Joint Resource Allocation for Integrated Localization and Computing in Edge-intelligent Networks

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***Abstract*—In this paper, we investigate the issue of integrated localization and computing (ILAC) in edge-intelligent networks. By exploiting the dual-function radio frequency (RF) signals, we put forward a unified design framework for ILAC in edge-intelligent networks where the localization task and the computing task are conducted cooperatively by multiple user equipments (UEs) and multiple base stations (BSs). In particular, a joint resource allocation algorithm is proposed for ILAC by optimizing the available radio and computing resources with the goal of minimizing the weighted total energy consumption while ensuring the performance requirements of the localization task and the computing task. Finally, numerical results verify the effectiveness of the proposed algorithm over baseline ones.**

***Index Terms*—Edge-intelligent networks, integrated localization and computing, joint resource allocation.**

I. Introduction

With the rapid growth of a series of emerging data-driven applications such as smart cities, autonomous driving, and immersive extended reality, edge-intelligent networks are required to offer intelligent services and ubiquitous connectivity with ultra-low latency and ultra-high reliability [1], [2]. Generally, edge-intelligent networks are not only required to provide real-time target detection and environment sensing by using localization techniques, but also to conduct low-latency data computing by using mobile edge computing (MEC) techniques [3]. In order to improve the overall performance of edge-intelligent networks, it is desired to design an integrated localization and computing (ILAC) framework.

Actually, target localization has been well studied in radar systems. In particular, by making full use of spatial diversity, multiple-input-multiple-output (MIMO) radar systems with the structure of widely distributed antennas can effectively improve the accuracy of target localization [4]. In fact, localization accuracy in MIMO radar systems mainly lies in radar deployment, effective signal bandwidth, target radar-cross section, and transmit power [5]. To this end, a series of works about resource allocation have been proposed to enhance the accuracy of target localization. For example, a power allocation scheme was put forward to minimize the total power transmit while ensuring the Cramer-Rao bound (CRB) of localization mean squared error (MSE) [6]. Moreover, the authors in [7] studied the optimal transmit/receive antennas placement for distributed MIMO radar systems. On the other hand, for computing, uploading a huge-volume data from the network edge to the cloud servers for processing is undesirable since it leads to overloaded communication burden and excessive response latency [8]. In this context, it is appealing to handle these data at the network edge directly, which generates a new-brand distributed computing paradigm, namely mobile edge computing (MEC) [9]. According to the actual requirement, the latency-sensitive tasks can be executed at mobile devices locally or offloaded to the MEC servers for computing. In this context, resource allocation problem also becomes a key issue for achieving efficient data computing. For instance, [10] and [11] both designed joint task offloading and resource allocation schemes for multi-MEC severs systems with the goal of energy consumption minimization.

Most previous works investigate target localization and data computing, respectively. Since radar systems and communication systems have a lot of similarities in terms of radio frequency (RF) transceivers, channel characteristics and signal processing [12], it is possible to integrate localization and computing jointly in edge-intelligent networks. Moreover, considering limited radio resources in edge-intelligent networks, it is desired to integrate localization and computing in an effective way. In this context, this paper aims to design a joint resource allocation scheme to achieve the efficient ILAC according to the characteristics and requirements of edge-intelligent networks. The contributions of this paper are three-fold:

1) We provide a unified design framework for ILAC in edge-intelligent networks, where the localization task and the computing task are cooperatively conducted by multiple user equipments (UEs) and multiple base stations (BSs) based on dual-function RF signals.
2) We derive the CRB of targets' positions for the localization task and the required energy consumption and time delay for the computing task. Furthermore, we reveal

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the impacts of key system factors on the performance of the localization task and the computing task.

3) We design a joint resource allocation algorithm for ILAC in edge-intelligent networks by minimizing the weighted total energy consumption while guaranteeing performance requirements.

