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Towards Optimal Configuration in MEC Neural Networks: Deep Learning-Based Optimal Resource Allocation

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Abstract
Nowadays, the application of data caching in mobile edge computing networks is exponentially increasing as a high-speed data storage layer using deep learning (DL) approaches. This paper presents an DL-based resource allocation approach to find the optimal topology for cache-enabled backhaul networks. In the practical scenarios, a numerous of radial configurations of test systems have been applied for training stages. This paper also applied the continuation power flow analysis to achieve the maximum load limit in which the power of macro base stations with the caches of different sizes is provided through either smart grid network or renewable power systems. To increase the power efficiency index of this approach the power sharing capability was enabled among different layer of network components through smart grids. In order to obtain the optimal solution, the DL-based mathematical problem is reformulated into a neural weighting model considering convergence conditions and Lyapunov stability of the mobile-edge-computing under Karush–Kuhn–Tucker optimality constraints. The mathematical analysis and simulation results demonstrate that the performance of the proposed algorithm is better than other energy efficiency algorithms. The proposed approach can effectively increase the total system throughput and network's utility in addition to guarantee user fairness index.

Keywords Mobile edge computing (MEC) · Neural networks · Optimal configuration · QoS · Continuation power flow · Deep learning

1 Introduction

According to ITU technical reports [1] SLA-based services, which needs content delivery with low delay, now contain more than 60% of total data services. Considering the growing need for high quality services, resource allocation and load sharing problems in the mobile edge computing networks (multi layer network configuration), have become a critical problem [2]. To solve these problems, caching can be considered as a effective method to decrease the network delay and high utilization issues through data offloading among core networks and other layers of the hierarchical network. Some of the previous researches like

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[3–5] assessed the next generation mobile network's performance considering novel routing approaches for backhauling. Authors in [6–9] have focused on caching-based mobile edge computing.

Also, to find the optimal configuration of MEC systems, a mixed-integer quadratically constrained joint resource allocation with linear programming is suggested in this [10, 11] and assessed through different reliable NOMA scenarios. Many meta-heuristic approaches are applied in reconfiguration process with distinct goal functions. The genetic algorithm is extensively applied in detecting the effective switching solution with various altered forms of neural networks in [12]. Some of the meta-heuristic approaches are applied in reconfiguration process with security goal functions [13, 14]. Particle swarm optimization (PSO) [15], harmony search (HS) [16], and ant colony approaches [17] were used to find the optimal solution for the reconfiguration problems.

The authors in [18] has developed the cache-enabled demand queuing scheme for heterogeneous systems with focusing on the problem of optimal data transmission has been modelled as the problem of random optimization. In [19], it has been shown that cache efficiency can be improved by using a participatory relay. In [20, 21] it is assumed that the small cells can be divided into clusters and used in conjunction with their caches to store the content, increasing the probability of finding information in the cache hit. The authors in [22] has developed the problem of establishing a common cache and allocating the cache space to maximize the use of cache in the cellular device-to-device networks. 5G networks, which are one of the most significant platforms for using this key technology, are predicted to have much higher energy efficiency. Power optimization using renewable power sources can be considered as attractive method to increase energy efficieny. Because, some base stations that consume a lot of power cannot completely cache the demanded content, although some base stations may not have enough power to transmit content. Considering developments in conventional grids and the improvement of energy flow, energy cooperation has been proposed to reduce the problem of power balancing. Hence, base stations may provide extra energy to stations with power deficiency. Some of the researches have suggested power control policies and energy cooperation approaches.

Authors in [23], studied the problem of power sharing among microgrids has been investigated. The resource allocation and power sharing to increase EE index for heterogeneous networks has been investigated in [24]. Previous studies [25, 26], have laid the foundation for power optimization in caching-based and power cooperative systems, respectively. Nevertheless, no work has been done on resource allocation in energy-cooperative networks with common cache capability, and it is still a virgin area of research. With this in mind, the suggested approach propose a optimization framework for the UA resource allocation in the caching-based power-cooperative heterogeneous networks. The aim is in order to increase the system overall throughput and at the same time minimize the energy consumption of the conventional grids.

We assume that cache-enabled and energy-cooperative MEC networks include macro base stations (MBS) and pico base stations (PBS) in which each base station has a cache for storing the content files. Assume that B and U are the base station set and the user equipment (UE) set, respectively. The cache size of each macro and pico base station is LM and LS, respectively.

This research studied the common impact of optimized resource allocation in addition to the data flow of the available links in backhauling networks in mobile edge computing networks. In this paper, we intend to examine two approaches, considering the rigid constraints on throughput demand by all user equipment (UE) and, authorize the sending of an acceptable demand to the user's equipment. This small change has a significant effect on the formulation of both problems. The proposed scheme is convex and is also quasi-convex, so that in order to find an optimal souution, a bi-section method-based approach was suggested. The numerical results illustrate the effectiveness of the proposed approach compared to other base benchmark EE approaches.

The next generation MEC networks are expected to increase the data speed and greatly increase the bandwidth and, provide Internet coverage and connectivity everywhere, and significantly reduce the power utilization [27]. Some previous researchs in the field of 5G has focused on multi-layered hierarchcal resource allocation and optimization, which are key effective technologies [28]. In heterogeneous networks, base stations with transmit power, coverage range, carrier frequency and different types of BH (backhaul) links are used which it creates new problems in connecting all base stations to the core network via proper backhaul connections [29]. Thus, the base station may have to share the link with other base stations until backhaul traffic reaches the central network. To cope with the above problems, maximizing energy efficiency (EE) in heterogeneous networks separately in the field of access network [30] and backhaul networks and in combination has been reviewed. However, none of the above approaches 1- do not consider user fairness and energy efficiency as a function of the goal, but minimize power consumption and 2- They do not deal with the energy efficiency maximization algorithm, which simultaneously allocates the optimal data flows to the backhaul links, increases the power efficiency in the access and backhaul networks, and enhances the operational power of the access network. Also, most researchers assume that there is only one backhaul link between the base stations, which causes the backhaul network to have more problems during the failure of the link or channel blurring effects.

Two energy efficiency optimization techniques for the multi-layer backhaul network have been presented in this paper. Particularly, the achievements of the article have been shown as the following:

Considering a heterogeneous two-layer network with several available backhaul links, and provide two frameworks for optimizing the energy efficiency maximization:

- Joint MEC-Joint Energy Efficiency (EE) User Association (MEC-JEEUA): For strict request on the throughput of the user equipment (UE), the optimal power allocation and the transmission strategies will be determined for several backhaul links. Thus, we come to the problem of convex optimization, which can be solved for optimization.
- Joint Energy Efficiency, Resource Allocation, power control and throughput Scheme: considering the upper and lower limits of the data rate demand by the user equipment (UE), we develop the problem in a way that jointly maximizes data equipment demand and determines the optimal power optimization and allocates the flows to the backhaul carriers. Its obvious that this problem is nonlinear programming of the total ratio that can be reformulated in the form of a quasi-convex framework. We present an approach an bi-section approach to solve the quasi-convex framework.

The remainder of this paper is organized as follows. The basic theory of continuation power floe (CPF) and the optimization model is introduced in Sect. 2. Section 3 presents the proposed MEC-based computing system and the transmission strategies. The proposed usr association and power optimization algorithms of the MEC Network was presented in Sect. 4 and Numerical results and discussion of the proposed approach are presented in Sect. 5. Finally, Sect. 6 draws the conclusion and highlights future challenges to motivate the effective integration of edge computing with the diagnosis.

2 Continuation Power Flow (CPF) and Optimization

Continuation power flow is effective method to determine the maximum achievable load level for the backhaul system [31]. Continuation power flow as a solution for solving the problem of Jacobian matrix of SLA-based flow formulations, becoming optimal at the power stability limit by finding frequent load flow solutions according to the power-constraint environments [32].

