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Open Radio Access Networks Systems Throughput Improvement

Russul Q. Muhammed[1], Ismail S. Baqer[1]

Affiliations
[1]Department of Electrical Engineering,
College of Engineering,
Wasit University,
Al Kut, Wasit, Iraq

Correspondence
Russul Q. Muhammed,

rmuhammed@uowasit.edu.iq

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Abstract

Open Radio Access Networks (O-RAN) are expected to revolutionize communication systems. O-RAN enables virtualized Radio Access Networks where distributed components are attached through open interfaces and intelligent controllers optimize the performance. A new conceptual design has been created for network configuration, deployment, and functions. This design uses interchangeable components from various vendors and can be optimized for performance through a centralized inference layer and data-driven control. However, due to the large number of users and limited capacity of the fronthaul in dense wireless systems, it becomes challenging to achieve optimal resource allocation in such massive systems. In this work, we balance the spectral efficiency and the required power, which will reduce the signaling overheads and processing in high-density radio access networks. More specifically, a linear channel estimation (based on the MMSE technique) is employed to design the Conjugate Beamforming vectors. The suggested iterative approach, namely large-scale fading detection (LSF) and the intermediate value method (IV) (LSF-IV), to attain the balancing between users' uplink spectral performance. Concerning the algorithm validity and for a specific parameter setting scenario, the proposed approach can significantly enhance the spectral performance for the users in the worst channel conditions compared with the typical fractional PA. Adjusting a specific parameter can improve spectral performance by 45% with a 95% likelihood. This study found that using a more extended training sequence for channel estimation can result in a 27% improvement in spectral performance, based on a 95% likely percentage.

Keywords: RAN; O-RAN; 5G; Spectral efficiency; V-RAN

الخلاصة:

تهيمن اليوم شبكات الاتصال اللاسلكية المفتوحة Open RAN على عالم شبكة الهاتف المحمول. كونها تفصل وظائف الشبكات المفتوحة للاتصالات اللاسلكية وتنشئ واجهات مفتوحة بينها، تَعد شبكات الاتصال اللاسلكية المفتوحة Open RAN بمستقبل يخفض تكاليف مشغلي الهاتف المحمول الطويلة الأمد انخفاضا حادّا، ويزيد المنافسة بين المزودين، ويعزز مرونة الشبكة، ويوسع فرص الابتكار. في هذا العمل، نحاول تحقيق التوازن بين الكفاءة الطيفية والطاقة المطلوبة والتي بدورها سوف تقلل من أعباء الإشارة والمعالجة في شبكات الوصول الراديوي عالية الكثافة. وبشكل أكثر تحديدًا، يتم استخدام تقدير القناة الخطية (استنادًا إلى تقنية MMSE) لتصميم متجهات الحزم (Conjugate Beamforming vectors). ويستفيد النهج التكراري المقترح، وهو LSF-IV، من كشف التلاشي واسع النطاق (LSF) وطريقة القيمة المتوسطة (IV) لتحقيق التوازن بين الأداء الطيفي للوصلة الصاعدة للمستخدمين. ويمكن للنهج المقترح أن يعزز بشكل كبير الأداء الطيفي للمستخدمين في أسوأ ظروف القناة، على سبيل المثال، يبلغ كسب الأداء الطيفي حوالي 45% من التحسين للنسبة المئوية المحتملة البالغ 95%. بالإضافة إلى ذلك، فإن إحدى النتائج الرئيسية لهذه الدراسة هي أن استخدام تسلسل تدريبي طويل لتقدير القناة يمكن أن يحقق زيادة في الأداء الطيفي تبلغ حوالي 27% من 95% نسبة مئوية محتملة.

1. INTRODUCTION

A radio access network (RAN) attaches individual users' components to the core network via radio access technology (over a fiber or wireless backhaul connection). It is a key part of current communication schemes. The essential functionality of radio access networks is to address the management of the available resources of the wireless communication system. Usual radio access networks include two main units, the first one. is the Radio Unit (RU) which comprises antennas of the transceiver and its task is information dispatch/reception, and the second is the Processing Unit (PU) which is responsible for utilization, management, and sharing of radio resource [1]. The Radio Access Network (RAN) architecture has undergone significant transformations over the years to meet requirements. Four major architectural approaches have emerged: Distributed RAN, Centralized RAN, Virtual RAN, and Open RAN. Each approach brings unique benefits to the telecommunications industry.

Distributed RAN, or D-RAN, is an early architecture that is traditionally planned in a distributed and decentralized manner, in which the baseband Unit (BBU) and the Remote Radio Unit (RRU) are co-located at the site of each cell. This approach spreads the radio tasks across multiple parts or sites, with backhaul connections linking these parts to the network centre or core [2, 3]. Centralized RAN, or C-RAN, introduces a centralized architecture by moving the baseband processing to a central location known as the BBU pool. In C-RAN, RRUs are deployed at the cell sites and connected to the BBU pool through high-capacity fiber links. Such architecture enables effective sharing of the network resources with flexible, centralized, and real-time scheduling [4].Virtual RAN, or V-RAN, on the other hand, virtualizes RAN functions as software that isolates the remote heads from the base-band unit. As a result, this can enhance the sharing of the resources in the network and allow for more comfort in evolving to the newer generations of network technologies, also enables operators to scale their networks more efficiently [5-7]. The V-RAN, recently, has begun to develop from the idea of a centralized network, towards the vision of Open-radio access network (or O-RAN for short) [8]. The latest addition to the RAN architecture landscape is O-RAN, or Open RAN. Open Radio network denotes a new standard for radio access networks, which specifies the interfaces that sustain inter-operational functionality between equipment of different vendors and thus present a flexible network with reduced cost [9]. This novel architecture extends the principles of openness and standardization to RAN design. In this architecture, the RRH (and BBU combination is divided into three components: The Open Radio Unit (or O-RU for short), Open Centralized Unit (O-CU), and Open Distributed Unit (O-DU). Different from conventional radio networks' technology, O-RAN separates the bonds between software (S/W) and hardware (H/W) in the equipment of the network. This attribute submits a kind of flexibility for the operators of the network to install and develop the network element. This approach is suggested to allow three major purposes: the first one is to keep the original cloud tasks of the radio network by separating S/W and H/W segments, the second purpose is to employ effective intelligent techniques to allow advanced network orchestration and management, and the third purpose is to sustain different network interfaces [9]. As mentioned earlier, the network in the open architecture is divided into four major structure units, these are the Open-Centralized Unit (O-CU), Open-Distributed Unit (O-DU), Open-Radio Unit (O-RU), and Radio Network Intelligence Controller (RIC). The Radio Unit, which is located with the antennas, is in charge of receiving, transmitting, digitizing, and amplifying the radio signals. The Open-Centralized Unit (O-CU) and Open-Distributed Unit (O-DU) are the computation elements of the base station, i.e., both represent the former Based Band Unit in the legacy networks, where the Centralized Unit (O-CU) is deployed near the core; while the open distributed unit (O-DU) can be deployed near the O-RU. The Radio Network Intelligence Controller is qualified to address the automated and intelligent tasks associated with the network [9]. With the dis-aggregation of H/W and S/W, ORAN produces an integrated construction over multiple developments and carries multiple profits. The integration of the S/W-qualified construction qualifies the network to be appropriate for future network generations as well as current generations. In addition, the Dis-aggregation and software association make the network flexible for installation and up-gradation/extension. Since O-RAN is the software driven service specific network that behaves based on intended service and consequently selects the real time or on-line services, which need actual little latency through the less serious services. Also, the cost of operating may be reduced up to 80%. Moreover, locating the S/W at the core of the network allows the operators to preserve millions of dollars by combining the connectivity profits of all the generations under a single umbrella [1]. Fig. 1 contains the architecture of the D-RAN, C-RAN, vRAN, and Open RAN.