The rest of this paper is organized as follows. Section II introduces edge-intelligent networks with ILAC. Section III gives a joint resource allocation algorithm design. Section IV shows the numerical results to verify the effectiveness of the proposed algorithm. Finally, Section V concludes the paper.

II. System Model

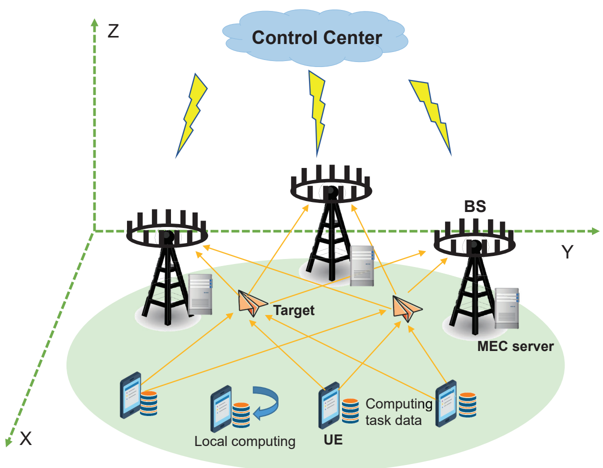

Fig. 1. An edge-intelligent network integrating localization and computing..

We consider an edge-intelligent network as shown in Fig. 1, which consists of a control center (CS), N BSs equipped with K antennas and deployed with a MEC server each, M single-antenna dual-function intelligent UEs and L targets need to be located. Each UE has a computing task to be completed and a localization task for tracking the targets' positions, where the computing task can be executed locally or offloaded to the MEC server for processing and the localization task is cooperatively completed by the UEs selecting for remote computing. Specifically, by transmitting the dual-function localization and computing (DFLC) signal, the UE selecting remote computing offloads its computing task to at most one BS and performs cooperative target localization simultaneously. Then, the BS receives the signal for further processing. On the one hand, it uploads position-related information to the CS for target localization. On the other hand, it decodes the data of the computing task and transfers it to the MEC server for data computing. After the computing task is completed, the result is returned to the corresponding UE.

Without loss of generality, it is assumed that the n-th BS is located at $\left(x_n^R, y_n^R, z_n^R\right)$, the m-th UE is located at $\left(x_m^T, y_m^T, z_m^T\right)$ and the l-th target is located at (x_l, y_l, z_l) in a three-dimensional (3-D) coordinate system. The search cell of the l-th target is limited to $\left(x_l \pm \frac{\delta c}{B}, y_l \pm \frac{\delta c}{B}, z_l \pm \frac{\delta c}{B}\right)$, where δ is given search coefficient, c is the light speed and B is the effective signal bandwidth [5]. Moreover, $R_{m,l}^T$, $\psi_{m,l}^T$ and $\varphi_{m,l}^T$ are the distance, the azimuth angle and the elevation angle of the m-th UE to the l-th target, respectively. Similarly, $R_{n,l}^R$, $\psi_{n,l}^R$ and $\varphi_{n,l}^R$ are the distance, the azimuth angle and the elevation angle of the l-th target to the n-th BS, respectively. Then, we use a binary offloading coefficient $\vartheta_{m,n} \in \{0,1\}$ to denote the offloading choice for the computing task with $\sum_{n=0}^{N} \vartheta_{m,n} = 1, \forall m$. In particular, if the computing task of m-th UE is executed locally, $\vartheta_{m,0} = 1$, otherwise $\vartheta_{m,0} = 0$, and if the computing task of the m-th UE is offloaded to the MEC sever at the n-th BS, $\vartheta_{m,n} = 1$, otherwise $\vartheta_{m,n} = 0$. For local computing, the UE executes the computing task by itself and thus does not participate in the cooperative localization task. While for remote computing, the UE offloads the computing task to the MEC server and perform target localization by sending a DFLC signal. Specifically, a set of unit-power orthogonal DFLC signal $s_m(t), \forall m$ are transmitted at the time slot t by UEs selecting remote computing with $\int_{\mathcal{T}_m} |s_m(t)|^2 dt = 1, \forall m$ and $\int_{\mathcal{T}_m} s_m(t) s_{m'}(t)^* dt = 0$ for $m \neq m'$, where $\mathcal{T}_m$ is the duration of the m-th transmitted signal. By combining the received signals of K antennas, the final received signal at the n-th BS from the m-th UE via l-th target is given by