This approach contains two steps. Prediction stage and correction stage. In this method, a tangent indicator is used to find the approximate next solution from a BS for a special load increase. The optimal solution is also obtained by the corrector step applying the N-R method of conventional power flow. This process will be continued until the tangent equation reaches equal to zero which it is equivalent to the critical point. This predictor–corrector procedure is exhibited in Fig. 1.

2.1 Mathematical Reformulation of Continuation Power Flow

In the model of the continuation power flow, for the i^{th} of n bus system, the power entry can be expressed as:

$$P_i = \sum_{k=1}^{n} |V_i||V_K|\left(G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik}\right) \tag{1}$$

$$Q_i = \sum_{k=1}^{n} |V_i||V_K|\left(G_{ik}\sin\theta_{ik} + B_{ik}\cos\theta_{ik}\right) \tag{2}$$

$$P_i = P_{Gi} - P_{Di};Q_i = Q_{Gi} - Q_{Di}; \tag{3}$$

In which, generation and load demand are demonstrated by G and D respectively. The load index λ is added with real and reactive resource demands in order to estimate the load fluctuation.

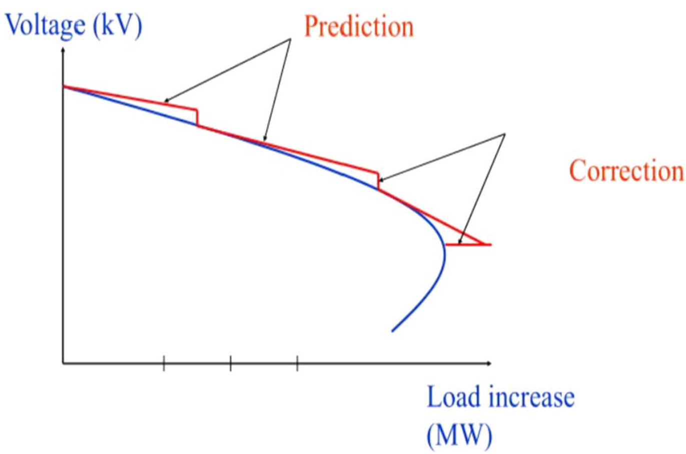

Fig. 1 An example of Predictor–Corrector concept

$$P_{Di} = P_{Dio} + \lambda \left(P_{\Delta base}\right) \tag{4}$$

$$Q_{Di} = Q_{Dio} + \lambda \left(P_{\Delta base}\right) \tag{5}$$

We can show the real load demands on the i$^{\text{th}}$ bus as P_{Dio}. Q_{Dio} and $P_{\Delta base}$ and $Q_{\Delta base}$ are selected to roughly scale λ. Considering new resource demands in (3) to (5) new formulation is achievable as:

$$F(\theta, V, \lambda) = 0 \tag{6}$$

In this formulation, θ denotes bus power angles, V is vector of bus power magnitudes. The primary solution is obtained with correspondence of $\lambda = 0$.

(1) Prediction Step: Linear approximation is used in this step by considering an appropriate sized step in tangent equation. So, based on two-sided derivation of Eq. 6 we have:

$$F_\theta d_\theta + F_V d_V + F_\lambda d_\lambda = 0 \tag{7}$$

$$\begin{vmatrix} F_\theta & F_V & F_\lambda \end{vmatrix} * \begin{vmatrix} d_\theta \\ d_v \\ d_\lambda \end{vmatrix} = 0 \tag{8}$$

The solution of this problem is achievable by fixing one of the tangent equation components to + 1 or −1 which is the continuation parameter and impose a value to the tangent vector and at the critical point, this causes Jacobian not to be singular.

$$\begin{vmatrix} F_\theta & F_V & F_\lambda \\ & e_k & \end{vmatrix} * \begin{vmatrix} d_\theta \\ d_v \\ d_\lambda \end{vmatrix} = \begin{vmatrix} 0 \\ \pm 1 \end{vmatrix} \tag{9}$$

In which, e_k denotes the proper row vector with the kth component equal to one and all other components equal to 0. Initially, λ demonstrates the continuation index. The tangent solution is obtained by solving (9) and the prediction is achieved as the following:

$$\begin{vmatrix} \theta \\ V \\ \lambda \end{vmatrix}^{p+1} = \begin{vmatrix} \theta \\ V \\ \lambda \end{vmatrix}^{p} + \sigma \begin{vmatrix} d_\theta \\ d_V \\ d_\lambda \end{vmatrix} \tag{10}$$

In these equations, the prediction is denoted by the sign $p + 1$ and σ represents the step size. Where the predicted result will be located interior of the convergence of the corrector.

(2) Correction Step: as it is obvious, the predicted step is obtainable in the corrector step using local parameterization. The real formulation will be extended to the selected value of state variable and this results in as the following:

$$\begin{vmatrix} F(\theta, V, \lambda) \\ x_k - \eta \end{vmatrix} = |0| \tag{11}$$

In which the state variable selected as continuation parameter is demonstrated by x_k and the predicted state variable is denoted by η. In continue, the optimal solution for (11) can be obtained by customized Newton–Raphson power flow method.

3 Network Model

In the MEC energy-cooperative networks, each base station receives power using either smart grid sources and renewable power systems. To decrease the computational complexity, the weighting coefficient l is used as the timing factor during the process. The transmission energy of base station i is equal to $P_i(i \in B)$, the utilized power of the base station i from the conventional grid is equal to Gi, the base station i can harvest special power of the renewable power systems equal to E_i. Base station i can share its power to base station i equal to E_i and the EE of the power sharing can be equal to $\beta \in [0, 1]$. It is also supposed that no energy is stored, because the power utilization time period can be much longer compared to the process of power optimization [12]. Thus, the following relationship must be established regarding the transmission capacity of the ith base station.

In the System model of the proposed cache-enabled MEC network, we consider one macro cell in addition to several small cell in each cellular cluster in which U and B indicates the set of user equipment and the base stations respectively. L_S and L_M represents the cache size of each small base station and macro base station in which, the energy of each cell can be supplied by both renewable resources and conventional. It is noted that in this energy cooperative network, the base stations are able to share their resources through smart grids. In accordance with the definitions, the system configuration this cache-enabled network has been illustrated in Fig. 2.

In this paper, it is assumed that there are several available hybrid backhaul links between pico base stations (PBS) and one backhaul connection among the cluster head and the macro base station. Without losing the whole discussion, it is assumed that the macro base station (MBS) is connected to the central network via a fiber link. Each pico base station is connected directly to the macro base station via the cluster head or through one or more density points of the pico base station. Two subcarriers frequencies can be used in

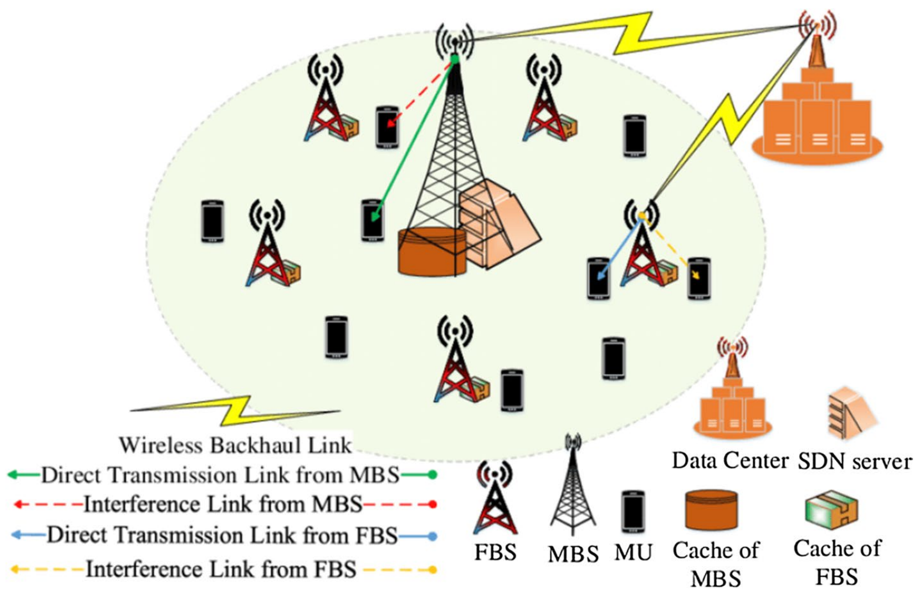

Fig. 2 MEC Network Configuration with caching strategy

backhaul system. The paper applied 73 GigaHz backhaul links (band E) for the communication between pico and macro base stations and 60 GigaHz band (V band) for several backhaul links between pico base stations. Drop path of millimeter-wave are divided into 2 distinct categories: outdoor path loss and millimeter wave transmission dissipation coefficients. These cases have been considered in accordance with [15].

