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Coalition-based Routing and Resource Optimisation Method for 5G User Communications

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***Abstract*—The fifth generation (5G) technology provides high transmission and low latency communication to users by integrating heterogeneous devices and maximum radio resource utilisation. Prolonged longevity and effective communication are achieved through active resource routing. In addition, interference-less routing and lossless resource allocation are essential for ensuring successful communication. The transmitting and receiving users rely on shared channels to maximise resource utilisation where interference has a significant issue. In this article, a coalition-based routing and resource optimisation (CRRO) method is proposed to improve the performance of 5G communications. The proposed method relies on the cooperative agreement between resource providers and allocation channels to distinguish the sharing intervals. Maximum routing conditions for devices, service providers, and user routing are met with high longevity. In the coalition-based resource selection, synchronisation between the communicating is considered to maximum interference-less routing efficiency. A modified deep transfer learning is included in the interference level verification based on longevity and low interference to verify the synchronised behaviour of the routing process. The proposed method significantly improves the performance of 5G networks. By dynamically optimising resource allocation, minimising interference, and extending the longevity of the routing, it adapts resource utilisation to the varying conditions of the network and the demands of the users. The proposed CRRO improves resource utilisation and routing longevity by 10.02 %, and 14.41 %, respectively, and reduces latency by 10.47 % for the maximum interval.**

***Index Terms*—5G mobile communication; Wireless sensor networks; Resource optimisation; Routing; Transfer learning.**

I. INTRODUCTION

Interference-free routing and device integration are two major contributions to fifth-generation communication systems [1]. Shared channels are widely used to effectively utilise resources and channels. Interference caused by different devices reduces performance and increases the delay in communication [2]. A better way to achieve effective routing is to deliver data on optimal pathways and avoid congested areas to maintain the transmission speed stability [3]. Without interference-free routing, network performance deteriorates, particularly in dense environments with many users. When various devices on a network are complexly integrated while maintaining clear communication, advanced techniques for simultaneous data transmission are necessary [4], [5]. Interference-free routing will ensure smooth and reliable communication in environments with the highest traffic loads. Minimising interference is important to keep fifth-generation services as reliable, fast-delivering, and low-delay communication [6].

Resource optimisation in the fifth-generation communication system comprises aspects of longevity that contribute to efficient performance [7]. The number of devices connected to the network increases bandwidth, spectrum, and other resources needed for continued network operation. Optimised resource management prevents network congestion and facilitates smooth continued operation over long periods [8]. Long-term optimisation strategies maintain a balance between resource exploitation and network stability, preventing sudden traffic spikes from overloading the system [9]. Resources such as bandwidth and power can be managed with full efficiency so that there is no waste in obtaining high-performance results [10]. Resource optimisation ensures that the network infrastructure is robust enough for peak usage, leading to an extended service life of the equipment and a reduced cost of operation. Resource lifetime becomes particularly crucial when its pattern of usage like to changes overnight in variable environments. Fifth-generation communication networks may offer fault-free service by optimising resource usage over time, even when traffic patterns change [11], [12].

Learning algorithms are becoming essential for resource allocation and routing management in fifth-generation networks. Predictive algorithms for traffic patterns in networks ensure efficient allocation of resources [13]. Continuous analysis of real-time data means that learning algorithms can adapt well and track the change in network conditions, thus ensuring optimal distributions of bandwidth and other such sensitive resources [14]. Such a prediction of future demand will help to avoid communication bottlenecks and ensure smooth communication, even at peak usage times. These algorithms also allow the network to self-adjust, while avoiding the need for heavy management and intervention from human sources [15], [16]. Therefore, learning algorithms prove to be very useful in such rapidly changing environments of demand in networks, which is a concern in

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cities or during large events [17]. Expansions of these networks enable optimisation of resources and routing for better overall network operation due to communication algorithms. Acceptance of learning algorithms promotes the continuous progress of fifth-generation communication technologies, as well as more efficient intelligent network operations [18].

In [19], an optimised planning for distributed (DU) and central (CU) processing placement was proposed in 5G packet networks. It is used to place the DUs and CUs at selected processing nodes where it maximises the quality range of the networks. A parallel multihop routing protocol for 5G backhaul networks is designed in [20]. The developed protocol uses high performance computing (HPC) and cloud platforms to manage the resource level and speed of the routing process to solve the massive data traffic ratio that occurs during routing and allocation services. The designed protocol elevates the flexibility and performance rate of 5G networks. The authors in [21] introduced a new routing optimisation strategy for the 5G cloud edge collaboration scenario.

The authors in [22] designed an artificial intelligence (AI)-enabled performance evaluation method for 5G networks. The developed method is a residual network-based method that evaluates scores according to key performances. The method generates accuracy performance based on indicators, which minimises the latency of the process. The developed method increases the accuracy and granularity range of the networks. In [23], a black-box optimisation approach-based baseband function placement method was introduced for 5G networks. It is also used as a traffic prediction method, which minimises the loss function ratio of the networks. The authors in [24] proposed a multidomain framework based on deep learning (DL) based on end-to-end services in 5G networks. A deep reinforcement learning (DRL) algorithm is employed to provide relevant resource allocation services to the networks. The DRL algorithm also provides effective alternate routes to overcome data traffic for sensor nodes. The proposed framework enlarges the overall quality of services (QoS) for all networks.

The authors in [25] proposed a multilayer 5G network slicing model. It is used as an optimisation model, which provides relevant solutions to the constrained problems. It also produces optimal distribution services to secure data distribution processes in the network. The developed model raises the feasibility range of the slicing process. The developed model enhances the effectiveness level of the 5G networks. A dynamic resource management algorithm for service chaining in cloud-edge-radio 5G networks was developed by the authors in [26]. The introduced algorithm analyses the resources that are required to perform the necessary tasks for the users. It also identifies the characteristics to produce feasible resource allocation policies for the process. Compared with others, the algorithm introduced improves the performance range of the networks. RL-based particle swarm optimisation (PSO) for end-to-end traffic scheduling was introduced in [27]. The developed model is used in time-sensitive networking (TSN)-enabled 5G applications. It is used to analyse the actual requirements of the process, which decreases the computational cost of the systems. The developed model maximises the accuracy and feasibility level of the scheduling process.

A new RL approach for virtual network embedding (VNE) for 5G networks was proposed by the authors in [28], [29]. The designed approach is used to identify the virtual embedding problems that cause severe problems to networks. A novel resource allocation method is implemented in the network, providing effective allocation services. The designed approach increases the overall QoS and performance level of the networks. In [30], a topology control algorithm was implemented that adjusted the coverage radius of 5G-based mobile ad-hoc networks (MANET) . It is used to adjust the flexibility and communication range of the MANET.

Resource-based routing, optimisation, and longevity depend on the path loss mitigation rate for shared radio channels. Path loss owing to increasing device densities and communication rates fluctuates the resource utilisation and the allocation. Therefore, the allocation routing remains unused at any noise-inducing interval. This requires an alliance between the devices and their demands to discover new resources and, thereby, adapt channel allocation.