$$\begin{aligned} r_{m,l,n}(t) &= \sum_{k=1}^{K} \sqrt{(1-\vartheta_{m,0})p_m} h_{m,l,n,k} s_m\left(t - \tau_{m,l,n}\right) \\ &+ w_{m,l,n}(t) \end{aligned} \tag{1}$$

where p_m is the transmit power of the m-th UE, $w_{m,l,n} \sim \mathcal{CN}\left(0, \sigma_w^2\right)$ is the additive white noise with σ_w^2 being noise variance and $\tau_{m,l,n} = \left(R_{m,l}^T + R_{n,l}^R\right)/c$ is the propagation delay from the m-th UE to the n-th BS via the l-th target. Moreover, $h_{m,l,n,k}$ is the channel coefficient from the m-th UE to the k-th antenna of the n-th BS via the l-th target, including the path loss, target radar cross section, the effects of amplitude and phase offsets between the transmit and receive antennas and the impact of the filters. Based on the received signal, localization and computing are conducted as follows.

A. Localization Task

The BS sends the received signal to the CS, and then the CS determines the targets' positions by using an unbiased estimator. To portray the performance of the localization task, we select commonly used CRB as the performance metric of localization, which represents the lower bound on the MSE of the target location estimation [5]-[7]. For convenience, we define a vector of unknown position parameter $\mathbf{u}_l = [x_l, y_l, z_l]^T$ for the l-th target. For a given vector parameter $\mathbf{u}_l$, the unbiased estimation $\hat{\mathbf{u}}_l$ satisfies the following inequality

$$\mathbb{E}\left\{(\hat{\mathbf{u}}_l - \mathbf{u}_l)(\hat{\mathbf{u}}_l - \mathbf{u}_l)^T\right\} \geq \mathbf{J}_l^{-1}, \forall l, \tag{2}$$

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where $\mathbf{J}_l$ is the Fisher Information matrix (FIM) derived in Appendix A. Then, the CRB matrix $\mathbf{C}_l^{x,y,z}$ is equal to the inverse of the FIM $\mathbf{J}_l$, i.e.,

$$\mathbf{C}_l^{x,y,z}(\bar{\mathbf{p}}) = \mathbf{J}_l^{-1} = \left(\sum_{m=1}^{M} (1-\vartheta_{m,0}) p_m \mathbf{G}_{l,m} \right)^{-1}, \quad (3)$$

where the vector $\bar{\mathbf{p}} = \left[(1-\vartheta_{1,0})\, p_1, ..., (1-\vartheta_{M,0})\, p_M\right]^T$, the matrix $\mathbf{G}_{l,m} = \begin{bmatrix} g_{l,m}^{x} & g_{l,m}^{xy} & g_{l,m}^{xz} \\ g_{l,m}^{xy} & g_{l,m}^{y} & g_{l,m}^{yz} \\ g_{l,m}^{xz} & g_{l,m}^{yz} & g_{l,m}^{z} \end{bmatrix}$ with the elements $g_{l,m}^{x} = \sum_{n=1}^{N} \phi_{m,l,n} \bar{x}_{m,l,n}^2$, $g_{l,m}^{xy} = \sum_{n=1}^{N} \phi_{m,l,n} \bar{x}_{m,l,n} \bar{y}_{m,l,n}$, $g_{l,m}^{y} = \sum_{n=1}^{N} \phi_{m,l,n} \bar{y}_{m,l,n}^2$, $g_{l,m}^{yz} = \sum_{n=1}^{N} \phi_{m,l,n} \bar{y}_{m,l,n} \bar{z}_{m,l,n}$, $g_{l,m}^{z} = \sum_{n=1}^{N} \phi_{m,l,n} \bar{z}_{m,l,n}^2$, $g_{l,m}^{xz} = \sum_{n=1}^{N} \phi_{m,l,n} \bar{x}_{m,l,n} \bar{z}_{m,l,n}$, and $\phi_{m,l,n} = \frac{8\pi^2 B^2}{c^2 \sigma_w^2} \sum_{k=1}^{K} \left| h_{m,l,k,n} \right|^2$. To present the sum of the MSEs of all location estimation for the l-th target, we compute the trace of CRB matrix as below