According to the main sources in this field, there is no standard model for energy consumption in MEC backhaul networks. However, the application nonlinear prediction energy consumption in millimeter wave has attracted more satisfaction. Here, this paper use adaptive resource allocation in which the backhaul connection has been modeled, in which C5 and C6 are the maximum transmission power constraints for pico and macro base stations, respectively.

3.1 Content-Caching Model

In this network, we suppose that content can be modelled as a distinct set of packet data as $\mathcal{F} = \{\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_f, \dots, \mathcal{F}_F\}$ which $\mathcal{F}_f$ represents the f-th data frame. The request probability for data frame f is expressed as

$$p_f(0 \le p_f \le 1), \quad which, \sum_{f=1}^{F} p_f \le L_i, \qquad \forall f \in \mathcal{F}, \tag{12}$$

It should be noted that the caching model presented for this paper is stochastic caching so that we can calculate the probability of caching data packet f via base station i $0 \le q_{f_i} \le 1$ where L_i illustrates the cache size. In addition, $\{q_{f_i}\}$ of base station i should satisfy below condition:

$$\sum_{f=1}^{F} q_{f_i} \le L_i, \qquad \forall i \in \mathcal{B}, f \in \mathcal{F}, \tag{13}$$

$L_i = L_M$ means the cell is macro cell, otherwise, $L_i = L_S$.

3.2 Resource Control Model

Based on the approach's principles, the resources of the base stations can be supplied by conventional smart grid and renewable energy harvesting. During this scenario, the transmit power relevant to base station i can be demonstrated by $P_i (i \in B)$, and the applied energy from the grid network is illustrated by G_i. The harvested renewable resource is shown as E_i. Based on the enabled power sharing capability, the shared power among cell i and cell i' is equal to $\varepsilon_{ii'}$, where $\beta \in [0, 1]$ denotes the power-sharing index among base stations. So, we can conclude that $(1 - \beta)$ is equal to the loss percentage in the power sharing stage. The following condition should be satisfied during the power sharing process.

$$P_i < G_i + E_i + \beta \sum_{i' \in \mathcal{B}, i' \neq i} \varepsilon_{i'i} - \sum_{i' \in \mathcal{B}, i' \neq i} \varepsilon_{ii'}. \tag{14}$$

According to the defined conditions, the overall power efficiency can be affected by the transmission strategies, power sharing and the level of harvested energy from renewable resources.

3.3 Transmission Model

Taking fairness into account, we tried to provide data rate balancing throughout the network. In which, $x_{ij}(i \in \mathcal{B}, j \in \mathcal{U})$ denotes the UA indicator, for example, $x_{ij} = 1$ represents that UE j is associated to BS i and otherwise the user has not been associated to the base station. Subsequently, $k_i = \sum_{j \in \mathcal{U}} x_{ij}$ represents the number of users associated to cell i. $\left(\sum_{f=1}^{F} p_f q_{f_i}\right)^{k_i}$ express the probability of serving k_i associated UEs by base station i. if $x_{ij} = 1$, we can calculate the efficiency of the j-th user equipment as $\mu_{ij} = \log\left(R_{ij}\right)$ which R_{ij} is the user throughput so that the R_{ij} is obtainable as.

$$R_{ij} = \left(\sum_{f=1}^{F} p_f q_{f_i}\right)^{k_i} \frac{\mathcal{B}}{\sum_{j \in u} x_{ij}} \log\left(1 + \gamma_{ij}\right) \tag{15}$$

In this framework, the ratio of signal to interference-noise can be computed via (16)

$$\gamma_{ij} = \frac{P_i h_{ij}}{\sum_{i' \in \mathcal{B}, i' \neq i} P_{i'} h_{i'j} + \sigma^2} \tag{16}$$

In this formulation, h_{ij} and $h_{i'j}$ indicate the main channel gain and the interfering channel gain respectively, B denotes the frequency bandwidth. σ^2 is also noise figure. We can consider the goal function equivalent to minimization of the applied grid power. Consequently, we have the goal function as the following.

$$\begin{aligned}
&P1: \quad \max_{q,x,P,\varepsilon,G} \sum_{i \in \mathcal{B}} \sum_{j \in u} x_{ij}\mu_{ij} - \eta \sum_{i \in \mathcal{B}} G_i \\
&s.t. \quad C1: \sum_{i \in \mathcal{B}} x_{ij}\gamma_{ij} \geq \gamma_{\min}, \quad \forall j \in u, \\
&C2: \sum_{i \in \mathcal{B}} x_{jm} = 1, \quad \forall j \in u, \\
&C3: P_i < G_i + \beta \sum_{i' \in \mathcal{B}, i' \neq i} \varepsilon_{i'i} - \sum_{i' \in \mathcal{B}, i' \neq i} \varepsilon_{ii'} + E_i, \quad \forall i \in \mathcal{B}, \\
&C4: \sum_{f=1}^{F} qf_i \leq L_i, \forall i \in \mathcal{B}, \quad f \in \mathcal{F}, \\
&C5: 0 \leq q_{f_i} \leq 1, \forall f \in \mathcal{F}, \quad \forall i \in \mathcal{B}, \\
&C6: x_{ij} \in \{0, 1\}, \forall i, \quad \forall j \in u, \\
&C7: G_i \geq 0, \varepsilon_{ii'} \geq 0, \quad \forall i \in \mathcal{B}, \\
&C8: 0 \leq P_i \leq P^i_{\max}, \quad \forall i \in \mathcal{B},
\end{aligned} \tag{17}$$

In which, $\mathbf{q} = \left[q_{f_i}\right]$, $\mathbf{X} = \left[x_{ij}\right]$, $\mathbf{P} = \left[P_i\right]$, $\boldsymbol{\varepsilon} = \left[\boldsymbol{\varepsilon}_{\mathrm{ii'}}\right]$, $\mathbf{G} = \left[G_{\mathrm{i}}\right]$, γ_{min} illustrates the $SINR_{min}$ to guarantee the reliability of the connection between UEs and the base station. And η represents a weighting factor for assessing the power efficiency. The multi hop strategy of backhauling in the presented MEC network and the configuration of the network has been exhibited in the Fig. 3.