The integration of collaborative strategies with unmanned aerial vehicles (UAVs) enhances communication efficiency and optimises resource utilisation. Task driver operations are made possible by forming a coalition of UAV's that addresses the problems faced in the aerial environment [31]. A heuristic task allocation method is introduced for different types of UAV to develop resource allocation. The authors have introduced a different framework to identify the priority and benefits of the task employing a utility function for the UAV task relationship [32]. The collaboration operation in dynamic environments among many UAVs is addressed. The growth of single-to-multiple UAV requires a new networking model to specify concerns such as connectivity, mobility, and routing [33]. Coalition game theory is employed to create groups of similar UAVs while considering stable communication and task attributes [34]. Significant enhancement in utility by employing a preference gravity-guided tabu search (PGG-TS) algorithm to overcome the limitations of traditional coalition formation models in heterogeneous UAV networks [35]. The development of a novel technique for content distribution, vehicular edge computing (VEC), is emphasised. This is achieved using fuzzy logic and coalition graph games [36]. Problems faced by rapid vehicle movement of vehicles and less channel capacity are specified by the coalitional graph game model that enables data transfer to road units [37]. The emphasis on the various applications of coalition game theory in 5G networks is introduced by improving network operation when devices in the network share resources [38]. The requirement for ultrareliable low-latency communication (URLLC) is discussed for better optimisation in narrow-band device-to-device (D2D) communication within 5G networks [39]. The survey on energy routing protocols for the Internet is highlighted by the incorporation of metaheuristics, AI, and multiagent systems. By this method, energy efficiency and the utilisation of renewable energy are optimised [40].

A detailed review of FANET networks for future works, applications, problems faced, and different technologies are adopted for effective communication. These conditions are necessary for delivery, surveillance, and monitoring of the surroundings [41]. The necessity of maintaining performance cost and contentment of costumers was developed by the exploration of multiobjective coalition formation in horizontal supply chain collaboration. It also focusses on the optimisation of logistics and constant service quality [42]. The resource trading and coalition formation among devices are addressed by a novel technique for real-time processing [43].

The contributions of the article are to perform a background study of different works related to 5G resource optimisation, longevity, and routing techniques that propose a novel coalition-based resource routing optimisation method to improve the longevity and resource management of 5G communication networks. To compute the performance of the proposed method, using resource allocation, utilisation, path loss, latency, and routing longevity metrics, the performance of the proposed method is verified using a comparative analysis of the above metrics with the existing TFACR [30], BBOA [23], and PMHRP [20] methods.

The organisation of this article is as follows. Section I presents the related works discussing the resource optimisation and routing concepts in 5G. Section II presents the discussion of the proposed method using illustrations and mathematical derivations. In Section III, the comparative analysis using different metrics and methods is presented followed by the conclusions and future work in Section IV.

II. PROPOSED COALITION-BASED ROUTING AND RESOURCE OPTIMISATION METHOD

A. *Introduction*

In the evolution of modern communication, fifth-generation (5G) technology offers high transmission speeds, low latency, and supports a variety of features for connected devices. In this, a coalition-based routing and resource optimisation (CRRO) method is proposed to perform cooperative agreements between resource providers and communication channels. A diagrammatic illustration of the proposed method is given in Fig. 1.

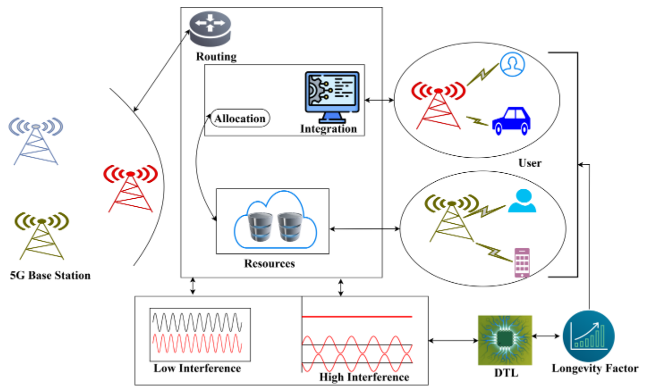

Fig. 1. Diagrammatic illustration of the proposed CRRO method.

Due to increased density of the device and interference issues, efficient utilisation of radio resources remains a challenge in heterogeneous networks. Normal routing and resource allocation methods often struggle to optimise performance while minimising interference. To address these issues, coalition-based strategies have been introduced to promote network cooperation. For optimal power allocation to improve system performance, the coalition technique in wireless communication that optimises resource allocation is used [44]. This method improves the use of resources and the longevity of communication, which is shown in Algorithm 1. A modified deep transfer learning model is incorporated to verify and reduce interference that maximises resource utilisation and improves the base power efficiency (φ_{base})

$$\varphi_{base} = \text{Ᵽ}_{trans} \times \text{C}_{gain} \times \left(\frac{1}{f \times d}\right) \times (1 - I_{inter}) \times \\ \times \ (1 - \text{Ᵽ}_{loss}) \times B_{allocate.} \quad (1)$$

The power transmission from the base station is denoted as Ᵽ_{trans} with the channel gain as C_{gain} to ensure strong signal transmission. The transmitted signal will experience a power loss when travelling over a distance that is represented as d, and frequency is denoted as f where $\text{Ᵽ}_{loss} \propto \left(\frac{1}{f \times d}\right)$. The high frequency experiences more loss for longer transmission. The interference is represented as I_{inter} where high interference will reduce effective power transmission. Power loss is denoted as Ᵽ_{loss} that reduces the signal strength when it is received during communication. The data capacity was analysed by the bandwidth allocation and is represented as $B_{allocate}$ to manage resources and the allocation process during communication. Due to the increased density of the device and interference issues, efficient utilisation of radio resources remains a challenge in heterogeneous networks. To enhance the routing process, the following CRRO method is incorporated and is discussed below.

Algorithm 1. Algorithm of coalition-based routing and resource optimisation (CRRO).

