is analyzed with the potential game with the parameters in the resource allocation with the Lagrange multiplier. The proposed model is analyzed with the convergence in the simple scheme and the offloading optimization for the cost effective analysis in the mobile edge detection.

3. Proposed design and CA based resource management

The agent paradigm is assumed to be of the mobile edge computing performed with the resource collaboration for resource management. The cognitive agent is assumed to be of the flexibility with the user request and interact with the resources [39]. The terminal users request is estimated by the upper core network with the base station. The communication resources are managed with the personalized model in the users to meet the requirements in the set up to follow the terminal users such as IoT, manufacturing and smart systems as shown in Fig. 2.

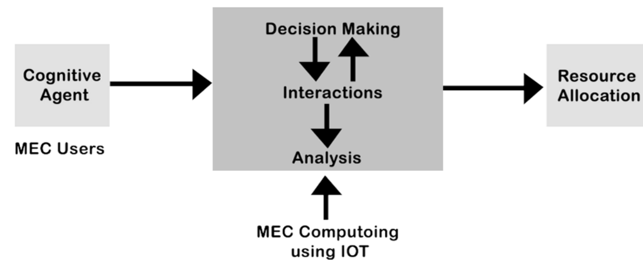

Fig. 2. Mobile computing with edge devices for resource allocation using decision analysis.

The three entities in Fig. 2 are MEC, MEC computing using IoT and resource allocation. The agent paradigm is assumed to be of the mobile edge computing performed with the resource collaboration for resource management. The cognitive agent is assumed to be of the flexibility with the user request and interact resources. The terminal user's request is estimated by the upper core network with the base station. The communication resources are managed with the personalized model in the users to meet the requirements in the set up to follow the terminal users such as IoT, manufacturing and smart systems.

(a) Information Base (IB): The user hierarchy is known as the data to the model. The user devices are associated with the data generation in the device using the storage network. The information base is assumed to be of the network environment to be sensed by the device.

(b) Decision approach and task assignment: The cognitive agent is assumed to factories the users request with the resources and the execution of the cache response in the behavioral track in the responsible patterns. The resource requested is assumed to be of the mobile edge computing at the time of transmission, and the requested resource is collaborating with the other devices to make it an efficient parameterized resource sharing.

(c) Data processing and predictions: The incremental learning and the online learning are apply to the data learning in the updated information in the behavioral pattern. The learning samples have been estimated with the cognitive agent assignment with the system environment. The CA has the ability to analyze the system environment in the complete transmission of resource sharing in the edge connected devices [40]. The action taken has been guaranteed with the proportionate of understanding the data analysis.

(d) Cognitive agent interaction: The cognitive agent is assumed to be about the neighbor information sharing in the resource allocation. The network resources are in larger quantity to be estimated with the request reason with the MEC and the quantity of interaction is measured by the aligned resources in the prediction of the actions in the surrounded transmission without the delay in the concurrent network [41]. The information sharing is assumed to be of the greatest information exchange in the neighboring agents in the particular range of distance.

The information is assumed to be of in the preliminary synthesis on the model basis on the goal of achieving the data inputs within the IoT controller devices. The resource allocation in the data estimation is provided by the address resolution RAR protocol. The header has the control over the stimulated control within the Hadoop processing HDFS environment [42]. The data allocation has been applied in the format of chunks for the information base and the mapping and reduce has been used by the resource allocator for the communication networks in the prescribed network channel. The task allocation is performed within the energy optimization of the resource controller.

The heuristic based optimized algorithm is used to frame the content within the volume of read and the format of write operation on the loud integrated environment [43]. The heterogeneous cloud computing derives a solution in the smart optimization condition within the sub optimal analysis in the series of operations with the dynamic programming algorithm with the help of task allocation using the fog and edge computing [44]. The research has been carried out with the independent data sets pertaining to the heterogeneous protocol in the segmentation of the operations in the dynamic input task addressing the major impact of the reversed paradigm in the smart task allocation. The decision making pattern has been enabled with interactions and analysis in Fig. 3 as mentioned.