$$\mathrm{tr}\left(\mathbf{C}_l^{x,y,z}(\bar{\mathbf{p}})\right) \le \sigma_{x,l}^2 + \sigma_{y,l}^2 + \sigma_{z,l}^2, \quad (4)$$

where $\sigma_{x,l}^2$, $\sigma_{y,l}^2$ and $\sigma_{z,l}^2$ are the MSEs on x, y and z location for the l-th target, respectively.

B. Computing Task

Meanwhile, the BS transfers the received signal to its MEC server for data computing. For easy notation, the computing task from the m-th UE is defined as $\Omega_m \triangleq (D_m, C_m)$, where D_m and C_m are input data size (in bits) and the computing intensity (in CPU cycles per bit, namely the required computing resource for computing one bit of the input data), respectively. It is well known that the computing task is usually sensitive to the time delay and the energy consumption, thus we characterize the computing task from these two perspectives. At first, we consider the local computing task. The local execution time (in second) of the computing task is given by

$$T_m^{\mathrm{loc}} = \vartheta_{m,0} \frac{D_m C_m}{f_m^{\mathrm{loc}}}, \quad (5)$$

where f_m^{loc} is the computing power (in CPU cycles per second) of the m-th UE. Moreover, the required energy consumption (in Joules) for completing the computing task can be expressed as

$$E_m^{\mathrm{loc}} = \vartheta_{m,0} \kappa_m^U D_m C_m \left(f_m^{\mathrm{loc}}\right)^2, \quad (6)$$

where κ_m^U is the energy coefficient related to the chip architecture of the m-th UE. Then, for remote computing, the execution time mainly consists of two parts (the return part is ignored due to the tiny size of computing result), i.e., the transmission time T_m^{tra} via uplink and the computing time T_m^{ser} at the MEC server, which is given by

$$T_m^{\mathrm{off}} = T_m^{\mathrm{tra}} + T_m^{\mathrm{ser}} = \sum_{n=1}^{N} \vartheta_{m,n} \frac{D_m}{R_{m,n}} + \sum_{n=1}^{N} \vartheta_{m,n} \frac{D_m C_m}{f_{m,n}^{\mathrm{ser}}}, \quad (7)$$

where the data rate related to the m-th UE offloading its computing task to the MEC server at the n-th BS is

$$R_{m,n} = B \log_2 \left(1 + p_m \sum_{l=1}^{L} \sum_{k=1}^{K} \left| h_{m,l,n,k} \right|^2 / \sigma_w^2 \right), \quad (8)$$

and $f_{m,n}^{\mathrm{ser}}$ is the computing power allocated by the MEC server of the n-th BS to the computing tasks from the m-th UE. Similarly, the energy consumption for remote computing also mainly consists two parts, i.e., the transmission cost E_m^{tra} via uplink and the computing cost E_m^{ser} at the MEC server, which can be expressed as

$$\begin{aligned} E_m^{\mathrm{off}} &= E_m^{\mathrm{tra}} + E_m^{\mathrm{ser}} & (9) \\ &= \sum_{n=1}^{N} \vartheta_{m,n} p_m \frac{D_m}{R_{m,n}} + \sum_{n=1}^{N} \vartheta_{m,n} \kappa_n^M \left(f_{m,n}^{\mathrm{ser}}\right)^2 D_m C_m, \end{aligned}$$

where κ_n^M is the energy coefficient related to the chip architecture of the MEC server of the n-th BS.