1: Initialisation of the essential parameters (N_{noise}, I_{inter}, P_{recv}, P_{trans}, C_{gain}).
2: The initial transmission from Base_station
3: Transmit power (P_trans) -> Base_station
4: Determination of signal_quality (Y_qual)
5: If (y_qual >= N_noise)
6: Then selection of optimal routing (Y_opt) for transmission takes place
7: Else
8: Check that the interference level lies within the limit
9: Check the latency lies between the limits
10: Then calculate the routing quality (y_qual)
11: Repeat from step 6
12: Then the optimal routing selection takes place according to (3)
13: If (A_allocate >= min(Y_opt))
14: Allocate resource
15: Else
16: Compute the allocation demand by each user (K_i)
17: Then if (k_i > A_allocate)
18: Allocate bandwidth (B_allocate)
19: Else
20: Check latency and interference
21: Then determine total power and update the system
22: P_tot = P_trans + P_req and base
23: Then compute the effective integration (O_integrate) from (5)
24: Calculate the resource utilisation (R_utilise)
25: If (R_utilise = R_share)
26: Set R_opt = True
27: R_allocate <-updated
28: Else
29: Compute the reintegration of Y_opt using O_integrate
30: Check if (O_integrate>Y_opt)
31: The final quality-based update takes place

32: Else
33: Recompute the essential parameters

B. Routing and Resource Optimisation

The emphasis on user fairness and service quality has been placed by optimising the resource allocation in device-to-device (D2D) communication. This led to enhanced resource allocation and utilisation in 5G networks compared to other algorithms [45]. Therefore, our research incorporates this method. In 5G networks, cooperative agreements between different entities were promoted by coalition-based routing and resource optimisation, which measures resource providers and users to maximise resource utilisation and minimise interference. Depending upon the real-world demands, the service providers cooperation let us to the formation of coalition between resource providers and allocation channels. By employing energy-efficient resource allocation model modifies D2D in 5G networks to enhance energy, power, bandwidth, channel allocation, throughput, and network data speed while reducing latency. In addition, due to coalition formation among D2D users, resource allocation is optimised and system performance is improved. Thus, the coalition formation technique is applied to this work [46]. Coalitions were formed by connecting multiple devices in which resources were shared according to their individual needs and network conditions. On the basis of the network conditions, devices collaborate to allocate and route these resources more efficiently rather than competing for resources. This leads to better synchronisation and communication longevity. The resource-sharing intervals were carefully managed to reduce interference, and cooperation allows for the optimal distribution of communication that is shared in the channels. Deep transfer learning is incorporated to monitor interference levels. This ensures that resources are allocated and maintains high-quality communication with minimal disruptions. Hence, this method helps improve performance with minimal interference and better resource utilisation, leading to improved overall network efficiency. From this method, the optimisation of routing is computed as y_{opt} in the following:

$$\begin{cases} y_{qual} = \frac{Ᵽ_{recv}}{N_{noise}+I_{inter}}, \\ Ᵽ_{total} = Ᵽ_{trans} - Ᵽ_{recv}, \\ y_{cong} = \exists_{traffic} + L_{latency}. \end{cases} \tag{2}$$

$$y_{opt} = \max_{Ᵽ}\left(\frac{y_{qual}}{y_{cong}}\right) = \\ = \max_{Ᵽ}\left(\frac{Ᵽ_{recv}}{(N_{noise}+I_{inter})\times(\exists_{traffic}+L_{latency})}\right) \times Ᵽ_{total.} \tag{3}$$

The routing quality is determined as y_{qual}, which depends on the received power ($Ᵽ_{recv}$) with noise (N_{noise}) and interference (I_{inter}). When $y_{qual} = \max\left(\frac{Ᵽ_{recv}}{N_{noise}+I_{inter}}\right)$, better routing quality is assured. In this, $y_{qual} \geq \min N_{noise}$, were $y_{qual} \propto \frac{1}{N_{noise}}$ show strong signals that are required for quality routing. The total power is denoted as $Ᵽ_{total}$, which is measured by the difference between $Ᵽ_{trans}$ transmissions from received power. This ensures power transmission and availability during routing. Congestion that occurs during routing is termed as y_{cong}, in which the traffic demand ($\exists_{traffic}$) and latency ($L_{latency}$) are measured as $\exists_{traffic}$ *and* $L_{latency}$. These parameters control the impact of congestion and ensure efficient routing. The optimal routing is achieved as $y_{opt} = \max_{Ᵽ}\left(\frac{y_{qual}}{y_{cong}}\right)$, which is used to select the optimal path for transmission. This balances signal quality and congestion to improve efficient data transmission. As a result, this ensures that high-quality communication is obtained with minimum congestion to maximise the efficiency of the network. The following equation $A_{allocate}$ formulates the allocation of resources in the network

$$A_{allocate} = \min Ᵽ_{total} \times \sum_{i=1}^{n}\Big(K_i \times \log\Big(1 + \\ + \frac{Ᵽ_{trans,i}\times Ϲ_{gain,i}}{N_{noise}+I_{inter}}\Big)\Big) \geq \min(y_{opt}). \tag{4}$$

The above equation minimises total power with various factors to enhance resource allocation, where n represents the total number of users. The allocation demand of each user is represented as K_i. The term $\log\left(1 + \frac{Ᵽ_{trans,i}\times Ϲ_{gain,i}}{N_{noise}+I_{inter}}\right)$ measures the relationship between power and channel gain received by the user for interference level. This ensures the handling capacity of the network based on the user's demands. The optimal resource allocation relies on $(y_{qual} \geq N_{noise})$ and $\left(A_{allocate} \geq min(y_{opt})\right)$ condition satisfactions. The P_{trans} and P_{req} are differentiated by N_{noise} and I_{inter} as the d separates the base station and n. The final quality-based update is the $P_{total} = (P_{trans} + P_{req})$ and ψ_{base} that aids in similar $B_{allocate}$ and C_{gain} through Y_{opt}. However, the failing cases require I_{inter} and K_i estimation to verify communication latency and $B_{allocate}$, K_i satisfaction, and $\exists_{traffic}$ update along the P_{total}. Depending on the P_{total}, the ψ_{base} efficiency is estimated and further selection is performed. This $A_{allocate} \geq \min(y_{opt})$ enhances resource allocation ($A_{allocate}$) and achieves throughput with minimum routing. This equation measures the need to balance efficient power transmission for the optimum allocation of resources based on user demand. Effective resource utilisation is achieved by effective integration that is expressed as $O_{integrate}$ in the following equation

$$O_{integrate} = \sum_{i=1}^{n}\left(Ϲ_{gain} + Ᵽ_{trans} + B_{allocate}\right) \times (Ᵽ_{loss} - \\ - N_{noise}) \geq y_{opt}. \tag{5}$$

Here, the integration of resources is obtained by incorporating channel gain, power transmission, and bandwidth. This evaluates the efficiency of integration in the network. The term $(Ᵽ_{loss} - N_{noise})$ measures the impact of loss that occurred based on noise in the signal. The value of $O_{integrate} \geq y_{opt}$ ensures that the integration satisfies the routing process for reliable communication. A high value of $O_{integrate}$ indicate better system performance with integration. This equation ensures optimal communication with optimal integration in the network. From this allocation and integration, the following equation R_{opt} formulates resource optimisation:

$$\begin{cases} R_{initial} = B_{allocate} \times (1 + Ᵽ_{trans}) \times \frac{Ꞔ_{gain}}{N_{noise}}, \\ R_{utilise} = \frac{n}{K_i} + R_{share}, \\ R_{allocate} = (R_{initial} \times R_{utilise}) - I_{inter}. \end{cases} \quad (6)$$

$$R_{opt} = \max R_{allocate} + \sum_{i=1}^{n} Ᵽ_i \leq Ᵽ_{max} + \\ + \sum_{i=1}^{n} B_i \leq B_{max} \times \left(A_{allocate} + O_{integrate}\right). \quad (7)$$