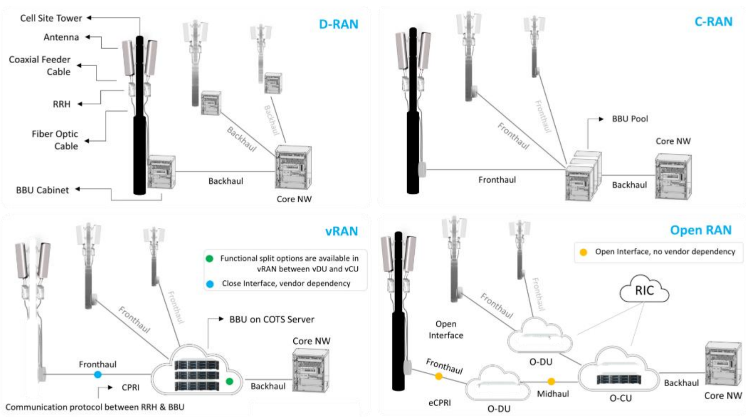

Fig. 1 D-RAN, C-RAN, vRAN, and OpenRAN Archtetucure [10]

Table 1 contains a comparison that outlines the differences between D-RAN, C-RAN, vRAN, and OpenRAN in terms of setup, RAN components, hardware, software, connectivity, vendor dependency, resource sharing, operational costs, and intelligence.

Table 1: D-RAN, C-RAN, vRAN, and OpenRAN comparison

Aspect	**D-RAN**	**C-RAN**	**vRAN**	**OpenRAN**
Setup	Distributed	Centralized	Centralized (Virtualized)	Centralized (Virtualized)
RAN Components	RRH and BBU co-located at each site	RRH at cell site, BBU centralized	RRH at cell site, BBU centralized (virtualized)	RRH at cell site, BBU centralized (virtualized)
Hardware	Vendor-specific for both RRH and BBU	Vendor-specific for both RRH and BBU	Vendor-specific for RRH, COTS servers for virtualized BBU	Open to various vendors for RRH, COTS servers for virtualized BBU
Software	Vendor-specific	Vendor-specific	Vendor-specific for RRH, virtualized for BBU	Open to various vendors
Connectivity	Point-to-point backhaul to core network	Fronthaul to centralized BBU	Fronthaul to centralized (virtualized) BBU	Fronthaul to centralized (virtualized) BBU
Vendor Dependency	Yes	Yes	Yes	No
Resource Sharing	Limited	Dynamic sharing among multiple sites	Dynamic sharing among multiple sites	Dynamic sharing among multiple sites
Operational Costs	High	Reduced	Reduced	Reduced
Intelligence	N/A	N/A	Limited by vendor dependencies	Intelligent with RIC

2. RELATED WORKS

The authors of [10] proposed a Beam Management approach that employs location-based information kept in a Radio Environment Map. The approach employs maps of the received power, and the patterns of the user's mobility to improve the Beam Management procedure through the application of Reinforcement Learning and the Policy Iteration strategy with various objective metrics (the reduction of beam re-selections process or enhancement of received power), where the suggested approach is appreciative of the architecture of the Open-RAN, promoting the realistic undertaking of such open networks. Also, the authors justified via the simulation that the suggested Beam Management approach can minimize the number of radio connections to defeat or beam re-selections in comparison to a certain benchmark approach. In [11] the authors proposed a Reinforcement Learning-assisted approach to handle data traffic while enduring the benefit of the Open-radio networks in terms of eco-friendliness. The approach acquires regular messages from the Open Distributed Unit (O-DU) regarding the situation of the network to adjust, dynamically, the resource allocation (RA) and recognizes the related modulation and coding system that most suitable matches the condition of the channel and per-flow data traffic. This Reinforcement Learning-assisted approach for resource allocation aims at minimizing the maximal disparity between the real and required data rate, over all dynamic traffic flows. The approach is incorporated into a platform of the Open-radio networks. The submitted structure is very adaptable and the architecture can be adjusted according to the traffic flow number. Also, it is likely to make several approach-independent paradigms, that serve successively a subset of clients, enhancing the scalability of the structure. In [12], the authors present an energy-aware, real-time learning-aided scheduling strategy for virtualized remote units in open radio access networks. The objective is to enhance scheduling procedures that lower the cost of energy while increasing the virtualization gain. They present a non-real-time RIC Policy Decider paradigm to learn and execute optimal approaches, which can be modified according to the requirements of the user and the network. Through the A1 interface, the policy decision is associated with near-real-time timescales optimization, and the Data Monitor estimates the reward according to energy consumption and executed performance, which is, at the finish of every decision time slot and through the O1 interface (Interface connecting the Service Management and Orchestration (SMO) framework to other O-RAN components), transmitted to the Policy Decider. Built on testbed measures and real-world data traffic trails, data-driven trials are completed to estimate the significance of the suggested approach and compare it to advanced baseline techniques. The presented technique exceeds the baselines and performs energy conserving in the range of 74% and 35%, as indicated via data-driven investigations with testbed measures and real-world data traffic trails.

Amid network operation, the dynamic feature of open-RAN conditions usually requires reconfiguring of the network virtualization which in turn, causes extra overhead prices and fluctuation of the network traffic performance. To cope with this issue, the authors in [13] submitted an optimization formula that tries to reduce the re-configuration overhead and computational cost of virtualization at the same time. The submitted approach depends on deep reinforcement learning and restrained combinatorial optimization in which an agent aims to reduce a disciplined cost function emanating from the presented optimization formula. The justification of this method shows significant gains, e.g., a notable 76.0% decrease in re-configuration virtualization overhead, attended by almost an increase of up to 23.0% in expenses of computation. Also, the suggested method achieves a bandwidth conserving of almost 76.0% at the cost of nearly 27.0% of CPU resources over-provisioning in comparison to traditional networks that do not attain re-configurations of virtualization.