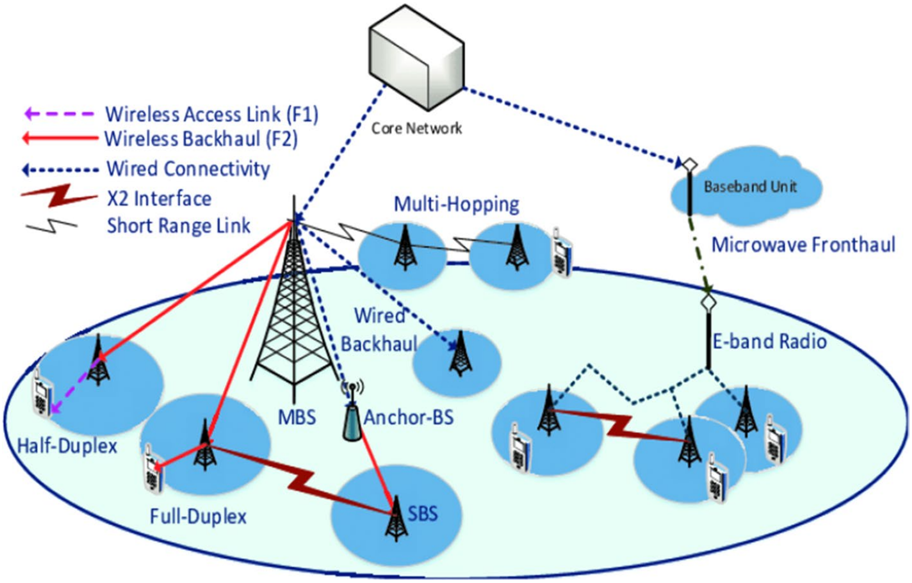

Fig. 3 Multi-hop backhauling model in the MEC architecture

4 Proposed User Association and Power Optimization in MEC Network

The problem of user association and power allocation in this approach may be modelled as problem P2 which itself can be considered as the optimal solution for the primary problem P1. Taking $k_i = \sum_{j\in\mathcal{U}} x_{ij}$, into account, this problem is expressed as the following.

$$\begin{aligned} P2: \quad & \max_{q,x,P,\varepsilon,G} \sum_{i\in\mathcal{B}} \sum_{j\in u} x_{ij} \log\left(c_{ij}\right) + \sum_{i\in\mathcal{B}} k_i^2 \log\left(\sum_{f=1}^{F} p_f q f_i\right) - \sum_{i\in\mathcal{B}} k_i \log\left(k_i\right) - \eta \sum_{i\in\mathcal{B}} G_i \\ s.t. \quad & C1, C2, C3, C4, C5, C6, C7, C8, \\ & C9: \sum_{j\in u} x_{ij} = k_i, \forall i, \end{aligned} \tag{18}$$

where $c_{ij} = Blog\left(1 + \gamma_{ij}\right)$.

4.1 Data Caching-based User Association Algorithm

In this framework, P2 as a NL mixed integer programming problem is not a convex problem and as Lemma 1 indicated, the sub gradient method will be the best approach to solve it. Taking $\{P, \varepsilon, G\}$ into account, the UA problem will be mathematically modeled as follows.

$$P2.1: \quad \max_{q,x} \sum_{i\in\mathcal{B}} \sum_{j\in u} x_{ij} \log\left(c_{ij}\right) + \sum_{i\in\mathcal{B}} k_i^2 \log\left(\sum_{f=1}^{F} p_f q f_i\right) - \sum_{i\in\mathcal{B}} k_i \log\left(k_i\right) \tag{19}$$
$$s.t. \quad C1, C2, C4, C5, C6, C9$$

Lemma 1: considering $p_{(1)} \geq \ldots \geq p_{(f)} \geq \ldots \geq p_{(F)}$ as the probability of demanded payload (f), the optimal solution for P2.1 is achievable as the following.

$$q^*_{f_i} = \begin{cases} 1, f_i = (1), \ldots, \left(L_i\right) \\ 0, \quad otherwise \end{cases}, \quad \forall i \in \mathcal{B}. \tag{20}$$

Proof 1: as mentioned before, P2.1 shows that obtaining the optimal value for $\sum_{f=1}^{F} p_f q_f$ is the target in which, the demanded payload is itself consists of L_i sections $\mathcal{F}_l\left(l = 1, \ldots, L_i\right)$, and the probability $\mathcal{F}_l$ is more than $\mathcal{F}_{l+1}$. Therefore, we have:

$$\sum_{(f)\in\mathcal{F}_l} q^l_{(f)_i} = 1, \sum_{l=1}^{L_i} q^l_{(f)_i} = q_{(f)_i} \; and \; \bigcup_{l=L_i} \mathcal{F}_l = \mathcal{F}$$

Also,

$$\sum_{f=1}^{F} p_f q_{fi} = \sum_{l=1}^{L_i} \sum_{(f)\in\mathcal{F}l} p_{(f)} q^l_{(f)i} \leq \sum_{l=1}^{L_i} p_{(l)} \left(\sum_{(f)\in\mathcal{F}l} q^l_{(f)i} \right) \Rightarrow \sum_{f=1}^{F} p_f q_{f_i} \leq \sum_{l=1}^{L_i} p_{(l)},$$

Consequently, according to (20), this theory is confirmed. So, we can conclude that

$$\tilde{P}2.1: \quad \max_{x} \sum_{i\in\mathcal{B}} \sum_{j\in u} x_{ij} \log\left(c_{ij}\right) + \sum_{i\in\mathcal{B}} k_i^2 \log\left(\sum_{f=1}^{L_i} p_{(f)}\right) - \sum_{i\in\mathcal{B}} k_i \log\left(k_i\right) \tag{21}$$
$$s.t. \quad C1, C2, C6, C9.$$

For simplicity of process of finding the optimal solution of $\tilde{P}$ 2.1 as a combination of several sub-problems, we work on its dual problem. Therefore, the target function should be reformulated as follows:

$$\begin{aligned} \mathcal{L}(x, k, \mu, \nu) = & \sum_{i\in\mathcal{B}} \sum_{j\in u} x_{ij} \log\left(c_{ij}\right) + \sum_{i\in\mathcal{B}} k_i^2 \log\left(\sum_{f=1}^{L_i} p_{(f)}\right) \\ & - \sum_{i\in\mathcal{B}} k_i \log\left(k_i\right) - \sum_{j\in u} \mu_j \left(\gamma_{\min} - \sum_{i\in\mathcal{B}} x_{ij}\gamma_{uj}\right) \\ & - \sum_{i\in\mathcal{B}} \nu_i \left(\sum_{i\in u} x_{ij} - k_i\right), \end{aligned}$$

where in this formulation,$\upsilon = \left[\nu_i\right]$, $k = \left[k_i\right]$ *and* $\mu = \left[\mu_j\right]$. It should be noted that ν_i and μ_j represent Lagrangian multipliers. In continue, we can define the problem's dual function $\mathcal{D}(.)$ as the following

$$\mathcal{D}(\mu, \nu) = \begin{cases} \max_{x,k} \mathcal{L}(x, k, \mu, \nu) \\ s.t. \; C2, \; C6. \end{cases} \tag{23}$$

Subsequently, the dual problem of $\tilde{P}$ 2.1 (21) will be formulated as

$$\min_{\mu\geq 0, \nu\geq 0} \mathcal{D}(\mu, \nu). \tag{24}$$

μ_j and ν_i are coefficients of the dual problem and solution of the goal function cab be obtained as the following steps

$$x_{ij}^{*} = \begin{cases} 1, & if \quad i = i^{*} \\ 0, & otherwise \end{cases}, \tag{25}$$

In (25), $i^{*} = \arg max_i(\log\left(c_{ij}\right) + \mu_j \gamma_{ij} - \nu_i)$. Considering k_i, the second derivation of the goal function results in

$$\frac{\partial^2 \mathcal{L}}{\partial k_i^2} = 2log\left(\sum_{f=1}^{L_i} p_{(f)}\right) - \frac{1}{k_i}. \tag{26}$$

As it is obvious, $\sum_{f=1}^{L_i} p_{(f)} \leq 1$, so, $\frac{\partial^2 \mathcal{L}}{\partial k_i^2}$ cannot be a positive amount. With setting $\frac{\partial^2 \mathcal{L}}{\partial k_i^2}$ equal to zero, k_i^{*} is achieved as the optimum degree of k_i

$$k_i^{*} = -\frac{W\left(-2log\left(\sum_{f=1}^{L_i} p_{(f)}\right)e^{\nu_i - 1}\right)}{2log\left(\sum_{f=1}^{L_i} p_{(f)}\right)}, \tag{27}$$

In (27), $W(z)$ shows the Lambert-W factor as a response for $z = we^{w}$. According to (25), the optimal solution (μ^{*}, υ^{*}) cannot be achieved by differentializing of $\mathcal{D}(\mu, \nu)$,. Therefore, applying the iterative gradient approach will be useful.

$$\mu_j(t+1) = \left[\mu_j(t) - \delta(t)\left(\sum_{i\in\mathcal{B}} x_{ij}(t)\gamma_{ij} - \gamma_{min}\right)\right]^{+}, \tag{28}$$

$$\nu_i(t+1) = \left[\nu_i(t) - \delta(t)\left(k_i(t) - \sum_{j\in u} x_{ij}(t)\right)\right]^{+}, \tag{29}$$

In this formulation, $x_{ij}(t)$ and $k_i(t)$ can be renewed in an iteration via (25) and (27). The step size was shown by $\delta(t)$ and we have $[a]^{+} = \max\{a, 0\}$,t also indicates the iterations quantity.