In (6), the term $R_{initial}$ measures the initial resource formation, which includes bandwidth and power transmission. The term $\left(\frac{Ꞔ_{gain}}{N_{noise}}\right)$ ensures the channel gain with the noise in the signal. This captures the effective resource formation by the network to the user. To maximise system throughput and to minimise latency, coalition in wireless communication optimise resource utilisation by making D2D users allocate resources [47], [48]. Henceforth, resource utilisation is measured by the term $R_{utilise}$ with several users by their demand for the resource. This is then combined with R_{share}, which is denoted as resource sharing. This improves resource utilisation according to demand and improves overall performance. The term $R_{allocate}$ computes the allocation of resources by combining $(R_{initial} \times R_{utilise})$ and differentiates with the interference to ensure optimal allocation. The power and bandwidth allocation for individual devices are represented as $Ᵽ_i$ and B_i, respectively, along with their corresponding maximum values as $Ᵽ_{max}$ and B_{max}. The optimisation maximises the allocation with $Ᵽ_i \leq Ᵽ_{max}$ and $B_i \leq B_{max}$ to utilise resources with power and bandwidth constraints. This reduces latency by improving resource sharing and network performance. Constraint identification is the tedious process of handling K_i for multiple allocation intervals. The P_{trans} for $A_{allocate}$ relies on d and N_{noise} experienced before and after $O_{integrate}$. If $O_{integrate}$ the ratio increases, the y_{qual} and its associated constraints also increase. Depending on the available, intervals $(f, B_{allocate}, and\ R_{initial})$ are assigned. Considering the optimal condition of $\left(O_{integrate} \geq Y_{opt}\right)$, the $R_{utilise}$ is verified. In this case, if $(R_{utilise} = R_{share})$, then $R_{opt} = true$ and further $R_{allocate}$ is pursued. In these consecutive intervals, the R_{opt} is eased through (K_1 to K_i) demand suppression for $O_{integrate}$ under I_{inter} less routing. The constraints of y_{opt} are identified for $\left(O_{integrate} \leq y_{opt}\right)$ and this can be due to N_{noise} or I_{inter} that requires f with $B_{allocate}$. Therefore, identifying these constraints is prominent to reduce the interference from any K_i.

Important network parameters, such as user count, transmission power, bandwidth, and noise level, must be taken into account to initiate the CRRO algorithm. When evaluating the received signal power in conjunction with noise interference, the routing quality (y_{qual}) is calculated. The selection of the best path, congestion control, and maintenance of signal quality are achieved through optimised routing (y_{opt}). Furthermore, the algorithm ensures minimal interference by allocating resources $(A_{allocate})$ based on network conditions and user needs. Incorporating factors, such as channel gain, bandwidth, power transmission, and resource integration $(O_{integrate})$, enhances overall performance. For better resource allocation router efficiency and maximum network longevity, the coalition technique in the CGHR protocol is introduced [49]. Consequently, resource allocation (R_{opt}) and network output optimisation significantly improve the longevity and efficiency of communication.

Deep transfer learning is incorporated to optimise low-interference routing and high device integration for communication longevity, which is discussed below.

C. Deep Transfer Learning

Deep learning for radio resource allocation in 5G networks is used to optimise bandwidth and transmit power [50]. In the same way, in coalition-based 5G networks, deep transfer learning is integrated to optimise low-interference routing and high device integration for communication longevity. It can continuously learn from new data. This helps to adapt to a network condition that changes with varying interference levels, user density, and resource availability to ensure optimal performance. Initially, it identifies interference patterns by transferring knowledge from similar networks and trained on large datasets to capture various conditions, including different signal strengths and interference sources. Once trained, it can predict and detect potential interference zones based on the current state of the network. This can also reroute communication through less congested channels, minimising signal degradation $y_{cong} = ∃_{traffic} + L_{latency}$ for efficient data transmission. This also helps to decide, which coalition of devices should share resources. Dynamic routing decisions were enabled as $y_{opt} = \max_{Ᵽ}\left(\frac{y_{qual}}{y_{cong}}\right)$ based on gained knowledge of similar network topologies and traffic conditions. 5G networks consist of highly heterogeneous devices with varying communication needs. This model can optimise routes $\left(y_{opt} + R_{opt}\right)$ and find efficient device clusters and routes that maintain low interference by learning. The integration of multiple devices results in timing and synchronisation challenges when trying to maintain long-term stable connections. This model solves this by learning the patterns of device behaviour over time and communication over time with the network. This predicts and optimises synchronisation intervals for resource sharing to avoid communication collisions and improve longevity. Thus, deep transfer learning not only reduces interference, but also maximises the longevity and stability of communication over sessions. From this, the following equation a_{DTL} formulates the process of DTL:

$$\begin{cases} a_{train} = \emptyset\left(I_{inter}^{low}, O_{integrate}^{high}\right). \\ a_{transfer} = \emptyset\left(I_{inter}, O_{integrate}\right) \to a_{train}, \\ where \\ a_{transfer} = a_{train} - \left(y_{opt} + R_{opt}\right). \end{cases} \quad (8)$$

$$a_{DTL} = \\ = \begin{cases} \min_{a_{transfer}} \left(a_{train}, a_{transfer}\right), \\ \min_{a_{transfer}} \left(I_{inter}^{low} + O_{integrate}^{high}\right) + \left| \begin{matrix} a_{train} - \\ -\left(y_{opt} + R_{opt}\right) \end{matrix} \right|^2. \end{cases} \quad (9)$$

The learning model (a_{DTL}) is trained to obtain low interference with high integration and is represented as $I_{inter}^{low}\ and\ O_{integrate}^{high}$ in the function $\emptyset$. The training of the model is represented as a_{train} that predicts the output. This trains the model with the information obtained from the previous datasets. The transfer of learning is defined as $a_{transfer}$ that integrates $\emptyset(I_{inter}, O_{integrate}) \rightarrow a_{train}$ the interference and integration. It identifies interference patterns by transferring knowledge from similar networks and trained on large datasets. The term $a_{train} - (y_{opt} + R_{opt})$ can optimise routes and find efficient device clusters and routes $R_{allocate} \geq y_{opt}$ that maintain low interference by learning. Once trained, it can predict and detect potential interference based on $R_{opt} \rightarrow Ᵽ_i \leq Ᵽ_{max}$ the current state of the network. The final deep transfer learning is achieved by minimizing $a_{transfer}$ with the interference and integration as $O_{integrate} \geq y_{opt}$ in the network for the prolonged network. This $y_{opt} = \max_{Ᵽ}\left(\frac{y_{qual}}{y_{cong}}\right)$ avoids overfitting of resources and ensures effective transfer of learning from the source. This model uses α_{DTL} and α_{train} to perform $\alpha_{transfer}$ to ensure ϕ identifies y_{opt}. The $R_{initial}$ is the sharing-initiated interval for K_i such that $R_{utilise}$ is required to be high. If the utilisation is high, then R_{opt} is valid, from which I_{inter}^{low} and I_{inter}^{high} are classified. This classification follows $[A_{allocate} \geq min\,(y_{opt})]$, $(R_{opt} \rightarrow P_i \leq P_{max})$, and $(O_{integrate} \geq y_{opt})$ conditions to define ϕ. This turns out to be the verification condition, the α_{train} is the preknowledge gained scenario, where $B_{allocate}$ and $A_{allocate}$ are balanced under I_{inter}^{low}. Therefore, $O_{integrate}$ is the defining constraint for y_{opt} and $\alpha_{transfer}$ that retains the same. Now, $\phi(I_{inter}, O_{integrate})$ are fused to identify multiple y_{opt} solutions (without N_{noise}) to maximise the training using $R_{utilise}$. Thus, the DTL process integrates various allocation and utilisation constraints to reduce its impact over y_{opt}. From this DTL, the following equation formulates how the low interference I_{inter}^{low} is achieved