In [14], the authors propose a new structure for open networks for predictive uplink slicing where a near-real-time RIC is merged with a machine learning approach to achieve aggressive RAN resource allocation for the uplink mode (UL) of operation. The proposed structure is tested and estimated through RAN radio in a real-world method. Although it presents multiple new interfaces, results are exhibited to be proximate to a design without open radio network observation. Accordingly, with increased spectral efficiency (SE), UL delays down to 5.0 msec are performed. Authors in [15] concentrate on the investment and supply of data to be employed with machine learning for xApps. A machine learning instance is prepared to perform network control through messages of the RIC control to revise radio unit configurations in real time. The assumed testbed model includes multiple access points and users' equipment, the model considers the scalability of the Open network configuration. Encouraging outcomes are attained for optimal transmit throughput while reducing the queue times of packets. To sum up the previous works, table 2 shows main related studies and their key findings.

In this study, we consider the work of [11, 12] in terms of LSF detection and data power control to enhance the spectral performance to be extended from the traditional cellular paradigm scenarios into O-RAN. The detection of the signal is attained jointly through the cooperation of the Distributed Units (O-DUs) in a multiple processing style. The physical layer functionality is separated across the O-RUs and the O-DUs (respectively, the low and the high physical layer tasks).

Table 2: The main related studies and their key findings.

Ref. No	**Methodology**	**Objective**	**Results**
[10]	Beam Management: Reinforcement Learning and Policy Iteration with Radio Environment Map	Improve Beam Management procedure	Simulations show reduction in beam re-selections
[11]	Reinforcement Learning for Traffic Handling: Reinforcement Learning-assisted approach for resource allocation	Dynamically adjust resource allocation	Demonstrates gains in energy conservation and reduced data rate disparity
[12]	Energy-Aware Scheduling Strategy: Real-time learning-aided scheduling strategy for virtualized remote units	Enhance scheduling procedures for energy conservation	Achieves energy conservation and virtualization gain
[13]	Optimization Formula for Virtualization: Deep reinforcement learning and combinatorial optimization	Reduce re-configuration overhead and computational cost	Decreases re-configuration overhead and computational cost
[14]	Predictive Uplink Slicing: Near-real-time RIC merged with machine learning for RAN resource allocation	Achieve aggressive RAN resource allocation for uplink mode	Achieves increased spectral efficiency and reduced UL delays
[15]	Data Investment and Supply with ML for xApps: Machine learning for network control through RIC messages	Optimize network control for optimal transmit throughput	Optimizes transmit throughput and reduces packet queue times

3. MODEL OF THE SYSTEM AND PROBLEM FORMULATION

In this study, we suppose a scenario with K single-antenna user equipment served by a number R of Open-Radio Units (O-RUs) with N antennas each over a square grid area (see fig. 2). More specifically, this section clarifies the uplink (UL) combiner analysis throughout a certain coherence block. All the UEs in this phase of transmission dispatch their information signals to the O-RUs concurrently. The architecture of O-RAN allows for the strategy of Large-Scale Fading Detection (LSF)[1] to be engaged in UL detection in three steps depending on the cooperation of interfaced O-DUs in terms of long-term channel statistics only. Firstly, each r^{th} O-RU estimates the signal $\widehat{y_r}$ of users under its service locally and transmits these regional estimations to its corresponding O-DU. Secondly, the corresponding O-DU, based on the LSFD weights of this user, calculates more precise estimations for the user's signal. Thirdly, the signal is then combined into the last signal estimation of the specified user. The obtained signal at the r^{th} O-RU can be expressed as follows [13-15].

$$y_r = \underbrace{\sum_{j\in|K|} \sqrt{P_j}\,\boldsymbol{h}_{jr}\, x_j}_{Useful\ Signal} + \underbrace{\boldsymbol{n}_r}_{AWGN} \quad \ldots(1)$$

given that x_j is the vector of the transmitted signal, , $x_k = [x_1, x_2, \ldots, x_K]$ with unity or normalized energy [16], i.e., $\Xi\,\{x_k\, x_k{}^H\} = \Xi\,\{|x_k|^2\} = 1, \ldots\ \forall\, k \in |K|$, $\boldsymbol{n}_r$ is the Additive-White-Gaussian-Noise (AWGN), $\boldsymbol{n}_r \in \mathbb{CN}(\boldsymbol{0}, \boldsymbol{\sigma}_r^2)$, P_{jr} represent the user transmitting power, g represents the channel from the kth user to the r[th] O-RU[2], and $\boldsymbol{h}_{jr}$ is the channel coefficient vector between r[th] O-RU and the j[th] user which can be described as [17],

$$\boldsymbol{h}_{jr} = \sqrt{\boldsymbol{\beta}_{jr}}\, \boldsymbol{g}_{jr} \quad \ldots(2)$$

here $\boldsymbol{\beta}_{jr}$ denote the path loss and shadowing effects i.e., large scale fading coefficient that varies slowly and accordingly can be followed and estimated exactly. The assumption here is that $\boldsymbol{\beta_{jr}}$ coefficients for all O-RUs and users are well known at the O-DU. In addition, it is worth noting that the slow-fading $\boldsymbol{\beta_{jr}}$ can be assumed to be independent of N elements of the O-RU antenna array. This fact is due to the space between the O-RU's antenna elements being very small (half of the wavelength) corresponding to the space between the O-RU unit and the kth user. Also, $\boldsymbol{g}_{jr} \in \mathbb{CN}(0,1)$, represents the coefficients of the small-scale fading (i.i.d. random variables) which are assumed to be independent in various coherent intervals and remain unchanging over the coherent interval. For Channel Estimation process, in this study, the presumption is that the time division duplexing (TDD) protocol is employed. Firstly, all UEs dispatch pilot-signals ϕ_k synchronously to be received by all O-RUs. Next, these O-RUs and the corresponding O-DU carry out the channel estimation i.e., compute the coefficients $\widehat{\boldsymbol{h}}_{jr}$ of the channel $\boldsymbol{h}_{jr}$ which in turn can be used in beamforming data signals toward all UEs. In the channel training stage, the received signal at the r[th] O-RU is [18],

$$\mathbf{y}_{\mathrm{r}} = \sqrt{\mathrm{q_r}\, \tau} \sum_{\mathrm{j}\in|\mathrm{K}|} \mathbf{h}_{\mathrm{jr}}\, \phi_{\mathrm{j}} + \mathbf{n}_{\mathrm{r}} \quad \ldots(3)$$