Figure 4 illustrates the general flow chart of the scheme. All stages of the user association approach based on the proposed transmission strategies have been summarized in Algorithm 1. It should be noted that this algorithm is definitely converged because it satisfies all convergence conditions mentioned in [33].

4.2 Power Optimization

According to the previous section, we have the pair $\{q, x\}$ as the results of the user association algorithm. In this section we try to apply the results of the UA algorithm into the power optimization and resource allocation procedure. First, the primary power optimization problem **P.2** is defined as follows.

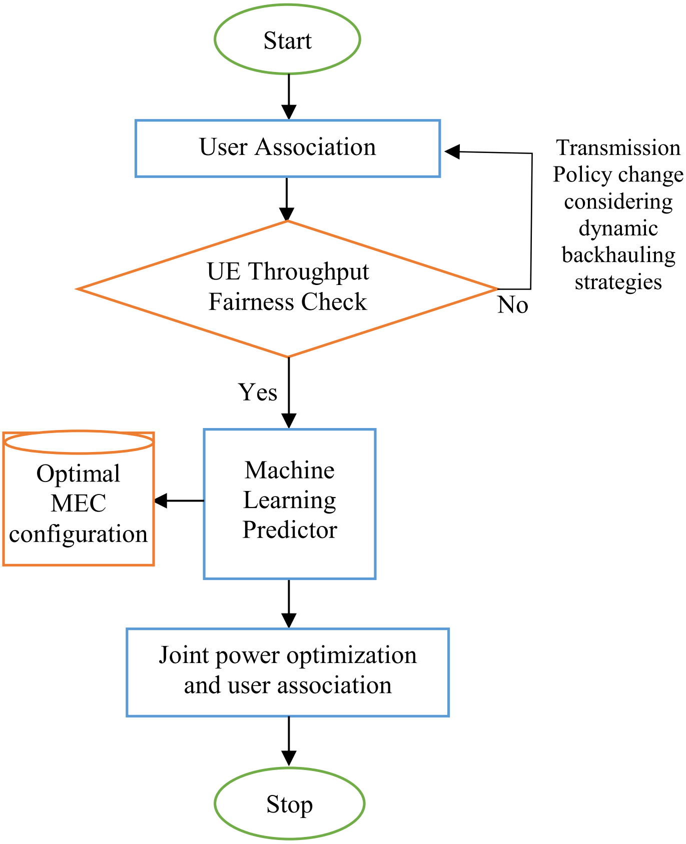

Fig. 4 The overall flow chart of the proposed approach

$$\begin{aligned} P2.2: \quad & \max_{P,\varepsilon,G} \sum_{i\in\mathcal{B}} \sum_{j\in u} x_{ij} \log\left(c_{ij}\right) - \eta \sum_{i\in\mathcal{B}} G_i \\ s.t. \quad & C1, C3, C7, C8. \end{aligned} \tag{30}$$

As it is obvious, this subproblem is NP-hard taking $\{P_i\}$ into account and an iterative sub gradient approach was utilized to obtain the solution P_i of the problem. So, P2.2–1 can be expressed as follows.

$$\begin{aligned} & P2.2-1: \quad \max_{P} \sum_{i\in\mathcal{B}} \sum_{j\in u} x_{ij} \log\left(c_{ij}\right) \\ & s.t. \quad C1, C3, C8. \end{aligned} \tag{31}$$

It's noticeable that applying Newton–Raphson's method can significantly decrease the problem complexity and this method could be effective for solving subproblem $P2.2-1$. In accordance with the mentioned conditions in [33], we can claim that this procedure is not only efficient, but also so fast-converged. Considering the user throughput fairness condition of the approach, we define the dual function of the $P2.2–1$ as the following.

$$\begin{aligned} & P\,2.2-1: \quad \max_{P} \sum_{i\in\mathcal{B}} \sum_{j\in u} x_{ij} \log\left(c_{ij}\right) - \sum_{j\in u} \theta_j \left(\gamma_{\min} - \sum_{i\in\mathcal{B}} x_{ij}\gamma_{ij} \right) \\ & s.t. \quad 0 \le P_i \le \varphi_i, \quad \forall i, \end{aligned} \tag{32}$$

In this formulation, $\{\theta_j\}$ denotes dual coefficient and $\varphi_i = min\left\{ P^i_{max}, G_i + \beta \sum_{j'\in\mathcal{B},j'\neq i} \varepsilon_{ji} - \sum_{j'\in\mathcal{B},j'\neq j} \varepsilon_{ii'} + E_i \right\}$ is achieved according to conditions C_3 and C_8. The optimum value of θ_j is also obtainable applying the sub-gradient approach based on (28). In continue, we focus on the proposed dynamic resource allocation approach taking θ_j into account as a constant factor. In which in the system model, $f(P_i)$ is the goal function of $\tilde{P}$ 2.2–1. The first and the second degrees of derivations of $f(P_i)$ are also achievable as (33) and (34) respectively.

$$\begin{aligned} \frac{\partial f(P_i)}{\partial P_i} = & \sum_{j\in u} \frac{\gamma_{ij}}{a_{ij}\left(1+\gamma_{ij}\right)} \frac{x_{ij}}{P_i} - \sum_{i'\in\mathcal{B},i'\neq i} \sum_{j\in u} \frac{h_{ij}\gamma^2_{i'j}}{a_{i'j}\left(1+\gamma_{i'j}\right)h_{i'j}} \frac{x_{i'j}}{P_{i'}} \\ & + \sum_{j\in u} \theta_j \gamma_{ij} \frac{x_{ij}}{P_i} - \sum_{i'\in\mathcal{B},i'\neq i} \sum_{j\in u} \theta_j \frac{h_{ij}\gamma^2_{i'j}x_{i'j}}{h_{i'j}P_{i'}}, \end{aligned} \tag{33}$$

And

$$\begin{aligned} \frac{\partial^2 f(P_i)}{\partial P_i^2} = & -\sum_{j\in u} \frac{1+a_{ij}}{a^2_{ij}\left(1+\gamma_{ij}\right)^2} \left(\frac{\gamma_{ij}}{P_i}\right)^2 x_{ij} \\ & + \sum_{i'\in\mathcal{B},i'\neq i} \sum_{j\in u} \frac{h^2_{ij}\gamma^3_{i'j}\left(2a_{i'j} + \gamma_{i'j}\left(a_{i'j}-1\right)\right)}{h^2_{i'j}P^2_{i'}a^2_{i'j}\left(1+\gamma_{i'j}\right)^2} x_{i'j} \\ & + \sum_{i'\in\mathcal{B},i'\neq i} \sum_{j\in u} 2\theta_j \frac{h^2_{ij}\gamma^3_{i'j}}{h^2_{i'j}P^2_{i'}} x_{i'j}, \end{aligned} \tag{34}$$

where $a_{ij} = log(1 + \gamma_{ij})$ To decrease the complexity of the solution, we applied the Newton–Raphson's approach as $\Delta P_i = \frac{\partial f(P_i)}{\partial P_i} / \left| \frac{\partial^2 f(P_i)}{\partial P_i^2} \right|$. So, the target problem can be reformulated as follows.

$$P_i(\varrho + 1) = \left[P_i(\varrho) + \delta(\varrho)\Delta P_i \right]_0^{\varphi_i}, \tag{35}$$

In this procedure, the optimal P_i^* is achievable after the last round of iterations. The indicator ϱ also represents the iteration index. Upon solving P2.2–1, (ε, G) is updated through finding the optimal solution for the subproblem P2.2–2

$$\begin{aligned} &P2.2-2: \qquad \min_{\varepsilon,G} \sum_{i \in \mathcal{B}} G_i \\ &s.t. \quad C3, C7. \end{aligned} \tag{36}$$

For solving this sub problem, we suggested CVX tool which is presented in [34] as a powerful mathematical framework for solving convex LP iterative problems.