$$\begin{cases} SINR_i = (Ᵽ_i \times Ꞇ_{gain}) - (N_{noise} + I_{inter}), \\ I_{inter} = \sum_{i=1}^{n}\left(\frac{(Ᵽ_i \times Ꞇ_{gain})}{SINR_i}\right) - N_{noise}, \\ R_i = O_{integrate} + R_{opt}. \end{cases} \tag{10}$$

$$I_{inter}^{low} = \min_{a_{DTL}} I_{inter} + \sum_{i=1}^{n} (SINR_i \times I_{inter} \times R_i) + \\ + \left(\frac{1}{d^2} - \quad -N_{noise}\right) + R_{allocate} \times Ᵽ_{trans} \tag{11}$$

In the above equation, $SINR_i$ is the signal-to-interference with noise ratio that measures the quality of data transfer in the network. This helps to identify how interference affects the quality of the signal. The term $I_{inter} = \sum_{i=1}^{n}\left(\frac{(Ᵽ_i \times Ꞇ_{gain})}{SINR_i}\right) - N_{noise}$ measures the relationship between power and channel gain with $SINR_i$. To maintain reliable communication $SINR_i \geq SINR_{min}$ and $Ᵽ_i \leq Ᵽ_{max}$. This maintains the interference level to obtain a strong signal, which improves prolonged user experience. The allocation of individual resources to the user is termed as R_i that includes integration and optimisation of the resources. The condition $I_{inter}^{low} \propto \frac{1}{d^2}$ with $d_i \geq d_{min}$ shows the interference increases with a decrease in distance that affects the quality of the signal for near than far locations. This I_{inter}^{low} ensures that the network minimises its interference by deep transfer learning and resource allocation. This helps to improve signal quality by optimising resources to ensure efficient data transfer in the network. This improves the reliability and performance of the network. The following equation $O_{integrate}^{high}$ formulates the high integration:

$$\begin{cases} H_{thr-put} = B_{allocate} \times \log\left(1 + \frac{Ᵽ_{trans,i} \times Ꞇ_{gain,i}}{N_{noise} + I_{inter}}\right), \\ R_i(H_{thr-put}) = \sum_{i=1}^{n} \frac{1}{K_i} \times (1 + Ᵽ_{trans}) + R_{share}, \\ R_{share} = \frac{R_{allocate} + I_{inter}}{R_{utilise}}. \end{cases} \tag{12}$$

$$O_{integrate}^{high} = \max_{a_{DTL}} O_{integrate} + (H_{thr-put} \times R_i(H_{thr-put}) \times \\ \times R_{share}) + R_{opt}, \tag{13}$$

where, $H_{thr-put}$ denotes the throughput for the user, which depends on bandwidth. This incorporates interference and noise to measure the relationship for resources. The term $R_i(H_{thr-put})$ indicates the resource for individual users based on the throughput condition. This incorporates the demand and resources that are shared to handle data processing in the network. Maximising $R_i(H_{thr-put}) \rightarrow \max R_i(H_{thr-put})$ also enhance high integration. The shared resource is calculated using the formula $R_{share} = \frac{R_{allocate} + I_{inter}}{R_{utilise}}$, where $R_{share} \propto \frac{1}{R_{utilise}}$, indicating that sharing increases as utilisation decreases. The longevity-satisfying condition is validated as $\sum R_i = R_{allocate}$ and $y_{opt} = R_{utilise}$ to maximise C_{gain}. Traditional methods, which often depend on static algorithms, tend to struggle with fluctuating network conditions. In contrast, the modified deep transfer learning (DTL) approach excels in dynamically adapting to these changes through insights gained from previous network states. DTL not only enhances accuracy, but also improves efficiency in managing interference by continually optimising routing decisions and forecasting interference patterns. This ensures more adaptable real-time solutions tailored to evolving network demands.

The DTL process is validated using α_{train} and $\alpha_{transfer}$ to maximise the $O_{integrate}$ under I_{inter}^{low}. These two conditions are validated through ϕ optimised outcomes for $A_{allocate}$. In this assessment process, y_{opt} is the target condition that is to be achieved for $R_{initial}$ and R_{opt}, for which α_{train} is pursued. Therefore, the training is induced for low N_{noise} and new resource allocation. The longevity for y_{opt} is improved from the α_{train} and new α_{DTL} processes allocated to maximise $R_{allocate}$ and $R_{utilise}$. High integration is obtained by maximising the integration factors like throughput, resource sharing, and optimisation of resources in the network with the help of deep transfer learning. This ensures that the network integrates its resources efficiently with minimum interference. From this high integration and low interference, the longevity of the network is achieved and expressed as L_{long} in the following equation:

$$\begin{cases} E_i = \left(\frac{H_{thr-put} \times N_{noise}}{P_{trans}(1+I_{inter})}\right), \\ L_{net} = E_i \times (a_{DTL}), \\ L_{long} = \max_{a_{DTL}} L_{net}\left(I_{inter}^{low} + O_{integrate}^{high}\right) \\ \quad \times \left(R_{opt} \times y_{opt}\right). \end{cases} \quad (14)$$

The efficiency of the network is computed as E_i, which incorporates the factors that affect the longevity of the network. The term $E_i = \left(1 + \frac{I_{inter}}{I_{inter}}\right)$ captures efficiency based on the noise and interference that the network transfers during transmission. The longevity of the network is denoted as L_{net} is computed with the help of deep transfer learning and efficiency. The overall longevity for the user is achieved by $E_i \propto L_{net}$ to maximise the network longevity along with a_{DTL}. This is obtained by the incorporation of low interference and high integrity with the optimisation of resources and $y_{opt} \geq y_{max}$ routing. Thus, a_{DTL} predicts and optimises synchronisation intervals for resource sharing to avoid communication collisions and enhance longevity. This optimises low-interference routing and high device integration for communication longevity. However, this addresses critical challenges between devices and optimises routing to improve the longevity and performance of the network.