The input task is allocated with the proposed solution to follow the optimization in the restricted adaptability in the input tasks parameterized in the fixed input task costs. The table is assumed to be the dynamic incoming metrics in the requirement of the implementation of the allocation strategies [43]. The mapping table is allocated with the ubiquitous allocations for the prior task allocations and optimization could effectively monitor with the dynamic set up.

4. Low cost system design using the table value

The Low cost system design is proposed as an application that deals with the cognitive agent.The proposed method is able to categorize the system with two core agents having the real-time effective cost mapping table with the RL and the QoF having the input mechanism in the proposed segmentation. The input task is allocated with the proposed solution to follow the optimization in the restricted adaptability in the input tasks parameterized in the fixed input task costs. The table is assumed to be the dynamic incoming metrics in the requirement of the implementation of the allocation strategies. The mapping table is allocated with the ubiquitous allocations for the prior task allocations and optimization could effectively monitor with the dynamic set up. The low cost table has been created with the set up for framing the QoE to make the table to adjust in the network. The RL is used in a sensitive approach to map the table with the current requirements in the network based on an initial table that has been framed with the real-time data fetched in the QoE to establish the table in the frequency domain. The objective is to focus the resource utilization in an efficient allocation paradigm besides the mapping of table values support the RL algorithm for efficient allocation. The cognitive agent is assumed to be about the neighbor information sharing in the resource allocation. The network resources are in larger quantity to be estimated with the request reason with the MEC and the quantity of interaction is measured by the aligned resources in the prediction of the actions in the surrounded transmission without the delay in the concurrent network.

The proposed method is able to categorize the system with two core agents having the real-time effective cost mapping table with the RL and the QoF having the input mechanism in the proposed segmentation [45]. The mechanism has two segments in the resource allocation with the core system doing the parametrical approaches. The cognitive agent has been showcased at the table updating parameter in the quality level implications as shown in Fig. 3. In Fig. 3 the process flow includes (a) The processing of the application for resource scheduling using the RL algorithm where the cognitive agent is utilized in the application for processing with the quality level reward in the application to monitor the action utilized, (b) The table updation is the process where the values are checked with the cognitive agent for the RL algorithm to predict the state that allocates the path for the resource optimization and, (c) finally a feedback mechanism is optimized using the MEC paradigm

In the initial process a mapping table has been designed with the N tuple having a task with $T_1 \ldots$ Tn. The cost is said to minimize and the cost is considered to be of the low state with the periodical information having $CS_{Tn} = \{CS_{T1}, CS_{T2}, \ldots, CS_{Tj,m}\}$ where the CS denotes the current state of the information transferring the data in the network. The low cost table has been created with the set up for framing the QoE to make the table to adjust in the network to be followed. The RL is used in sensitive to map the table with the current requirements in the network based initial table has been framed with the real-time data fetched in the QoE to establish the table in the frequent domain [46]. The action mechanism is assumed to follow the most associated value in the cost mapping table to provide a state path in the formulation of awards in the reward information. The feedback is assumed to be about the control over the optimal state in the revised network. The value of CS_{T1} has been predominantly increased with the return value to spread the network in the optimal solution to be assigned in the network evolution.

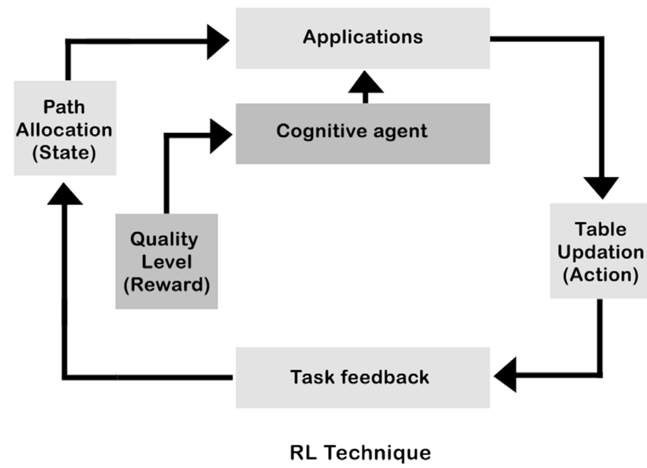

Fig. 3. RL based mapping table updation.