Where τ is the length of pilot signals, and q_r denotes the transmitting power of the uplink-pilot. This study suggests, for channel estimation, an essential optimization benchmark i.e., the linear Minimum Mean-Square Error Method (MMSE) which is widely used in multiple signal processing domains, such as identification, detection, and estimation of signals. Consequently, the O-CU determines the MMSE estimation of the channel vector h as follows [19],

$$\widehat{\boldsymbol{h}}_{jr} = \frac{\sqrt{q_r\, \tau}\, \boldsymbol{\beta}_{jr}}{\boldsymbol{1} + q_r\, \tau\, \boldsymbol{\beta}_{jr}} \cdot \boldsymbol{\phi}_j{}^H \ \boldsymbol{y}_r \quad \ldots(4)$$

Which are random vectors with zero mean and a covariance of, $\frac{q_r\, \tau\, \boldsymbol{\beta}_{jr}{}^2}{\boldsymbol{1} + q_r\, \tau\, \boldsymbol{\beta}_{jr}}$ i.e., $\widehat{\boldsymbol{h}}_{jr} \in \mathbb{CN}\left(0, \frac{q_r\, \tau\, \boldsymbol{\beta}_{jr}{}^2}{\boldsymbol{1} + q_r\, \tau\, \boldsymbol{\beta}_{jr}}\right)$, and in this case, the error in the estimated vector will be as follows [20],

$$\widetilde{\boldsymbol{h}}_{jr} = \boldsymbol{h}_{jr} - \widehat{\boldsymbol{h}}_{jr} \quad \ldots(5)$$

Each O-DU performs a regional decoding for every user data symbol first in advance of transferring it to the O-CU[3]. At the decoder of the r[th] O-RU, the regional processed signal of the kth user is given as,

$$\widetilde{\boldsymbol{y}}_r = \mathbf{w}_{\boldsymbol{kr}}{}^{\boldsymbol{H}}\ \boldsymbol{y}_r \quad \ldots(6)$$

where $\mathbf{w}_{\boldsymbol{kr}}$ indicates the weights of the decoding vector. Now, considering a simplest solution (Conjugate Beamforming technique[4]) for the receive combiner i.e., assigning $\mathbf{w}_{\boldsymbol{kr}} = \widehat{\boldsymbol{h}}_{jr}$. Next, to detect the UL data signal $\widehat{\boldsymbol{y}}_k$ of the kth user, the O-CU employs the LSF strategy. It is noteworthy that, in terms of 95%- likely per-user spectral performance, employing the LSF approach can attain a two-fold gain over employing the MRT beamforming alone. In this work, to reduce the effects of interference among the UEs, we utilized LSF decoding (second-layer detection) that is performed at the O-CU. The decoding approach especially relies on involving a simple Conjugate Beamforming technique at the O-DUs (first-layer detection), after that delivering the resultant signal to the O-CU. In the O-CU a weighting combination is achieved by employing a specific optimal weight vector that enhance the spectral performance. In other words, at the O-CU site, the UL signal is detected jointly where joint decoding of multiuser signals at the O-CU depends on compiling the production of the UE channels' conjugate and the information signals. such that,

$$\widehat{\boldsymbol{y}}_k = \sum_{r\,\in\,|R|} \boldsymbol{v}_{kr}{}^{\boldsymbol{opt.}}\ \widetilde{\boldsymbol{y}}_{kr}, \quad \ldots(7)$$

.

where the vector $\boldsymbol{v}_{kr}{}^{\boldsymbol{opt.}}$ represents the optimal coefficients of the large-scale fading decoding. Sharing the channel information between the O-CU and the serving O-DUs is crucial for certain BF methods such as the zero-forcing approach. Nevertheless, this sharing comes at the cost of a considerable burden on the backhauling process. In contrast, other BF methods such as MMSE could be a more suitable approach in terms of limited channel information sharing.

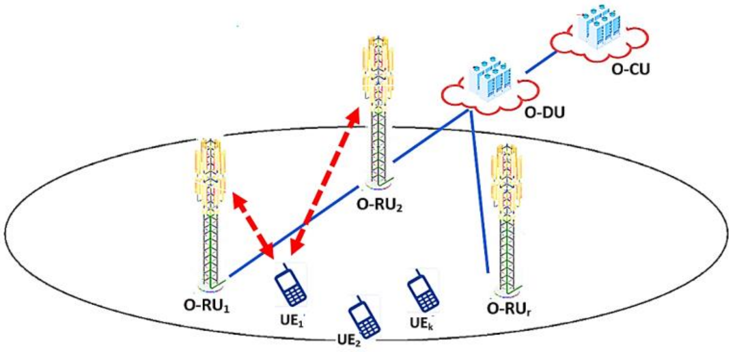

Fig. 2 The proposed O-RAN system model.

Since the capacity of the network is a key metric in any wireless system [24], therefore this work will address this aspect in O-RAN architectures. Leverage the same approach that is applied in [21], the spectral performance of the kth user in terms of (nats/sec/Hz) can be stated using the following logarithmic function [17],

$$\eta_k^{SE} = \delta \,.\, \ln[1+\boldsymbol{\Gamma}_k], \qquad \dots (8)$$

Where the ratio $\delta = \frac{length\ of\ the\ UL\ samples}{length\ of\ the\ coherent\ block}$, and $\boldsymbol{\Gamma}_k$ is the ratio of the signal to interference plus noise level (effective value employing expectation process),

$$\boldsymbol{\Gamma}_k = \frac{p_k \,.\, |\boldsymbol{v}_k{}^{\boldsymbol{H}} \;\; \mathbf{f}_{\boldsymbol{k}}|^2}{\boldsymbol{v}_k{}^{\boldsymbol{H}}\left(\sum_{j\,\in\,|K|} \;\; p_j \,\boldsymbol{Q}_{kj}\right)\boldsymbol{v}_k - p_k \,.\, |\boldsymbol{v}_k{}^{\boldsymbol{H}} \;\; \mathbf{f}_k|^2 + \boldsymbol{v}_k{}^{\boldsymbol{H}}\boldsymbol{Z}_k\boldsymbol{v}_k} \quad \dots (9)$$

The operator, $|\boldsymbol{v}_k{}^{\boldsymbol{H}} \;\; \mathbf{f}_k|^2 = \boldsymbol{v}_k{}^{\boldsymbol{H}} \;\; \mathbf{f}_{\boldsymbol{k}} \;\; \mathbf{f}_{\boldsymbol{k}}{}^{\boldsymbol{H}} \;\; \boldsymbol{v}_k$ is the square of the two-vectors' inner product [22], $\mathbf{f}_k = E\left\{\mathbf{w}_{kr}\;\boldsymbol{h}_{kr}{}^{H}\right\}$,

$$\boldsymbol{Q}_k = E\,\left\{\left|\,\mathbf{w}_{kr}\;\boldsymbol{h}_{kr}{}^{H}\,\right|^2\right\}, \text{and } \boldsymbol{Z}_k = E\,\{|\,\mathbf{w}_{kr}\;\boldsymbol{n}_r{}^{H}\,|^2\} \quad \dots (10)$$