4.3 Power Optimized User Association Algorithm

Based on the analysis of sections III-A and III-B, In this part we formulated jointly power optimization and user association ideas to achieve an effective approach which not only guarantees user fairness, but also maximizes the energy efficiency with a dynamic process. The functionality and the step-by-step explanation of the proposed algorithm has been summarized in Algorithm 1. It's noticeable the user association and resource allocation have identical goal function during each repetition, so algorithm will definitely be convergent [33].

Algorithm 1: Power optimized user association with the proposed transmission power strategy

1: **if** $t = 0$

2: **Initialize** $\mu_j(t), P_i, G_i, E_i, \ \forall i,$ SINR calculation by each UE to obtain c_{ij}.

3: $v_j(t)$ calculation through interception process and CPF

4: each UE determine i^* to find the best potential serving BS

$$i^* = arg\,max_i\,(log(c_{ij}) + \mu_j \gamma_{ij} - v_i)$$

5: the coefficient $\mu_j(t)$ using (28)

6: **else if**

7: $t \rightarrow t + 1$

8: algorithm 1 can be applied to achieve $q_{f_i}$and $x_{ij}(t)$ taking $(\boldsymbol{P}, \boldsymbol{G}, \boldsymbol{\varepsilon})$ into account and the faireness index

9: Determination of $k_j(t)$ using (26)

10: Hit probability pattern applying **Lemma 1**

11: UA $matrix\ X$ is determined via each BS.

12: Renew $v_j(t)$ based on (29)

13: **end if**

Evaluate the feasibility condition (32);

14: **if** feasibility of function confirmed (32), **then**

15: update $u_b = \hat{\alpha}_{(i)}$;

16 **else if**

17: update $l_b = \hat{\alpha}_{(i)}$;

18: **end if**

19: The DRL controller at the BS assesses the control channel's quality of all UEs for determination of the initial state s_1. Based on PF1 as

$$\sum_{\substack{\forall s \\ i+j+k=C \text{ and } k=0}} \frac{\lambda_1 j}{C-j} \pi_{i,j,k,m,n}$$

20: $i \rightarrow i + 1$;

21: return pair $(\boldsymbol{G}, \boldsymbol{\varepsilon})$ as the result of UA algorithm to RA

22: determination of efficiency index $\boldsymbol{P}$ based on:

Loop:

a) calculate θ_j, loop over $i \in \mathcal{B}$:

obtain the new value for P_i (35) and the Fairness Index

go on until convergence.

b) calculate θ_j applying subgradient approach

go on until convergence.

23: **for** $i = 0, 1, \ldots, T_{max}$ **do**

Determination of the service completion index as

$$SCR_i = \sum\nolimits_{\forall S} j \mu_k \pi_{i,j,k,m,n}$$

24: **If** μ_k can satisfy the throughput lower bound, controller considers current EE as reward r_t. Otherwise, there isn't any reward.

25: in accordance with the new power efficiency index P, obtain G_i and $\mathcal{E}_{ii'}$ which is equivalent to find the optimal solution for $\boldsymbol{P2.2-2}$ utilizing CVX.

26: continue to convergence

27: broadcast the optimal power strategy

$$(\boldsymbol{q}^*, \boldsymbol{x}^*, \boldsymbol{P}^*, \boldsymbol{\mathcal{E}}^*, \boldsymbol{G}^*)$$

28: **break**

29: **elseif**

30: **end if**

5 Numerical Results

In this section, we evaluate the performance of the proposed algorithm, MEC-Joint Energy Efficiency User Association (MEC-JEEUA), using MATLAB simulations and we compare the performance of this approach in two modes, 1) with power sharing (PS) capability, and 2) without power sharing, with some other schemes such as Fixed Power Allocation (FPA), Random Power Allocation (RPA) and Cooperative NOMA Simultaneous Wireless Information and Power Transfer (CN-SWIPT) [35]. In fixed power allocation, all base stations allocate equal maximum transmission power to user equipment and backhaul links and each of the backhaul links and user equipment applies all the assigned resources. Regardless the goal function, the random power allocation follows each t contained in C1 to C5. Beside the deep learning based UA and RA algorithms presented in a distinct mathematical model, the deep learning approach is able to effectively search for the optimal network configuration, bringing the best continuation power flow with the maximum achievable load limit. The different deep learning algorithms are applied to predict the output parameters. Note that the main simulation factors in addition to their primary values have been listed in Table 1.

Figures 5 and 6 compare the average total throughput of MEC-JEEUA approach in comparison with other EE schemes considering equal maximum transmission power and the UE density. Figure 5 shows the results of the simulation based on the uniform user

Table 1 Main implementation factors

Parameter	Value
System Configuration	Hexagonal network, X-sectored BSs
SC distribution pattern	uniform (U) and hotspot (Hs),
Functional Frequency	3500 Megahertz
Bandwidth	10 Megahertz
Transmission backoff	1.5 dB
MBS Maximum transmit power	43 dBm
Codec model	Adaptive multi-rate
Inter site distance	150 m
Hopping strategy	Synthesized
Rx_loss & Tx_loss	5 dB
Propagation model	Standard propagation model
Fairness Index	User throughput
Upper bound of iteration	500
$L_{m\arg in}$	10 dBm
Millimeter wave backhauling frequency	3500 Megahertz
Learning factor $c_1 = c_2$	1.4
Weighting factor $\omega_{\max}$ MAX	0.90
Weighting factor $\omega_{\min}$ MIN	0.35
MBS Power utilization P_m^o	90 w
SBS Power utilization P_s^o	5 w
SC radius	30 m
Antenna model	APE3390R5-0066X_CO-P43_0AT