The current state of the information is assumed to be about the control in the current position of the state that is assumed of the optimal solution with $R_V(CS)$. The value is assumed to be used with the discount rate of interest depicted as γ and the parameter has a range from $(0, 1)$ as shown in Eq. (1) The value parameter is established with the cost depiction function in terms of $R_{Wf_{I(m+1)}}$ measures the reward factor with the value function of (m+1) adjustments have been made in the function estimation [47]. The state transition probability to new states is measured using the reward function and the value is obtained using the $R_W(CS_{Tj,A})$. The optimal return value is predicted with the action 'A' and the processing of the particular action is predicted using the $P(CS, A)$ and it automatically updates the reward function as shown in Eq. (2)

$$\begin{aligned} RV\,(CS) &= \max_A \text{Pred}\left[R_{Wf_{I(m+1)}} + \gamma RW(CS_{Tj,A}) \middle| CS_{Tj} = S, PR_{P=}\ A\right] \\ &= \max_A \sum_{CS',j} P(j', f|j, A)\,[Y + \gamma RV\,(CS)] \end{aligned} \tag{1}$$

$$\begin{aligned} P\,(CS, A) &= E\left[R_{Wf_{I(m+1)}} + \gamma RW\left(CS_{Tj,A}\right)\middle|\middle| CS_{Tj} = S, PR_{P=}\ A\right] \\ &= \sum P(P(j', f|j, A))\left[Y + \gamma \max_A RV\,(CS)\ P\left(CS', A'\right)\right] \end{aligned} \tag{2}$$

The reward are estimated with the QoF from the feedback estimation of the value low cost table predicted with the Eq. (2) and the maximum reward is assumed to be followed in the user centric side and N tuple is associated with the acceptable boundary condition in the creativity value of the tuple in the accelerated boundary value in the predetermined condition for the boundary condition to perform a quality based performance indicators. The negative boundary is sent back if the assumption does not meet the boundary condition predominantly.

5. Dynamic reinforcement learning based resource allocation

The cognitive agent is designed to dynamically design a decision based on the task allocated within the surrounding actions, task and current state. The proposed RL based resource allocation in IoT is done with the data capture from dynamic heterogeneous data sources and it has been collected [48]. The data has been sent to the data management

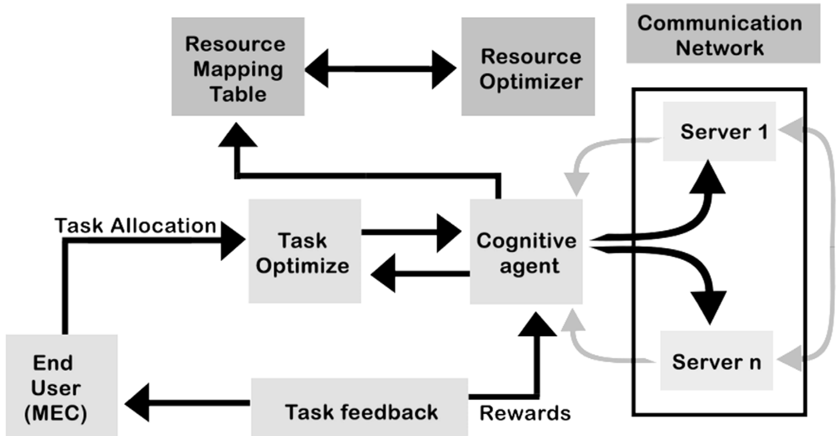

Fig. 4. IoT mobile edge computing based RL resource allocation.

layer to do data preprocessing and the task allocations has been processed with the remote locations for the efficient resource allocation. The task optimization process is explained in the Fig. 4 as the resource utilization enlarges the IIoT MEC device data connections. In Fig. 4, cognitive agent in the application utilizes the resource optimizer for mapping the resource table updation where the task is analyzed with the available resource and hence the allocation is based on with the end user. The rewards are utilized for the task optimization. The cognitive agent communicates with the server using the communication network and hence the agent supplies the task scheduling with the current state to allocate the work flow for the various resources in an efficient manner.