To achieve this spectral performance (corresponding to the specified signal-to-interference-plus-noise ratio), , the vector of the optimal coefficients for the LSF detection can be expressed as follows [10],

$$\boldsymbol{v}_k{}^{optimal} = \left(\sum_{j\in|K|} \boldsymbol{\beta}_{jr}\,\boldsymbol{\beta}_{jr}{}^{H}\;\rho_r\,q_r + \boldsymbol{\Lambda}_j\right)^{-1} \boldsymbol{\beta}_{jr} \quad \dots (11)$$

Where, $\boldsymbol{\Lambda}_j$ is a diagonal vector given as, $\boldsymbol{\Lambda}_j = diag.(\lambda_{j1}, \lambda_{j2}, \dots \dots .. \lambda_{jR})$, and λ_{jr} is given as,

$$\lambda_{jr} = \left(1 + \sum_{r\in|R|} \boldsymbol{\beta}_{jr}\,\rho_r\right)\,[\,1 + \sum_{r\in|R|}\;\sum_{k\in|K|} \boldsymbol{\beta}_{kr}\,q_r] \quad \dots (12)$$

with, q_r denotes the pilot power, and ρ_r is the signal power. Now, the formula for achieving a fair spectral performance among all the users in the network under the power-allocation constraint can be written as follows,

$$\underset{v_k\,,P_k}{\textbf{maximize}}\;\underset{k}{\textbf{min}}\;\ln(\,1+\boldsymbol{\Gamma}_{kr}\,). \qquad \dots (13)$$

Subject to: $\quad \boldsymbol{C_1};\quad P_k \,\geq\, 0, \quad \text{for all} \quad k \in |K|$

$$\boldsymbol{C_2}; \qquad \sum_{r\,\in\,|R|}\;\sum_{k\,\in\,|K|} P_{kr} \,\leq\, P_t\,, \quad \text{for all } k, r$$

This optimization problem in (13) aims to reach a fair quality of service (i.e., best QoS) among all the users, $\Gamma_0 = \min_k \boldsymbol{\Gamma}_{kr}$ denotes the minimum amount of SINR value that each UE should have, or in other words, it signifies the quality of service to approve the UE's fairness achievement, Γ_{kr} refers to SINR, and P_t stands for the total power transmitted by the overall system. So, the proposed formula will achieve a rate balance that maximizes the smallest of all users' SINR under the per-user power constraints. The above task is difficult, not only because of the non-convex expression but also as a result of the variables to be optimized is involved with each other. So, due to the big dimension of the optimization variables, it is improper, computationally, to search directly for the optimal solution. To solve this problem, this paper suggests a sub-optimal solution with promising performance and low computational complexity. Without loss of generality, the problem of eq. (13) can be rewritten by introducing a new variable, "namely Γ_0, "to simplify the Problem which can be re-written as follows,

$$\underset{P_{kb}}{\textbf{maximize}}\ (\Gamma_0) \qquad \ldots.(14)$$

Subject to:

$$\boldsymbol{C_0};\quad \frac{p_k \cdot |v_k{}^H\ \mathbf{f}_k|^2}{v_k{}^H(\sum_{j\in|K|} p_j \boldsymbol{Q}_{kj})\, v_k - p_k \cdot |v_k{}^H\ \mathbf{f}_k|^2 + v_k{}^H Z_k v_k} \ \geq\ \Gamma_0, \ldots \quad for\ all\quad k \in |K|$$

$$\boldsymbol{C_1};\quad P_{kr} \ \geq\ 0,\ \ for\ all\ \ \mathrm{r} \in |R|\ and\ k \in |K|$$

$$\boldsymbol{C_2};\quad \sum_{r\in|R|}\sum_{k\in|K|} P_{kb} \ \leq\ P_t$$

where the constraints $\boldsymbol{C_0}$ are necessary and sufficient conditions for Γ_0 to be the minimum achievable SINR among the served UEs. On one hand, since Γ_0 is the minimum value, the attainable $\boldsymbol{\Gamma}_k$ value of each UE must not be less than Γ_0.On the other hand, there is at least one UE whose reachable SINR is equal to Γ_0; otherwise, we can always recover Γ_0 to minimize the SINR gap between different UEs. Now, with a fixed value of Γ_0, the problem can be evaluated efficiently using advanced methods in a distributed manner to achieve any point on the Pareto boundary on the total performance region.

$$\underset{P_{kb}}{\textbf{minimize}} \sum_{k\in|K|} p_k \qquad \ldots(15)$$

Subject to:

$$\boldsymbol{C_0};\quad (1+\Gamma_0)\, p_k \cdot |\boldsymbol{v}_k{}^{\boldsymbol{H}}\ \ \mathbf{f}_k|^2 - \Gamma_0\, \boldsymbol{v}_k{}^{\boldsymbol{H}} \boldsymbol{Q}_{kj_k} \boldsymbol{v}_k - \Gamma_0\, \boldsymbol{v}_k{}^{\boldsymbol{H}} \boldsymbol{Z}_k \boldsymbol{v}_k \ \geq\ 0, \ldots \quad for\ all\quad k \in |K|$$

$$\boldsymbol{C_1};\quad p_k \ \geq\ 0,\ \ for\ all\quad k \in |K|$$

$$\boldsymbol{C_2};\quad \sum_{r\in|R|}\sum_{k\in|K|} P_{kr} \ \leq\ P_t$$

It is easy to show that problem of eq. (15) is nearly convex. Therefore, the intermediate value approach can be used to obtain the optimal solution to this problem by sequentially solving the power minimization problem of eq. (15) for a given target SINR, namely "Γ_0"across all users. In every iterate of this method, the operating interval is reduced to (0.5) that of the previous interval by computing the midpoint, namely Γ_{temp}. So, firstly we set the initial upper and lower boundaries of the root search working domain,

$$\Gamma_{\max}{}^{(\mathrm{t})} = \min_{k}\ \boldsymbol{\Gamma}_{kr}, \qquad and\ \ \Gamma_{\min}{}^{(\mathrm{t})} = 0 \qquad \ldots(16)$$

where the superscript (t) denotes the current iteration of the algorithm, then, divide the interval working domain,

$$\Gamma_{\mathrm{temp}}{}^{(\mathrm{t})} = \frac{\Gamma_{\max}{}^{(\mathrm{t})} + \Gamma_{\min}{}^{(\mathrm{t})}}{2}. \qquad \ldots(17)$$

Now, this intermediate value of the SINR can be used to evaluate the solution of the convex min-problem in eq. (15) as depicted in Table 2. The Pseudo code in this table illustrates the full detailed step of the proposed power allocation algorithm which can attain a minimum quality of service for all users in various beams in just a few iterations.