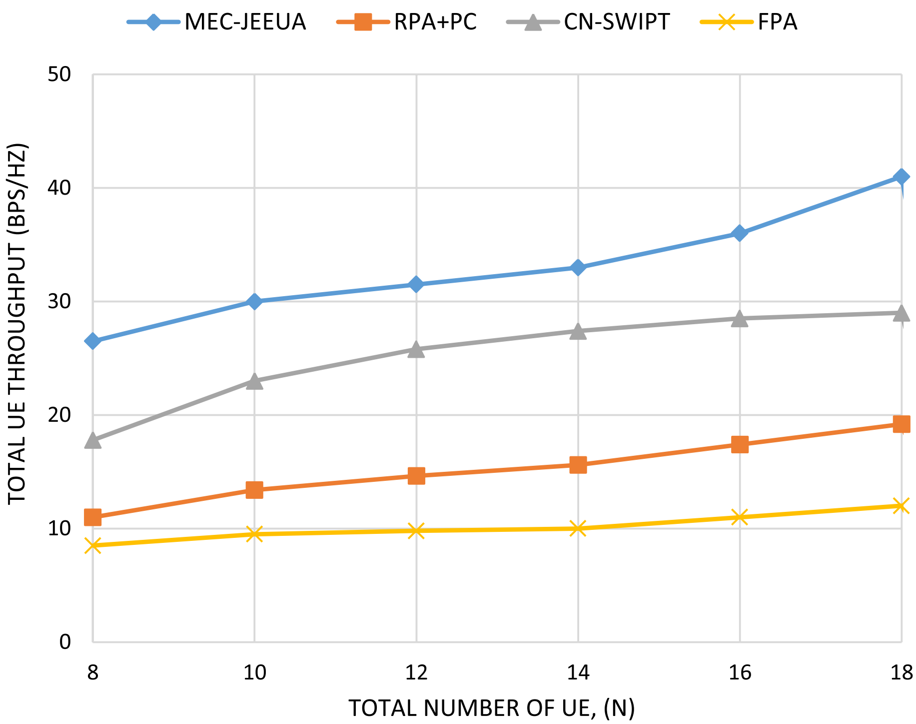

Fig. 5 Total UE throughput considering uniform user distribution model

distribution pattern and Fig. 6 exhibits the user throughput based on hybrid user distribution pattern (hotspot and mobile). According to these figures, it can be seen that MEC-JEEUA performs much better than other algorithms in term of higher total network throughput. Because this algorithm has the required flexibility to provide more throughput for the user equipment upon its adaptivity to time-varying fading parameters. This throughput can also decreases slightly with an increase in N, because the algorithm reduces the throughput available to each of the UEs in order to guarantee the fairness index. In contrast, the pattern of the users' demands is the same in all random power allocation, fixed power allocation, and MEC-JEEUA algorithms, because they all provide the minimum throughput for each N user set. As a result, the jointly random power allocation and discrete power control outperforms fixed power allocation, although both of them can significantly provide less throughput for UEs compared to CN-SWIPT and MEC-JEEUA due to lack of efficiency and smart user association. According to these Figures, the total network throughput increases almost linearly with increasing N in the MEC-JEEUA algorithm. While all three other algorithms show slight improvement.

Figure 7 shows the average total energy consumption in different energy efficiency algorithms. The Fixed Power Allocation has the worst performance, as each base station uses maximum transmission power on both the access network and its backhauling. Random power allocation has little energy savings because it controls the flow without maximizing or minimizing the goal function. CN-SWIPT and MEC-JEEUA algorithms have the lowest power consumption and MEC-JEEUA performance is slightly better than CN-SWIPT. It's why that, the CN-SWIPT algorithm merely focus on minimizing the utilized energy and

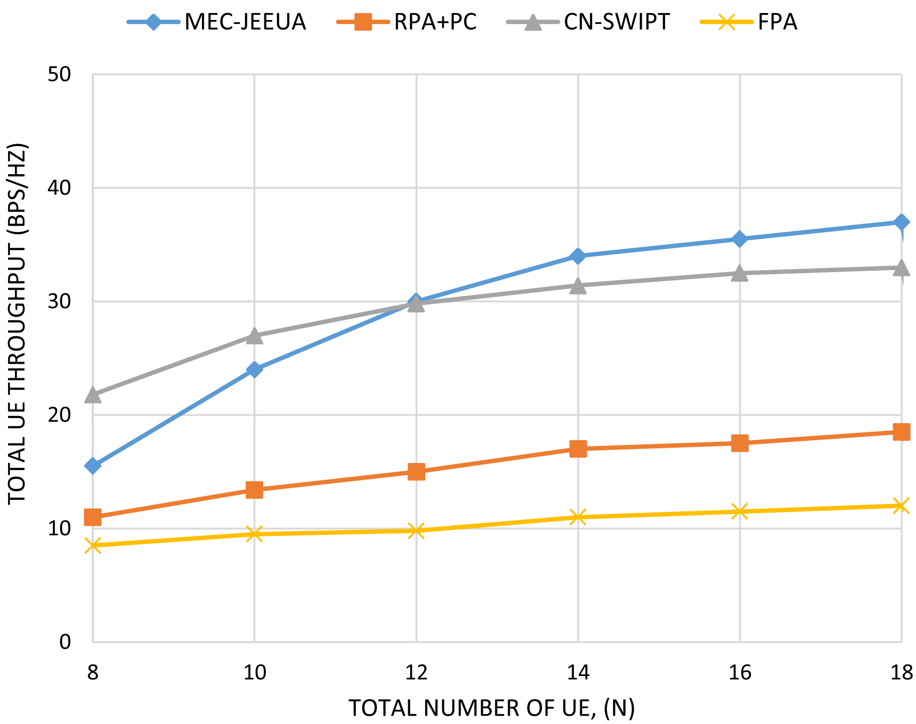

Fig. 6 Total throughput considering hotspot and mobile user distribution model

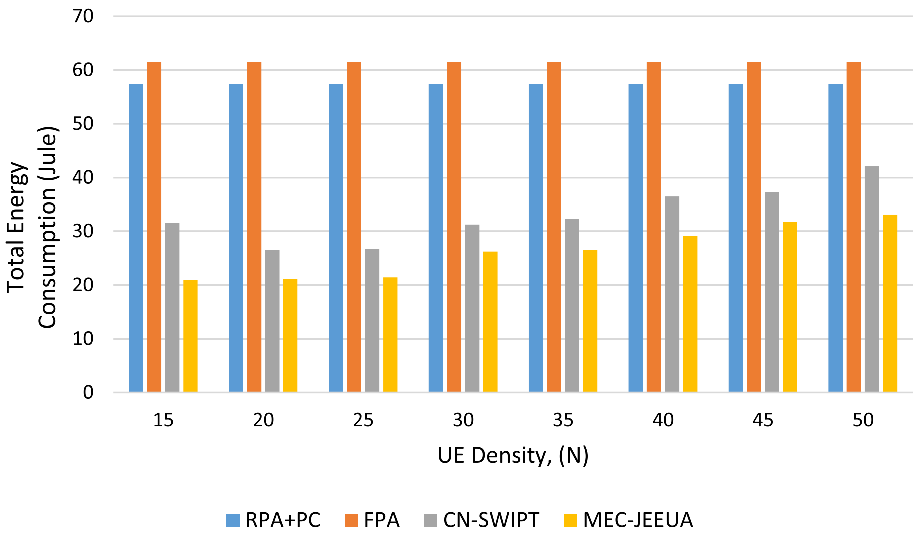

Fig. 7 Total energy consumption versus UE density

controls the flows, but MEC-JEEUA algorithm simultaneously minimizes the power and controls the flow. It is also able to maximize the throughput of the user's equipment.

Figure 8 presents the comparison of the average total power efficiency of different algorithms for different number of users. Based on this figure, it can be seen that the energy efficiency of CN-SWIPT and MEC-JEEUA algorithms is much better than random power allocation and fixed power allocation. Because, CN-SWIPT and MEC-JEEUA algorithms optimize power allocation and flow control in addition to dynamic user association. However, MEC-JEEUA performs better than CN-SWIPT due to differences between their goal functions. As mentioned before, the goal function of MEC-JEEUA is to maximize the energy efficiency. For this purpose, it simultaneously optimizes the demand of throughput of the user equipment and energy consumption in both the access network and backhauling. As the JEEUA curve shows, the throughput weight of the network is greater than the increase in power consumption for N UE set, which increases the energy efficiency when increasing the N with higher slope. But when N increases significantly, the energy efficiency remains constant, because increasing capacity will not be effective due to increased energy consumption. With increasing N, energy efficiency may also gradually decreases, because the network capacity can not provide the necessary balance in high energy consumption. But CN-SWIPT only optimizes energy consumption, while there is a serious operational limitation for the UE demands. This proves that from the energy efficiency point of view, it is better that the UE throughput demands, energy consumption and current control in backhaul links are optimized simultaneously.