The Reinforcement learning algorithm is provided by the tree graph using the graph structure $Gr = (V, E)$ where the node is depicted as the V that performs the computation for the various process and the edge E is denoted to provide the cost computation for the mapping table in the resource based allocation [49]. Each node is computed for the lowest cost estimation within the shortest edge to manipulate the node cost. The cost predominantly verifies the execution time, length and the calculation of the preserved model. The IoT based resource allocation is established with the calculation of the resource utilization in the data set and the computational node is denoted in the set $\{CN_i\}$, the total average packets is denoted by the $\{D_i\}$. The task allocation is performed on the variation in the number of nodes allocated within the data node region as shown in Eq. (3)

$$EN_h = \prod_{I=1}^{h} (EN^C - i + 1) \tag{3}$$

where the EN_h estimated the number of similar nodes with depth h and EN^C represents the number of computation nodes with the different key label in the predictive calculation in the allocation of the default node setting and the QoF mechanism is established with the allocation path formulates the various states in the action space. The depth of the tree is assumed to be of the order of the incoming trees in the predominant space for all the nodes. The layer is assumed to be of the performance measure in the action as shown in Eq. (4)

$$P(a) = P_{n-1(a')+RWn} \tag{4}$$

each node n is estimated with the reward in the performance for the action a in each of the children nodes has the resource utilization in the subsequent task and has the computation in the reward node to follow up the reward values and the set is assumed to be of the lowest cost in each of the network nodes to be estimated with the set of each parameters towards the reward in Eq. (5)

$$\begin{aligned} RW(T_j) &= \left\{ RW_{(TA_j)} | A_{CN_i} = a \right\} \\ &= \left\{ \min \left[CN\left(TA_j\right) \right] - CN_{(TA_j)} | A_{CN_i} = a \right\} \end{aligned} \tag{5}$$

$RW(T_j)$ denotes the reward with the task allocation for i nodes and the $RW_{(TA_j)} | A_{CN_i} = a$ action is assumed to be of the reward of the nodes for the computation nodes in the low cost for all the action mechanism. The layer mechanism for the data processing has been explained in Fig. 5 as illustrated in the different analysis. In Fig. 5, the three modules used are the (a) data input layer (b) data management layer (c) data analytics layer and the (d) resource management layer. The input layer deals with the process of connecting the edge devices and the input are given for the optimizer for performing the preprocessing and processing of data. The management layer deals the data processing with the modified segment for processing in the execution with allocation and storage of the current stated data. The resource management performs the operation with the task allocation and the state for the RL based mechanism. Finally, the data is analyzed with the task for resource utilization in MEC paradigm.

The path of all the nodes is estimated with the action in the reward mechanism for all the computational rewards from the root node till the child node [50]. The reinforcement learning resolves the computational modules in the action for the reward setup with the incoming task setup is estimated accordingly as shown in Eq. (6)

$$RW_K(a) = \left[RW_K | A_R = a \right] = \sum_{t=1}^{n} [\min[CN_{T_u} - CN_{(T_{u,Ci})}] | A_R] = a \tag{6}$$

Furthermore, the defined policy is returned with the reward calculation for the resource allocation strategy. Thus the $RW_K(a)$ has the reward value in the state of action in the predominant way of establishing the maximum number of nodes with the policy to implement the reward in the allocation of the action. The expected value of the action taken has been considered with the state and the policy β as shown in Eq. (7)

$$V_\beta(s) = E_\beta \left[C_{RW} | S_{Tj} = S \right] = E_\beta [\sum_{i=1}^{n} RW_K | S_{Tj} = S] \tag{7}$$

The nodes estimation has been performed with the cognitive agent parameter and the service nodes are highly monitored with the proper alignment in the estimation of the parameter setting for the computation nodes. The Eq. (7) estimates the optimal solution with the energy prediction for the CN in the reward estimates in the states S and for the task T_J.