Table 3. The Pseudo-value algorithm (LSF-IV)

code for the large-scale fading and the intermediate **Start Algorithm-I:**

Initialize the set of parameters for the system including: user's number $|\boldsymbol{K}|$, total transmit power P_t, vector $\boldsymbol{v}_k$ for the coefficients of the large-scale fading detection, and iteration index: $\mathrm{t} = 0$. Set the initial upper and lower boundaries of the root search working domain:

$$\Gamma_{\max}{}^{(\mathrm{t})} = \min_{k}\ \boldsymbol{\Gamma}_{kr}, \qquad and\ \ \Gamma_{\min}{}^{(\mathrm{t})} = 0$$

Iterative Sub-optimal approach;

1. Update iteration index: $\mathrm{t} = \mathrm{t} + 1$.
2. Divide the interval working domain: $\Gamma_{\mathrm{temp}}{}^{(\mathrm{t})} = \frac{\Gamma_{\max}{}^{(\mathrm{t})} + \Gamma_{\min}{}^{(\mathrm{t})}}{2}$
3. Compute the vector of p_k by solving (14) for constant values of Γ_0 and $\boldsymbol{v}_k$.

$$\underset{P_{kb}}{\textbf{minimize}} \sum_{k\in|K|} p_k \qquad \ldots(15)$$

Subject to:

$$\boldsymbol{C_0};\quad (1+\Gamma_0)\, p_k \cdot \left|\boldsymbol{v}_k{}^{\boldsymbol{H}}\ \ \mathbf{f}_k\right|^2 - \Gamma_0\, \boldsymbol{v}_k{}^{\boldsymbol{H}} \boldsymbol{Q}_{kj_k} \boldsymbol{v}_k - \Gamma_0\, \boldsymbol{v}_k{}^{\boldsymbol{H}} \boldsymbol{Z}_k \boldsymbol{v}_k \ \geq\ 0, \ldots \quad for\ all\quad k \in |K|$$

$$\boldsymbol{C_1}; \quad p_k \geq 0, \ \ for\ all \quad k \in |K|$$
$$\boldsymbol{C_2}; \quad \sum_{r \in |R|} \sum_{k \in |K|} P_{kr} \leq P_t$$

Check the power budget:

4. **If** obtained values of p_k are feasible
5. **Then** complete the Diagonal matrix $\boldsymbol{P}_k$ with the p_k elements.
6. Find the optimal vector of $\boldsymbol{v}_k$ via maximizing $\boldsymbol{\Gamma}_k$,

$$\boldsymbol{\Gamma}_k = \frac{p_k \,.\, |\boldsymbol{v}_k{}^{\boldsymbol{H}} \ \mathbf{f}_k|^2}{\boldsymbol{v}_k{}^{\boldsymbol{H}}(\sum_{j \in |K|} \ p_j \boldsymbol{Q}_{kj})\, \boldsymbol{v}_k - p_k \,.\, |\boldsymbol{v}_k{}^{\boldsymbol{H}} \ \mathbf{f}_k|^2 + \boldsymbol{v}_k{}^{\boldsymbol{H}} \boldsymbol{Z}_k \boldsymbol{v}_k} \quad \text{for every user.}$$

$$\boldsymbol{v}_k{}^{opt.} = \left(\sum_{j \in |K|} \boldsymbol{\beta}_{jr} \, \boldsymbol{\beta}_{jr}{}^{H} \ \rho_r \, q_r + \boldsymbol{\Lambda}_j \right)^{-1} \boldsymbol{\beta}_{jr}$$

7. Update rate upper bound: $\boldsymbol{\Gamma}_{\max}{}^{(t)} = \boldsymbol{\Gamma}_{\text{temp}}{}^{(t)}$
8. **Else:** Update rate lower bound & power allocation: $\boldsymbol{\Gamma}_{\min}{}^{(t)} = \boldsymbol{\Gamma}_{\text{temp}}{}^{(t)}, \ p_k{}^{*} = p_k{}^{(t)}$
9. **End If**

Check rate tolerance limit:

10. **If:** $\boldsymbol{\Gamma}_{\max}{}^{(t)} - \boldsymbol{\Gamma}_{\min}{}^{(t)} \leq \epsilon$, **Then**; Return ***power allocation*** p_k
11. **Else:** go to step **1 (**next iteration).
12. **End If**
13. Return ***power allocation*** vector $\boldsymbol{P}_k$.

NOTE; Γ_{temp} *Is the lower value of the signal-to-interference plus noise ratios when devoting the large-scale fading decoding weighting.*

Table 4 summarizes the proposed work steps, outlining the key processes involved in the methodology.

Table 4. Proposed Work Steps Summary

Step	Description
Signal Transmission Phase	• UEs dispatch information signals to O-RUs concurrently. • O-RUs estimate the signals of users locally and transmit regional estimations to corresponding O-DUs.
Channel Estimation Process	• Time Division Duplexing (TDD) protocol is employed. • UEs dispatch pilot signals synchronously, received by all O-RUs • O-RUs and corresponding O-DUs perform channel estimation.
Regional Decoding and Combiner Technique	• Each O-DU performs regional decoding for user data symbols. • Regional processed signals are obtained at O-RUs. • A receive combiner technique (e.g., Conjugate Beamforming) may be applied at O-RUs.
Uplink Data Signal Detection	• O-CU employs the Large-Scale Fading (LSF) strategy. • LSF decoding (second-layer detection) is performed at the O-CU. • Optimal weight vectors are employed at O-CU to enhance spectral performance.
Spectral Performance Evaluation	• Spectral efficiency is evaluated using a logarithmic function related to Signal-to-Interference plus Noise Ratio (SINR). • Optimization problem aims to achieve fair quality of service among all users under power allocation constraints.
Power Allocation Optimization	• Total power is minimized while maximizing the smallest SINR value among users under constraints. • Intermediate value approach is used to iteratively solve the optimization problem.
Algorithm Evaluation	• -Convergence, efficiency, and performance metrics are evaluated to assess the effectiveness of the proposed algorithm. • Computational complexity and convergence speed are considered.

4. NUMERICAL ANALYSIS

In this section, we evaluate the performance of the proposed LSF-IV algorithm (Algorithm-I) via numerical simulations. More specifically, spectral efficiency (eq. (7)) of the k^{th} user in terms of the Cumulative distribution function performance is computed after each evaluation of algorithm-I. Cumulative distribution functions are perfect for delivering the likelihood that the subsequent SE's observation will be smaller than or equivalent to the minimum SE's value that we specify.