Check (4)-(9), it is found that the performance of localization task and computing task are both affected by the computing offloading choice $\vartheta_{m,n}$ and the transmit power allocation p_m. Moreover, the computing power at the UE f_m^{loc} and the allocated computing power at the MEC server $f_{m,n}^{\mathrm{ser}}$ also have significant impacts on the required execution time and energy consumption for the computing task. Hence, it is necessary to design an efficient resource allocation scheme by jointly optimizing the offloading choice and power allocation for realizing the effective ILAC in edge-intelligent networks.

III. Joint Resource Allocation for ILAC

In this section, we design a joint resource allocation scheme from the perspective of minimizing the weighted total energy consumption of the computing task while ensuring the requirements of the execution time of the computing task and the accuracy for the localization task, respectively. In particular, the design can be formulated as the following optimization problem:

$$\begin{aligned} \min_{\mathbf{p},\boldsymbol{\vartheta},\mathbf{f},\mathbf{F}} \quad & \sum_{m=1}^{M} \lambda_m (E_m^{\mathrm{loc}} + E_m^{\mathrm{off}}) & \text{(10a)} \\ \text{s.t.} \quad & T_m^{\mathrm{loc}} + T_m^{\mathrm{off}} \le \varsigma_m, \forall m \in \mathcal{M}, & \text{(10b)} \\ & \mathrm{tr}(\mathbf{C}_l^{x,y,z}(\bar{\mathbf{p}})) \le \eta_l, \forall l \in \mathcal{L}, & \text{(10c)} \\ & \vartheta_{m,n} \in \{0,1\}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}', & \text{(10d)} \\ & \sum_{n=0}^{N} \vartheta_{m,n} = 1, \forall m \in \mathcal{M}, & \text{(10e)} \\ & \sum_{m=1}^{M} \vartheta_{m,n} f_{m,n}^{\mathrm{ser}} \le F_n^M, \forall n \in \mathcal{N}, & \text{(10f)} \\ & 0 \le f_{m,n}^{\mathrm{ser}} \le F_n^M, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, & \text{(10g)} \\ & 0 \le f_m^{\mathrm{loc}} \le F_m^U, \forall m \in \mathcal{M}, & \text{(10h)} \\ & 0 \le p_m \le P_m^{\max}, \forall m \in \mathcal{M}, & \text{(10i)} \end{aligned}$$

where the optimization variables are $\mathbf{p} = \{p_m, \forall m \in \mathcal{M}\}$, $\boldsymbol{\vartheta} = \{\vartheta_{m,n}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}'\}$, and $\mathbf{f} = \left\{f_m^{\mathrm{loc}}, \forall m \in \mathcal{M}\right\}$,

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$\mathbf{F} = \left\{f_{m,n}^{\text{ser}}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}\right\}$ with the collections $\mathcal{M} = \{1, \ldots, M\}$, $\mathcal{L} = \{1, \ldots, L\}$, $\mathcal{N} = \{1, \ldots, N\}$ and $\mathcal{N}' = \{0, 1, \ldots, N\}$. Moreover, $\lambda_m > 0$ denotes the priority of the m-th UE, ς_m and η_l are the threshold values of time delay for the computing task of the m-th UE and the CRB of the l-th target localization, respectively. F_m^U is the total computing power at the m-th UE, $P_m^{\max}$ is the transmit power budget at the m-th UE, and F_n^M is the total computing power of the MEC server at the n-th BS. It is seen that problem (10) is a computationally difficult mixed integer nonlinear programming (MINLP), thus it is difficult to obtain an optimal solution in polynomial time. In this context, we aim to develop a feasible algorithm for finding a sub-optimal solution that achieves competitive performance in practical implementation. Specifically, by exploiting the structure of the objective function and constraints of problem (10), we employ the alternating optimization (AO) method to decouple the original problem with high complexity into two subproblems with low complexity, i.e., one for offloading strategy design and another for power allocation design. Now, we address the first subproblem for offloading strategy optimization with fixed transmit power and computing power, which is formulated as