6. RL- MOACO edge computing resource allocation mechanism

The QoF feedback mechanism is considered for the resource allocation with the IoT model is described with the multi objective optimization setup in the conflicting nature to establish the Pareto optimality principles to satisfy the partial order and non dominated solutions in the ACO algorithms having the different choices [51].

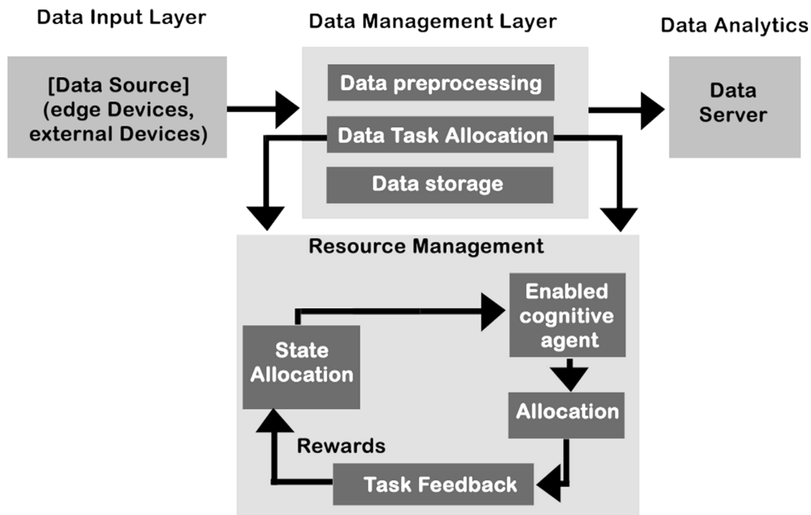

Fig. 5. Resource allocation architecture using RL.

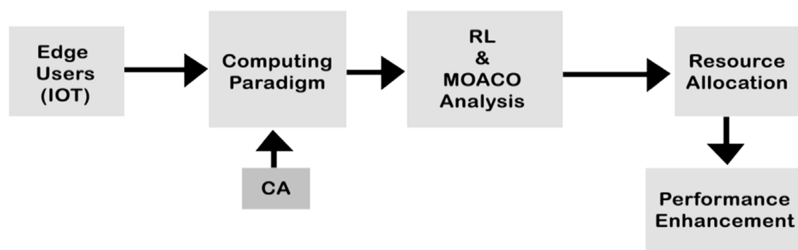

Fig. 6. Proposed model design with RL-MOACAO.

The Pareto optimality proposes a partial order among the solutions and the output of the algorithm becomes a set of non dominated solutions in the ACO with the equivalent design choices and a algorithmic framework establishes the MOACO algorithms and the formulation has been setup with the combination of the algorithmic framework as shown in Fig. 6.

6.1. Algorithm 1

MOACO metaheuristic resource allocation Algorithm:
Procedure:
MOACO Metaheuristic resource allocation for efficient task execution
Build Solutions for task allocation ()
Perform Local Search
Optional Actions()
Update Pheromones()
Reward estimation
Repeat the process of execution
Feedback Analysis
Wait until stop criteria
Output: Optimal solution obtained

The MOACO algorithm has the performance of the task allocation with the QoF estimated in the periodical assessment in the rewards for the parameter setting in the cost mapping table. The discount parameter is established with the discount factor of γ.

6.2. Algorithm 2

Reinforcement learning for the low cost estimation and table updating:

Table 1
Parameter setting.