Using deep transfer learning, the proposed method excels in adapting to the evolving demands of 5G networks. It integrates pretrained insights with real-time adjustments to optimise resource allocation, maintain synchronisation, and enhance communication efficiency.

III. PERFORMANCE ASSESSMENT

A. Experimental Setup

A network model similar to Fig. 1 is created in a simulation area of 1000 m × 500 m with 300 communicating devices. In this region, 11 base stations are used to handle 30 microcells with 6–10 devices/cell. The BS communication range is set at 500 m with an operating frequency of 3.7 GHz and 150 MHz. The transmit power of the BS is 0 W to 2.1 W and the noise power is -82 dBm. The number of intervals per user/bandwidth allocation is set to a maximum of 10 with a base latency of 0.15 ms. This setup creates a realistic testing environment for evaluating the coalition-based routing and resource optimisation (CRRO) method. This setup allows for the evaluation of the method performance in densely populated large networks with varying device counts and communication intervals. By doing so, it effectively verifies the scalability and efficiency of the CRRO method under demanding and dynamic conditions.

B. Comparative Analysis

Using the experimental setup described above, the proposed method is verified using metrics of resource allocation, utilisation, path loss, latency, and routing longevity. The variants are communicating devices (10 to 180) and intervals (1 to 10). The above metrics are compared with the existing methods TFACR [30], BBOA [23], and PMHRP [20] to verify the efficiency of the proposed method.

– Resource Allocation

The proposed CRRO method maintains low latency as the number of communicating devices and their intervals increase. When the number of devices increases, the system allocates resources to maintain optimal communication. For example, when a maximum number of devices are communicating, the method ensures high resource allocation. This is achieved by allocating resources $R_{allocate} = (R_{initial} \times R_{utilise}) - I_{inter}$ during every interval by prioritising shared resources like bandwidth and channels. This $y_{cong} = \exists_{traffic} + L_{latency}$ ensures an equal share of bandwidth without causing congestion. In deep transfer learning, $R_{allocate} \geq y_{opt}$ that maintains low interference. Resource allocation remains high even during an increase in device density. Overloading in the network was efficiently managed and prevented by incorporating the proposed method. The allocation changes based on the demand $R_{allocate} = \frac{R_{share} \times R_{utilise}}{I_{inter}}$ ensures the resources are distributed evenly without degradation. With the help of this method the performance of the network and device communication is enhanced (Fig. 2).

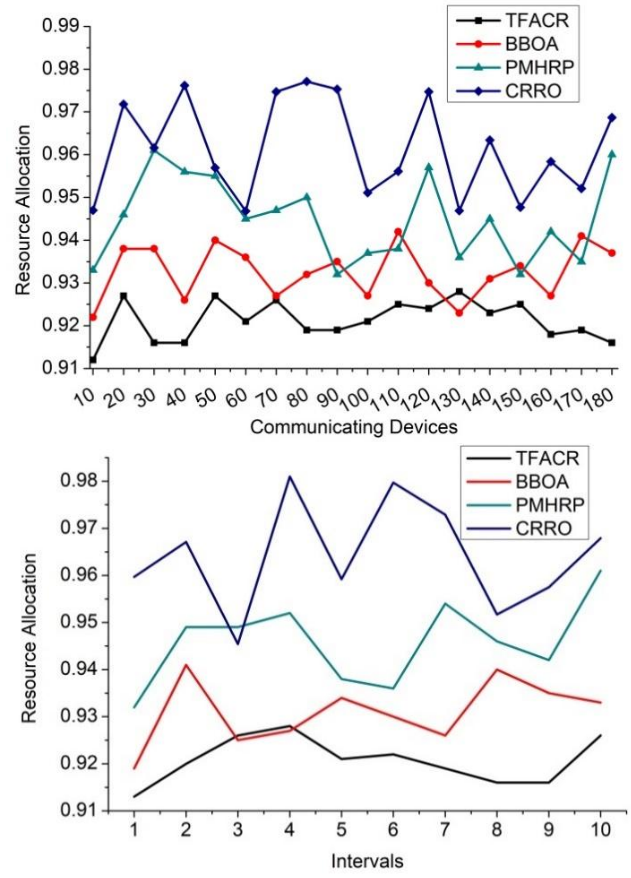

Fig. 2. Experimental results of resource allocation.

The resource allocation and delay graphs display a characteristic sawtooth pattern, reflecting the periodic adjustments made by the CRRO method. To ensure optimal communication, the system dynamically modifies resource allocation based on the number of active devices and traffic demands. When device activity or traffic is high, more resources are allocated, and when demand decreases, fewer resources are distributed. These distinct incremental changes create the oscillations observed in the graphs.

This behaviour plays a crucial role in maintaining effective network performance, preventing congestion, and ensuring low latency. However, it also results in recurring variations in both resource allocation and latency metrics due to continuous adjustments.

– *Resource Utilisation*

The utilisation of resources in the network is based on the number of communicating devices with their intervals and refers to how much of the available bandwidth, and power $\text{Ᵽ}_i \leq \text{Ᵽ}_{max}$ and $B_i \leq B_{max}$ are actively used for communication. The proposed CRRO method ensures high resource utilisation $R_{utilise} = \frac{n}{K_i} + R_{share}$ when more devices communicate with minimal wastage of resources. This $R_{utilise} = B_{allocate} \times \left(\frac{1}{f \times d}\right)$ process that the available resources like bandwidth and channel frequencies are utilised efficiently. For example, when more devices are communicating, this method shows that resource utilisation remains high $R_{opt} \to \text{Ᵽ}_i \leq \text{Ᵽ}_{max}$ across all intervals. This $R_{utilise} = \frac{R_{initial}}{R_{allocate}}$ indicates that the CRRO method can adjust to make the most of available resources without over-utilisation. The system operates R_{opt} efficiently when the number of devices increases, to avoid resource waste or underutilisation of resources (Fig. 3).