$$\begin{aligned} \min_{\boldsymbol{\vartheta}} \quad & \sum_{m=1}^{M} \lambda_m (E_m^{\text{loc}} + E_m^{\text{off}}) && (11) \\ \text{s.t.} \quad & (10b) - (10f). \end{aligned}$$

It is clear that problem (11) is an integer programming problem. Thus, we adopt the most commonly used branch and bound (BnB) algorithm to solve it, which finds the optimal solution by traversing the BnB search tree. In particular, problem (11) can be viewed as the root node of the BnB tree, which is constructed and searched by branching and bounding. For branching, a parent problem is divided into two subproblems by adding mutually exclusive constraints on the node, i.e., one leaf node for $\vartheta_{m,n} = 1$, and another for $\vartheta_{m,n} = 0$. For bounding, the current branch is determined to be retained or pruned by checking the upper and lower bounds of the objective of the subproblem. Note that the lower bound of the objective for each subproblem can be obtained by solving its relaxed optimization problem, where the binary constraint is relaxed to a continuous constraint. To obtain the lower bound of the objective value to problem (11), we construct the relaxation problem as below

$$\begin{aligned} \min_{\boldsymbol{\vartheta}} \quad & \sum_{m=1}^{M} \lambda_m (E_m^{\text{loc}} + E_m^{\text{off}}) && (12a) \\ \text{s.t.} \quad & (10b), (10c), (10e), (10f), \\ & 0 \le \vartheta_{m,n} \le 1, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}'. && (12b) \end{aligned}$$

It is noted that problem (12) is nonconvex due to the untractable constraint (10c) with a complicated structure, i.e., the trace of the inverse of the sum of matrix. To solve this issue, we introduce an auxiliary matrix variable $\boldsymbol{\Theta}_l \succeq \mathbf{J}_l^{-1}$. By exploiting Schur's complement [13], the matrix inequality $\boldsymbol{\Theta}_l \succeq \mathbf{J}_l^{-1}$ can be reformulated as

$$\begin{bmatrix} \boldsymbol{\Theta}_l & \mathbf{I} \\ \mathbf{I} & \mathbf{J}_l \end{bmatrix} \succeq \mathbf{0}. \tag{13}$$

In this context, constraint (10c) can be replaced by

$$\text{tr}\left(\boldsymbol{\Theta}_l\right) \le \eta_l. \tag{14}$$

Thus, problem (12) can be transformed as an equivalent convex optimization problem as below

$$\begin{aligned} \min_{\boldsymbol{\vartheta}, \boldsymbol{\Theta}} \quad & \sum_{m=1}^{M} \lambda_m (E_m^{\text{loc}} + E_m^{\text{off}}) && (15) \\ \text{s.t.} \quad & (10b), (10e), (10f), (12b), (13), (14). \end{aligned}$$

According to the principle of the BnB algorithm, the optimal solution $\boldsymbol{\vartheta}$ and the objective value to problem (15) can be viewed as the relaxation solution and the lower bound of the objective value to problem (11), respectively. Hence, the offloading strategy can be determined by solving problem (15) via the BnB algorithm during the process of branching and bounding.