Parameters	Values
Time of processing	100
The number of available servers	17
The number of MRU and MEC setup	13
Nodes	550
Path loss	$128 + 37 \log_{10}$
Reward	90%
Cost estimation	Reward – RV (CS)
D2D link loss	$148 + 40 \log_{10}$

Consider: ρ, γ, CN
Predict: ρ
1. Initialize the table $\rho.Input\gamma, CN$
2. Aware the rewards $RW \in CN$ $\forall$ the edge nodes do
3. if RW is not null then
4. Fix the element in the table ρ
5. $RV\,(CS) \cong \max_A \text{Pred}\left[R_{Wf_{I(m+1)}} + \gamma RW(CST_{j,A}) \middle| CS_{Tj} = S,\ PR_{P=A}\right]$
/* Table has been checked and the CN node is adjusted for the updating*/
6. Probability has been estimated with the updates allotted
7. Table has been updated
8. end if
9. end for
10. return ρ
/* Table has been updated with the required states*/

Lemma 1. *In the initial phase the initial table has been fixed without prior adjustments in the table, moreover the updating does not means the discount* *estimation of γ. The influence of the updation has been done on the table to represent the QoF mechanism to handle the data cases for resources.*

Lemma 2. *The condition if RW is not null fixes that the value has been adjusted to pose the negative value has been rewarded in the table. The performance is not matched with the QoF mechanism with the iteration manipulation in the action. The N various tuples identify the precision in the negative reward allocation and has been the maximum values.*

Lemma 3. *The rewards matching the condition and the reward values have been matched to the according condition to predict the non predictability and the computation has been estimated in the given adjustments [51].*

6.3. Algorithm 3

RL-MOACO metaheuristic resource allocation algorithm:
The dynamic programming has been fixed in the input tasks for the computation node has been predicted with the reserved prediction set of data tasks for the pre allocation of the mapping table to estimate the cost effective approach.
Predict: The task for the CN as S and the mapping table Tth
Consider: Policy for optimal solution $P(CS, A)$
Procedure: MOACO Metaheuristic resource allocation
1. Initialize a table with the temporary assignment $\partial \leftarrow Temp$ and a graph tree G
2. Build solutions for Task allocation // **MOACO Task allocation**
3. /* Columns in Temp = average number of computation nodes*/
4. $RW \in CN$ $\forall$ the edge nodes
5. for all $CN \in S$
6. Read each row in the table Tth
7. Perform Local search for the values to estimate the low cost
8. $P(CS, A)$ has the states and do
9. $V_\beta(s) = E_\beta\left[C_{RW}|S_{Tj} = S\right] = E_\beta[\sum_{i=1}^{n} RW_K|S_{Tj} = S]$
10. /*Update the table with the computational nodes in the estimation*/
11. end for
12. end for
13. For $\forall P(CS, A)$ do
14. $RW_K(a) = \left[RW_K|A_R = a\right] = \sum_{t=1}^{n}[\min[CN_{T_u} - CN_{(T_{u,Ci})}]|A_R] = a$
15. Estimate the action with the reward for the CN
16. end for
17. return $RW_K(a)$
18. Estimate the reward with the states for the consecutive task
19. Optimal solution predicted with the $RW_K(a)$ reward

Lemma 4. *The data has been read from the chunks and the information has been established in the cost information for the mapping table. Initialize a table with the reward computation and the tree for the policy preparation.*

Lemma 5. *The task has been created with the reward to the tree with the action in the resource allotted in the input task prior to the same allocation. the prediction of the optimal solution has been estimated with the predominant assignment in the sample values.*

7. Experimental methods and result

Consider a measurement of CA and its effectiveness is measured using the MEC data in the pattern of IoT support. The behavior analysis has been estimated with the pattern of user devices and the devices allocate the pattern of behavior data analysis. The task execution has been allocated with the delay is performed in the device and the communication resource in the caching does the handling capacity in the network [52]. The MEC has been upgraded in the CA requests in the base station in the parameter for the QoF supports the estimation. The data from different heterogeneous sources has been analyzed for estimating the [53]. The various path losses and link gain is predicted with the above Table 1 with the path loss and Device to device (D2D) link estimation for the data transfer and generated is assumed to be of with the hit rate and non hit rate. Where the hit rate is assumed to be off

Table 2
Throughput analysis with MOACO.