As a baseline algorithm for comparison, we resort to traditional Fractional Power-Allocation (F_PA) to enhance the information rate from the intended user where the allocation power is inversely proportional to the large-scale channel gains that affect the k^{th} user. It is the simplified interpretation of open-loop power allocation in long-term evolution networks that depends on downlink path-loss knowledge from the base station. This in turn qualifies the user to allocate appropriate uplink power according to its path-loss measure towards the serving node as follows, [17, 23].

$$\boldsymbol{P}_k = \frac{\eta}{\sum_{r \in |R|} (\boldsymbol{\beta}_{kr})^{\mu}}, \qquad \dots..(18)$$

where the factor μ controls the compression degree of the received power, $\mu \in [0, 1]$, and η is the scale to ensure that all powers should be in the range of [0, 1] with lower weights favouring the average signal-to-interference-ratio while higher weights promote fairness and cell-edge performance (users near the edge of the cell are needed to transmit at a higher level of power.) [28]. Table 5, introduces parameters configurations otherwise they are stated with each plot.

Table 5. System parameters applied in the simulation.

Parameter	***value***
Number of channel's investigation	10^4 realizations
carrier frequency	3.4 GHz
bandwidth	20 MHz
Radio units (O-RU) antenna number	$M = \{8, 16, 32\}$ elements
O-RU's number	R = $\{8, 16, 32\}$ Radio units
User's antenna number	Single element
Users; number K	25 users, otherwise they are specified with each plot.
Network size	10 Km^2
Transmit power budget	$P_t = [-30; 10]$ dB
Power of the UL- pilot	−35 dBm
Pilot symbol length for channel training	$\tau_{long} = 10$ for long sequence, and $\tau_{short} = 5$ for short sequence.
Benchmark algorithm for comparison	Fair-PA, Fractional-PA
The propagation environment:	
The noise power (variance) σ2	-106 dBm
Channel model	Rician
Channel path variance	$\sigma_{ij}^2 = 1,$ (Gaussian distribution)
Antenna Array	Squared planner sub-connected

Fig. 3 presents the system performance in terms of the cumulative distribution function of the users' spectral efficiency[5] for R = 15 O-RUs and M =16 antennas for each O-RU unit. This figure indicates that the proposed approach can greatly enhance the spectral performance for the users in the worst channel conditions in comparison with the typical Fractional-PA. More specifically, the figure shows that there is about 45% spectral performance enhancement for the likely percentage in this measure of 95%, i.e., we have 57 users out of 60 can attain the specified minimum spectral performance requirement. Consequently, the optimal UL fairly power allocation by the proposed LSF-IV algorithm achieves a higher minimum rate performance among all the UEs when compared to the traditional channel inversion algorithm.

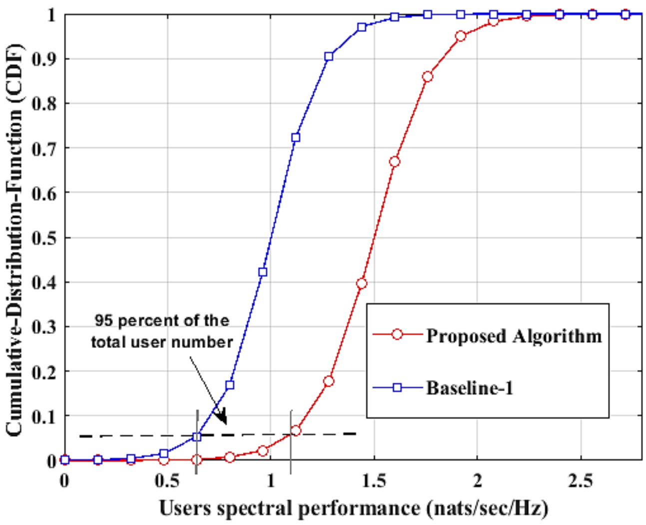

Fig. 3 The spectral performance of the proposed LSF-IV algorithm VS the traditional Ch. inversion algorithm.

In terms of the number of users who can be served in the network with at least the minimum data rate, fig. 4 illustrates the impact of increasing the number of these users in the range of {30, 40, up to 50} users for scenario-1, scenario-2, and scenario-3, respectively, with short sequence training pilot. As the number of users increased, the minimum attained spectral performance was lowered and this is because increasing the number of users will increase the probability of creating a user with bad channel conditions, especially for cell-edge users, which in turn forces the other users to lower their allocated power to enhance the fair performance of the bad conditions users. It is worth noting that, to increase the 95 likely percentage of the spectral performance which is about 0.65 nats/s/Hz for 50 users' scenario, for example, one can resort to increasing the DoF of the antennas array of the O-RU units.

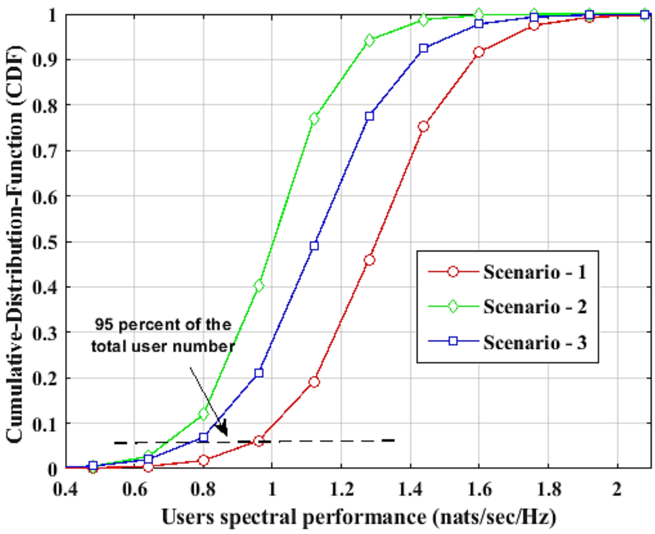

Fig. 4 The effect of the number of users on the spectral performance of the proposed LSF-IV algorithm

Fig. 5 shows the effects of increasing the number of the O-RU units (R) and their antenna elements number (M) on the user's spectral performance. Here, we include different scenarios for the setting of the pair {R, M} as follows, {32, 16}, {32, 8}, {16, 16}, and {8, 8}, for the cases 1,2,3, and 4, respectively. For instance, by raising the number of O-RU units from 8 units to 32 units we can attain a performance gain of almost 60% (from 0.65 up to 1.65 nats/s/Hz) in terms of the 95 percent likely. These results are predictable since increasing the number of O-RU units' means that we provide more DoF for the diversity of the system in addition, this will introduce a more distributed antenna that can attain a better performance than a collocated antenna scenario.