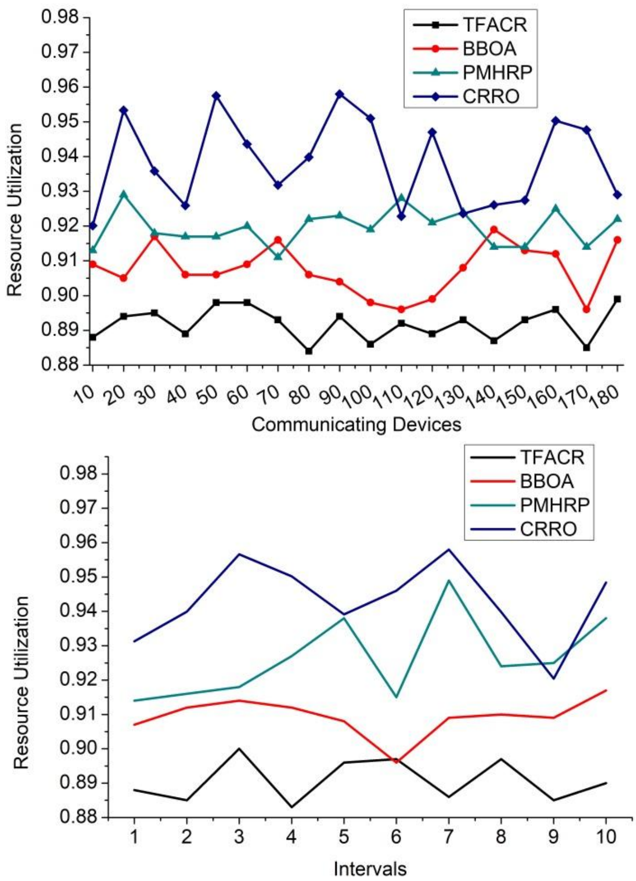

Fig. 3. Experimental results of resource utilisation.

– *Path Loss*

In our simulations, the term "interval" refers to the discrete time periods during which resources are allocated and adjusted throughout the network. These intervals represent specific moments when the system assesses communication requirements, redistributes resources, such as bandwidth and channels, and evaluates their impact on latency and device performance. The duration of these intervals is carefully chosen in the simulation setup to strike a balance between operational efficiency and system responsiveness.

Path loss refers to the reduction in signal strength and power loss when the data are transmitted from the transmitter to the receiver. The proposed CRRO method ensures less path loss for the number of communicating devices with their intervals. The computation of $y_{opt} = \max_{\text{Ᵽ}}\left(\frac{y_{qual}}{y_{cong}}\right)$ selects the optimal path for transmission. This $y_{cong} = \exists_{traffic} +$ ensures that the path loss is minimized even when the number of devices increases. This $A_{allocate} \geq \min(y_{opt})$ enhances resource allocation and achieves throughput as $H_{thr-put}$ with minimum routing. For example, the system with the maximum number of devices results in less path loss across all intervals due to interference-less routing by the CRRO method. The method ensures better communication quality as $y_{qual} = \frac{\text{Ᵽ}_{recv}}{N_{noise} + I_{inter}}$ and longevity by $O_{integrate} \geq y_{opt}$ optimising the transmission path and interferences. This enhances the ability of the network to maintain long transmissions that contribute to effective communication longevity (Fig. 4).

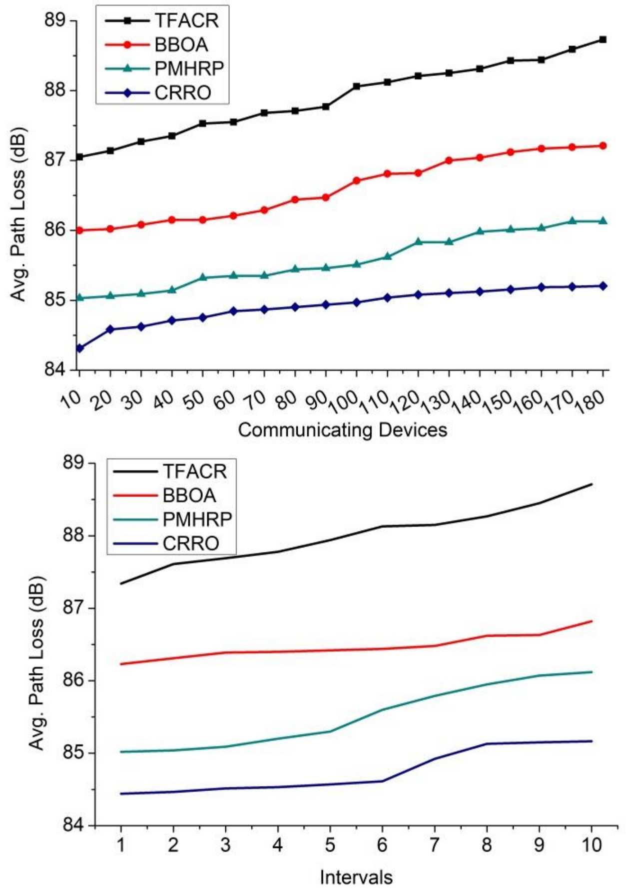

Fig. 4. Experimental results for path loss.

– *Latency*

The time when the delay occurs in communication between devices is measured as $L_{latency} = y_{cong} - \exists_{traffic}$ during data transmission. The proposed CRRO method maintains low latency when the number of communicating devices increases with their intervals. This works by optimising routing paths as y_{opt} and $A_{allocate}$ resource allocation. The model shows low latency across all intervals even when $y_{qual} \geq \min N_{noise}$ and $y_{qual} \propto \frac{1}{N_{noise}}$ the network handles a larger number of devices. This is ensured by the proposed method, which minimises the time it takes to travel between devices. The CRRO method adjusts $I_{inter}^{low} \propto \frac{1}{d^2}$ with $d_i \geq d_{min}$ according to the resource availability when the density of the device increases to avoid delays. The congestion is reduced $y_{cong} = \exists_{traffic} + L_{latency}$ to improve data transmission during routing. This ensures that the system maintains low latency with quick and efficient communication between devices (Fig. 5).

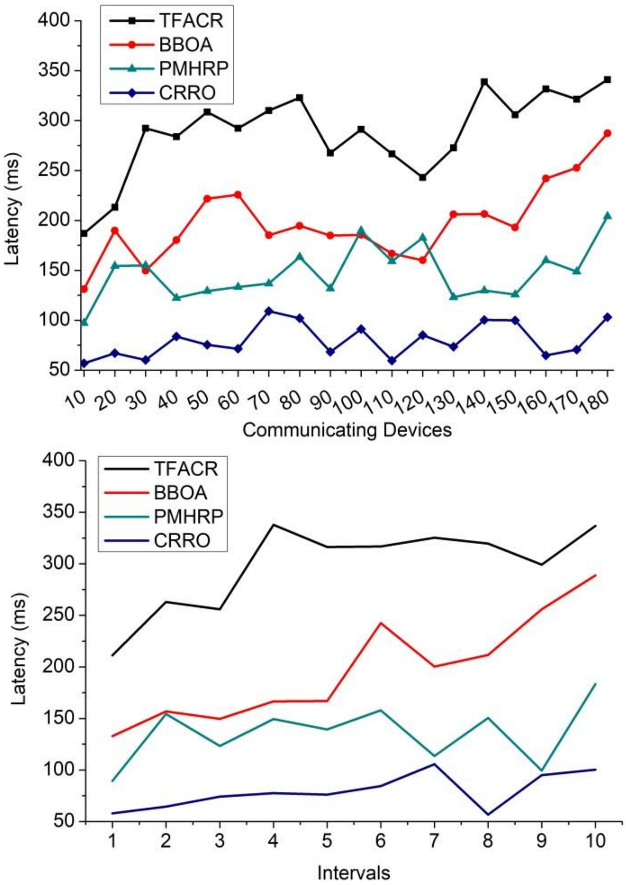

Fig. 5. Experimental results for latency.