Nodes	Proposed MOACO (J)	Genetic algorithm (J)	Artificial bee colony (J)
50	300	150	180
100	378.99	250	300
150	556.98	300	450
200	625.36	450.55	560.39
250	698.98	570.55	620.98
300	725.36	600.25	650.39
350	753.69	625.33	675.9

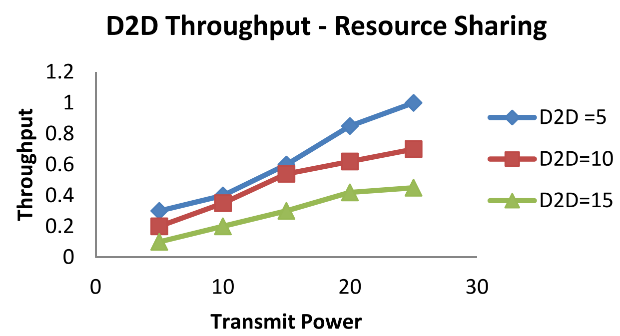

Fig. 7. Throughput in D2D.

$$Hit\ rate = \sum_{i=1}^{p} Xi,j \times 100\%$$

The Hit rate is calculated with the estimation of request assembled in user j with the time of I and X is assumed to be about the sum of services of the Q values. The D2D multiple resources have been accessed by the multiple cellular users and D2D users are collaborating with the resources in the coordination of the user communication devices. The resource sharing has been accessed with the throughput and performance has been monitored in the performance loss in D2D users. As observed in the D2D link gradually increases when the throughput increases, when the user increases the channel gain also increases in Fig. 7. The signal gain is associated with the increase in user ratio and the user may vary from 15 to 20, the performance measures increase gradually without delay in Fig. 8.

Besides the throughput has been compared using nodes up to 350 IoT nodes with the genetic algorithm and artificial bee colony algorithm and it is observed that the MOACO gives a significant performance as given in Table 2.

8. Conclusion

This paper investigates the key approach on examining the QoF mechanism that enables the dynamic resource allocation and an input table with the task allocation. The reinforcement learning and MOACO approach estimates the optimal solution in MEC with the IoT dataset. The factors affecting the delay and transmission power are predicted with mobile edge computing resources using the CA in D2D and the multicellular path. It assesses the performance in the neighboring user equipments. In this approach, the application is proposed with the cognitive agent supporting the resource optimization hence the paradigm is assumed to be that the mapping table helps the low cost values with the low state that makes the server communication and task allocation in an efficient manner. Besides the objective is task allocation with proper resource scheduling in that aspect the application is highlighted with the low cost mapping table for cognitive agent application. The

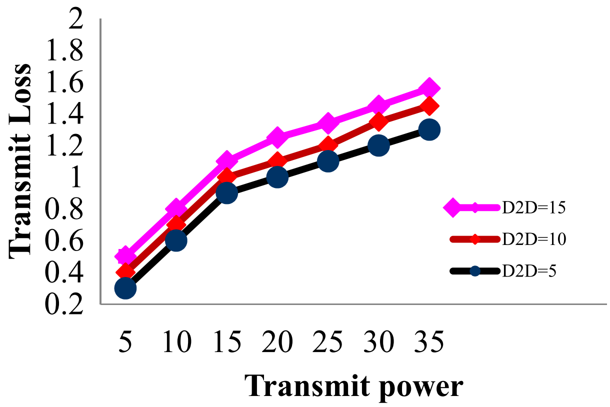

Fig. 8. Resource collaboration using CA in D2D.

effectiveness builds a cognitive agent model to assess the resource allocation and the communication network is established to enhance the quality of service with an optimal resource allocation. The work can be extended further by applying the futuristic optimization algorithms for big data applications to deal with the sensor data and the resource monitoring can be efficiently measured with the network throughput analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

S. Vimal: Conceptualization, Data curation, Validation. **Manju Khari:** Conceptualization, Formal analysis, Supervision. **Nilanjan Dey:** Formal analysis, Writing - original draft, Writing - review & editing. **Rubén González Crespo:** Conceptualization, Formal analysis, Writing - original draft, Writing - review & edition, Supervision. **Y. Harold Robinson:** Conceptualization, Data curation, Validation, Supervision.

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