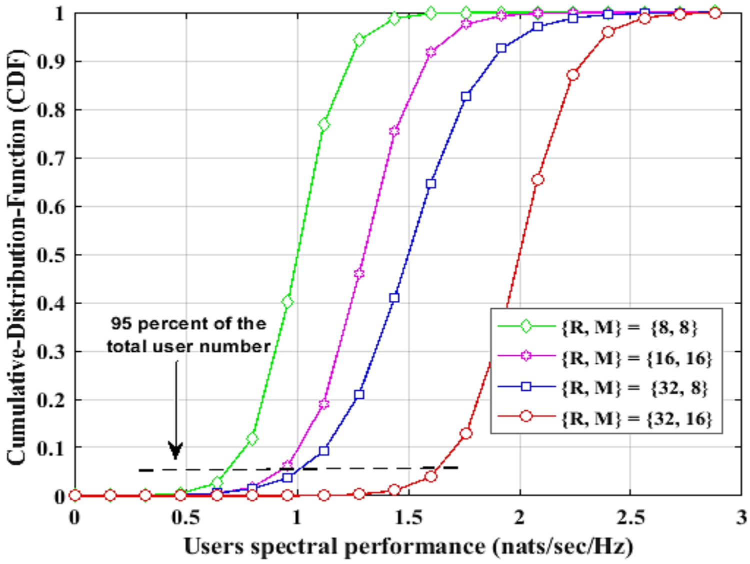

Fig. 5 The effect of the O-RU units' number and their antenna number on the spectral performance of the proposed LSF-IV algorithm

In addition, fig. 6 shows the Percentage of the UEs that achieve the required minimum SE for different O-RU units' and their antenna number. The impact of the increasing number of O-RU units is obvious and more significant than the increase of the antennas at the individual Radio unit as a result of the diversity gain obtained by the distributed antenna over the co-located one.

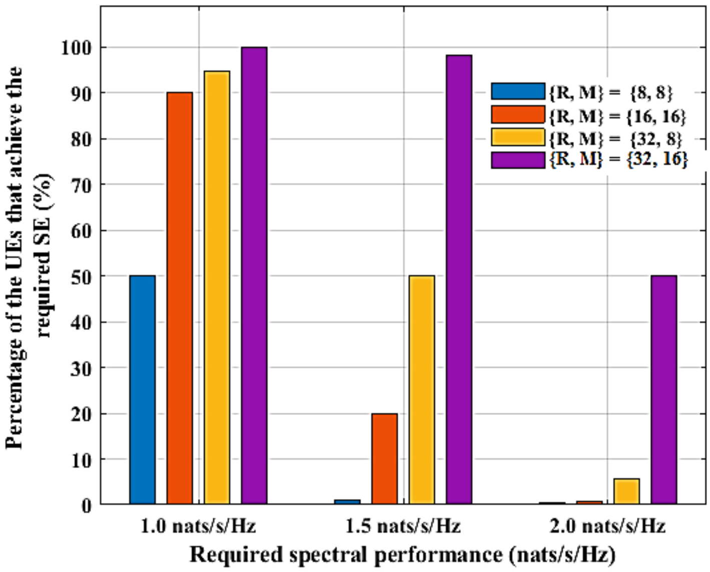

Fig. 6 Percentage of the UEs that achieve the required minimum SE for different O-RU units' and their antenna number

In order the check the effects of the channel training sequence on the minimum attained spectre performance for the users deployed within the network area, fig. 7 carries out two scenarios for the length of the pilot training sequence in the uplink symbol. As anticipated, employing a long training sequence can enhance performance where this strategy can achieve a spectral performance gain of about 27% in terms of 95 likely percentages. It is worth mentioning here that increasing the length of the pilot sequence will help in a more accurate estimation of the channel vectors, however, this will come at the cost of reducing the efficiency of the uplink symbols to deliver a higher information rate.

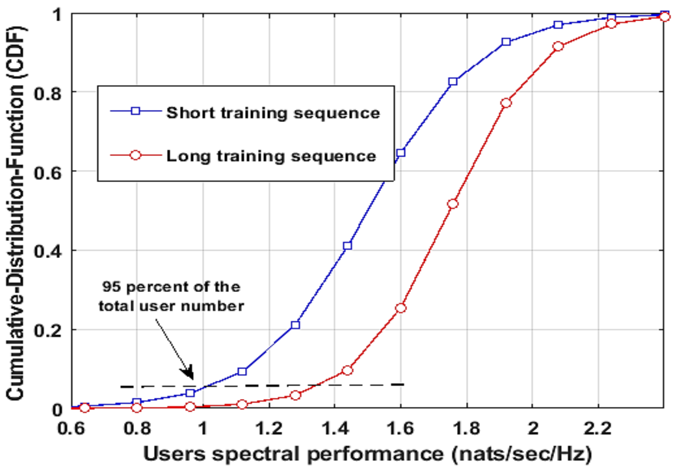

Fig. 7 The effect of the length of the pilot training sequence on the spectral performance of the proposed LSF-IV algorithm.

Finally, to sum up, table 6 highlights the main differences between the proposed approach and the existing baseline approaches.

Table 6. A comparative result for the baseline work

Metric: spectral performance of 57 users out of 60	Traditional Fractional Power-Allocation (F_PA) [20]	proposed approach
spectral performance with a short training sequence	achieve 0.4 nats/s/Hz	achieve 1.0 nats/s/Hz (40% enhancement).
spectral performance with a long training sequence	achieve 0.6 nats/s/Hz	achieve 1.3 nats/s/Hz (45% enhancement).

5. CONCLUSIONS AND FUTURE WORKS

To cope with the continued evolution of network data traffic and the increasing number/ services of subscribers, a novel paradigm is required to ensure that the available resources are utilized in the most economical mode. Open Radio networks presents the opportunities to allow a significant revolution in network developments and handle the deficiencies in the current RANs thanks to the intelligence and counted openness operation. However, due to the number of subscribers' equipment in such dense wireless systems and the limited capacity of the fronthaul it becomes difficult to achieve the optimal resource allocation in such huge systems. This work tries to create a balance between the spectral efficiency and the required power and hence reduce the signalling overheads in open radio access networks. Consequently, a linear MMSE-based channel estimation technique is utilized for the beamforming vectors. The suggested iterative approach, namely LSF-IV, leverages the large-scale fading detection (LSF) and the intermediate value method (IV) to attain the balancing between users' uplink spectral performance. Simulation results prove that the proposed approach enhances significantly the weakest users' uplink spectral performance in comparison with the traditional Fractional-power allocation. More specifically, there is about 45% spectral performance enhancement for the likely percentage in this measure of 95%.

The current study focuses on optimizing the spectral performance based on the physical layer of O-RAN systems, however, it is recommended for future works to address the case of carrying out the study based on cross-layer optimization to create a more robust O-RAN paradigm. Besides, additional suggestion is to employ a deep neural network (e.g., Convolutional neural network (CNN)) for the channel estimation or at least a hybrid technique that integrates both the ANN approach with the traditional signal processing strategies.

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