– *Routing Longevity*

Communication is maintained over time without frequent disruptions $L_{net} = E_i \times (a_{DTL})$ in the network. The proposed CRRO method ensures high routing longevity across different intervals with several devices. This is achieved by

$$L_{long} = \max_{a_{DTL}} L_{net}\left(I_{inter}^{low} + O_{integrate}^{high}\right) \times \left(R_{opt} \times y_{opt}\right) \quad (15)$$

optimising resource allocation and minimizing interference. High routing longevity is established $y_{opt} \geq y_{max}$ when a high number of devices are communicating for longer periods. The overall longevity of the user is achieved by $E_i \propto L_{net}$ and leads to more stable communication channels. In 5G networks, it is essential to maintain high routing longevity $E_i = \left(\frac{H_{thr-put} \times N_{noise}}{P_{trans}(1+I_{inter})}\right)$ for long-term communication stability. This enhances high performance during data transmission. Thus, a_{DTL} predicts and optimises synchronisation intervals for resource sharing to avoid communication collisions and enhance longevity (Fig. 6).

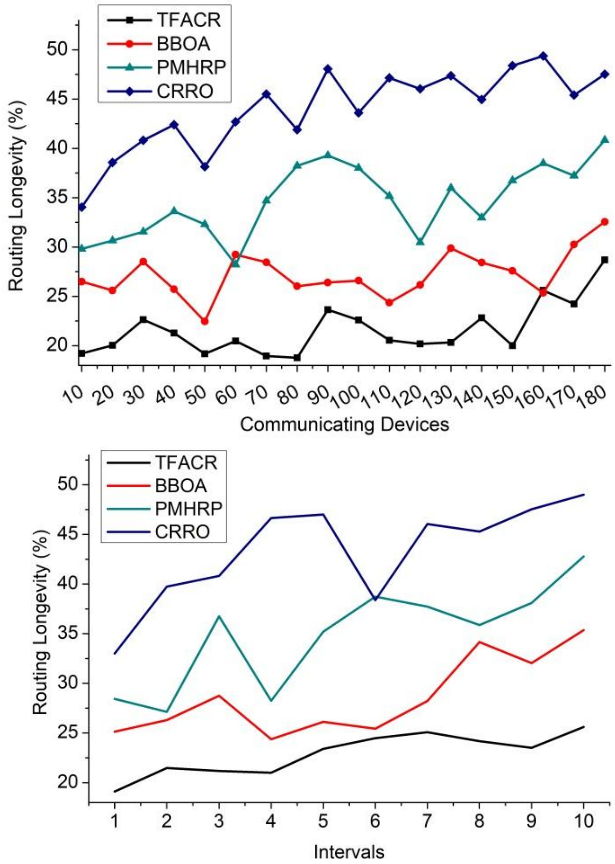

Fig. 6. Experimental results for routing longevity.

C. Summary

The summary is presented in Tables I and II for the results obtained above. These results are tabulated for the maximum communicating devices and intervals, respectively.

TABLE I. RESULT FOR THE MAXIMUM COMMUNICATING DEVICES.

Metrics	TFACR	BBOA	PMHRP	CRRO
Resource Allocation	0.916	0.937	0.960	0.9687
Resource Utilisation	0.899	0.916	0.922	0.929
Avg. Path Loss (dB)	88.73	87.21	86.13	85.205
Latency (ms)	340.98	287.17	204.18	103.019
Routing Longevity (%)	28.7	32.55	40.83	47.512

The proposed CRRO improves resource allocation, utilisation, and routing longevity by 9.31 %, 10.31 %, and 13.49 %, respectively. This method reduces the average path loss and latency by 12.31 % and 10.48 %, respectively.

TABLE II. RESULTS FOR THE MAXIMUM INTERVALS.

Metrics	TFACR	BBOA	PMHRP	CRRO
Resource Allocation	0.926	0.933	0.961	0.9679
Resource Utilisation	0.89	0.917	0.938	0.9484
Avg. Path Loss (dB)	88.71	86.82	86.12	85.166
Latency (ms)	336.82	288.83	183.28	100.296
Routing Longevity (%)	25.61	35.36	42.78	48.991

The proposed CRRO improves resource allocation, utilisation, and routing longevity by 8.37 %, 10.02 %, and 14.41 %, respectively. This method reduces the average path loss and latency by 11.76 % and 10.47 %, respectively.

Compared to TFACR, BBOA, and PMHRP, the coalition-based routing and resource optimisation (CRRO) method shows significant advantages. It optimises resource allocation, reduces latency by 10.47 %, and improves routing longevity by 14.41 %. Unlike traditional approaches, CRRO leverages a coalition-based adaptive strategy that minimises interference and enhances the longevity of communication. This makes it particularly effective in high-density networks, where conventional methods often encounter challenges such as congestion and inefficient resource management.

Using dynamic resource allocation, the CRRO method improves resource utilisation by 10.02 % and increases routing longevity by 14.41 %. Through the formation of coalitions, devices collaboratively share resources based on real-time demands, thereby reducing interference and congestion. This adaptability ensures superior performance in environments with high device density and extended communication intervals, where traditional methods may fail to maintain efficiency.

IV. Conclusions

The CRRO method is proposed to perform cooperative agreements between resource providers and communication channels. To validate and mitigate interference, a modified deep transfer learning model is included, which upgrades resource utilisation and the longevity of communication. In addition, a coalition-based routing with resource optimisation CRRO method is included to improve the performance operation of 5G networks, these techniques emphasise that the proposed method excels in areas like resource allocation, utilisation, and longevity while minimising path loss and latency. Furthermore, the method balances communication loads among devices and optimises resources in networks with a large number of devices. The targets defined for the proposed method are to maintain high resource efficiency, minimise delays, and ensure long-term network reliability. As a result, this method addresses solutions for networks, particularly in dense environments where traditional routing and resource allocation methods may fail to optimise resources. The proposed CRRO improves resource allocation and routing longevity by 8.37 % and 14.41 %, respectively, and reduces average path loss by 11.76 % for the maximum devices.

The improved longevity of the routing is based on limited channel allocation constraints using convergence optimisation. Therefore, low-power allocation constraints for noise reduction remain a routing problem for routing. Therefore, low-power routing with channel allocation and utilisation feasibilities over noise cancelling features is planned for future work. To address the challenges of scalability while implementing CRRO in real-world 5 G networks, dynamic coalition formation and deep transfer learning can be introduced. These techniques will focus on computational overhead in crowded networks. However, problems may arise due to network synchronisation across heterogeneous devices and increased latency that will require further optimisation in diverse environment and conditions. It will aim at regressing non-convex optimisation under high allocation intervals to improve the support for large device densities.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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