As we expect, Fig. 9 shows that MEC-JEEUA algorithm utilizes power sources better than other algorithms. Increasing the maximum transmission power to the saturation level, increases the energy efficiency. After reaching the saturation point, increasing the maximum transmission power does not affect the energy efficiency so that increasing maximum transmission power in Fixed Power Allocation (FPA), Random Allocation (RA) and

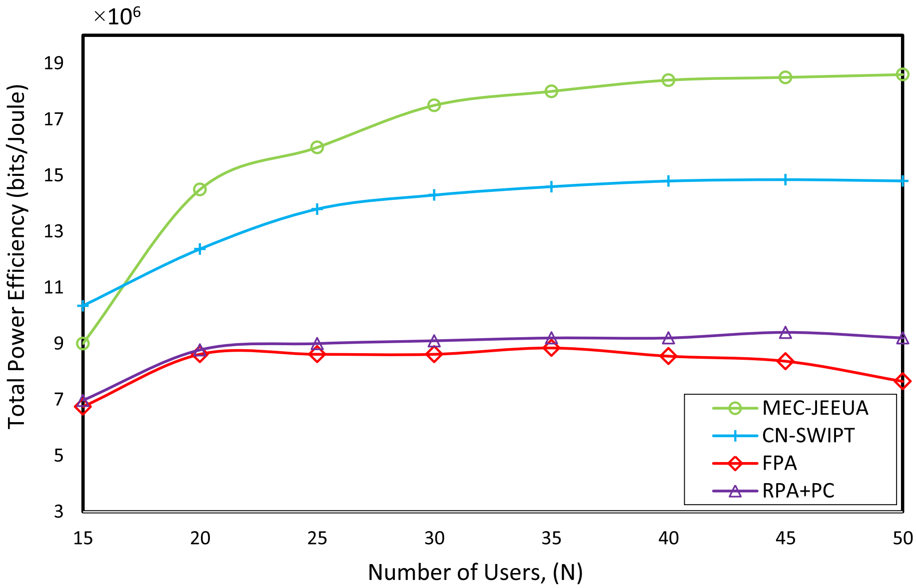

Fig. 8 Total power efficiency versus number of UEs

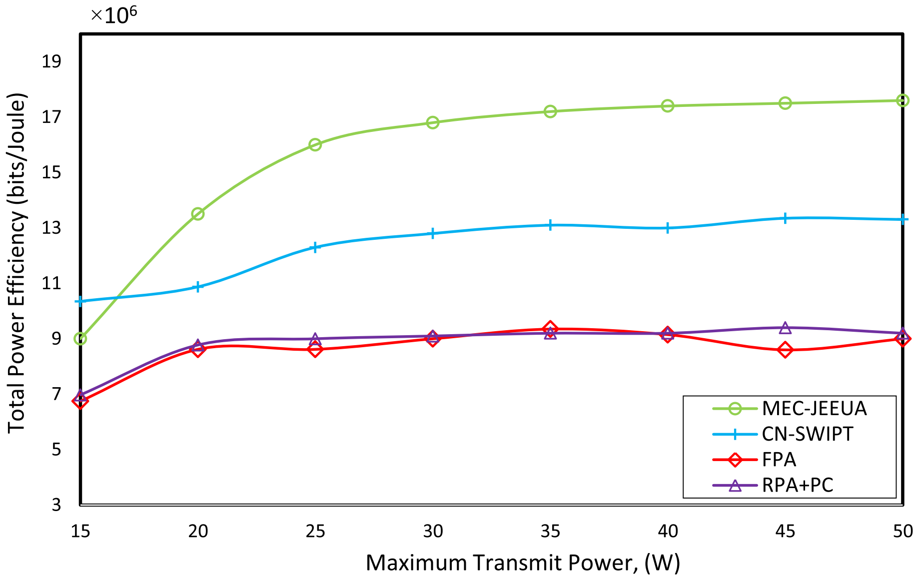

Fig. 9 Total power efficiency versus maximum transmission power

CN-SWIPT algorithms does not improve the energy efficiency. In this case, the performance of these algorithms is slightly worse. In the form of 1000 independent simulations, we investigated how many times each algorithm successfully obtains the optimal solution based on the predefined criteria in CVX.

Figure 10 shows the obtained results of comparison between MEC-JEEUA and other three algorithms from the Faireness perspective. This evaluation was done based on the Jain fairness indicator per user density so that the UE data rate should be checked within 120 consecutive time slots. As it is obvious from the plot, MEC-JEEUA is fairer than CN-SWIPT. Algorithm CN-SWIPT also has better fairness compared to the FPA and RPA schemes. Hence, with MEC-JEEUA higher data rate can be provided for cell edge and poor-coverage users than the values supplied by CN-SWIPT, FPA and RPA schemes because MEC-JEEUA is capable to dedicate a part of its resources to low-quality users. The plot also indicates that CN-SWIPT has better fairness than FPA and RPA. Based on CN-SWIPT main targets, the users are separated to d_v categories in accordance with their channel quality, and each user can only share subcarriers with the users of dissimilar group. In this resource allocation approach, more resource can be allocated to the users with poor channel quality to guarantee the UE fairness.

6 Conclusion

In this paper, we investigate the problem of maximizing energy efficiency in mobile edge computing networks with different backhaul link connections. We proposed an DL-based resource allocation approach to find the optimal topology for cache-enabled backhaul networks. In the practical scenarios, a numerous of radial configurations of test systems have been applied for training stages. This paper also applied the continuation power flow (CPF) analysis to achieve the maximum load limit in which the power of macro base stations with

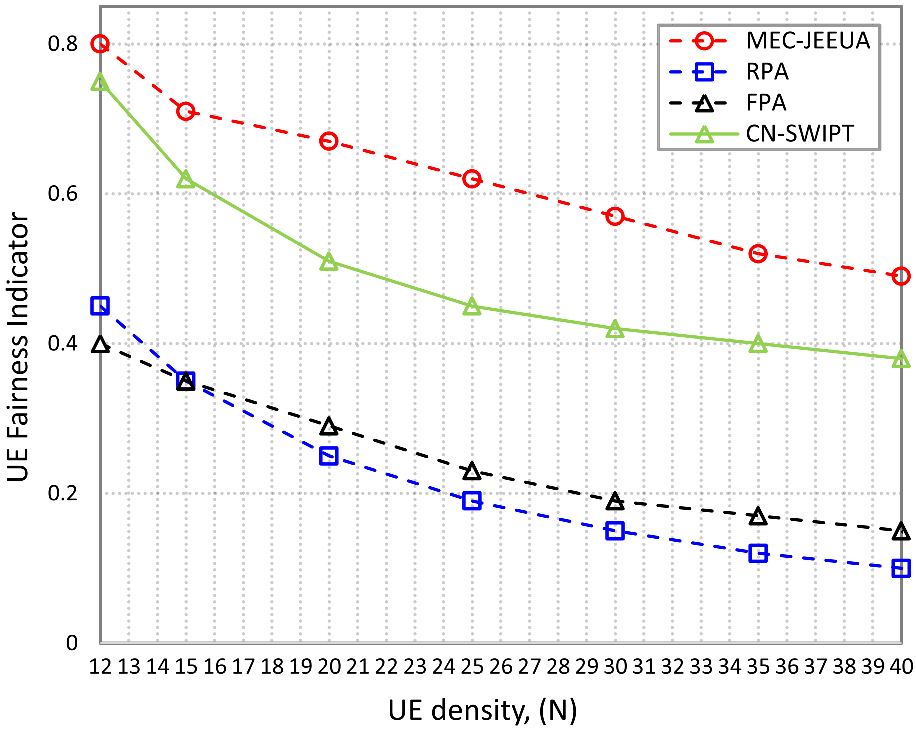

Fig. 10 UE fairness vs. UE density

the caches of different sizes is provided through either renewable power systems or smart grid. To increase the power efficiency index of this approach the power sharing capability was enabled among different layer of network components through smart grids. The numerical results illustrate that the suggested approach is able to obtain higher energy efficiency, total data rateand user faireness. It also outperforms compared to other algorithms that do not take into account the common impact on the total data rate maximization and energy utility. This research is currently underway to implement a low-complexity dynamic approach to implement the MEC-JEEUA model.

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