Then, for a given offloading strategy, the second subproblem of power allocation can be written as

$$\begin{aligned} \min_{\mathbf{p}, \mathbf{f}, \mathbf{F}, \boldsymbol{\Theta}} \quad & \sum_{m=1}^{M} \lambda_m (E_m^{\text{loc}} + E_m^{\text{off}}) && (16) \\ \text{s.t.} \quad & (10b), (10f) - (10i), (13), (14), \end{aligned}$$

where convex constraints (13) and (14) replace the constraint (10c) in the original problem (10). However, problem (16) is still not convex due to the complicated objective function. In particular, the consumed energy for the signal transmission during computing offloading can be viewed as a nonconvex function of the transmit power $p_m, \forall m$, which can be expressed as

$$E_m^{\text{tra}}\left(p_m\right) = \frac{(1 - \vartheta_{m,0}) p_m D_m}{B \log_2\left(1 + p_m \chi_m\right)}, \tag{17}$$

where $\chi_m = \sum_{l=1}^{L} \sum_{k=1}^{K} \sum_{n=1}^{N} \vartheta_{m,n} |h_{m,l,n,k}|^2 / \sigma_w^2$. To address the nonconvexity of $E_m^{\text{tra}}\left(p_m\right)$, we introduce an auxiliary variable $q_m = \frac{1 - \vartheta_{m,0}}{\log_2(1 + p_m \chi_m)} \ge 0$. Thus, $E_m^{\text{tra}}\left(p_m\right)$ can be rewritten as

$$E_m^{\text{tra}}\left(q_m\right) = \frac{D_m}{B \chi_m} q_m \left(2^{\frac{1 - \vartheta_{m,0}}{q_m}} - 1\right). \tag{18}$$

Then, constraint (10b) and constraint (13) can be transformed as

$$T_m^{\text{loc}} + \frac{q_m D_m}{B\left(1 - \vartheta_{m,0}\right)} + T_m^{\text{ser}} \le \tau_m, \tag{19}$$

and

$$\begin{bmatrix} \boldsymbol{\Theta}_l & \mathbf{I} \\ \mathbf{I} & \bar{\mathbf{J}}_l\left(\mathbf{q}\right) \end{bmatrix} \succeq \mathbf{0}, \tag{20}$$

respectively, where $\mathbf{q} = \{q_m, \forall m \in \mathcal{M}\}$ and $\bar{\mathbf{J}}_l\left(\mathbf{q}\right) = \sum_{m=1}^{M} \frac{1 - \vartheta_{m,0}}{\chi_m} \left(2^{\frac{1 - \vartheta_{m,0}}{q_m}} - 1\right) \mathbf{G}_{l,m}$. However, the transformed

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constraint (20) incurs nonconvexity in terms of auxiliary variable $\mathbf{q}$. To solve this issue, we apply the successive convex approximation (SCA) technique on constraint (20). Specifically, the first-order Taylor series expansion of $f(q_m) = 2^{(1-\vartheta_{m,0})/q_m}$ at point $\tilde{q}_m$ is given by

$$\tilde{f}(q_m, \tilde{q}_m) = 2^{\frac{1-\vartheta_{m,0}}{\tilde{q}_m}} + \frac{(1-\vartheta_{m,0})\ln 2}{\tilde{q}_m^2} \cdot 2^{\frac{1-\vartheta_{m,0}}{\tilde{q}_m}} (\tilde{q}_m - q_m), \tag{21}$$

where $\tilde{q}_m$ is the value of q_m in the last iteration and $\tilde{\mathbf{q}} = \{\tilde{q}_m, \forall m \in \mathcal{M}\}$. By replacing $\bar{\mathbf{J}}_l(\mathbf{q})$ with $\bar{\mathbf{J}}_l(\mathbf{q}, \tilde{\mathbf{q}}) = \sum_{m=1}^{M} \frac{1-\vartheta_{m,0}}{\chi_m}\left(\tilde{f}(q_m, \tilde{q}_m) - 1\right)\mathbf{G}_{l,m}$, constraint (20) can be further rewritten as the following linear matrix inequality:

$$\begin{bmatrix} \boldsymbol{\Theta}_l & \mathbf{I} \\ \mathbf{I} & \bar{\mathbf{J}}_l(\mathbf{q}, \tilde{\mathbf{q}}) \end{bmatrix} \succeq \mathbf{0}. \tag{22}$$

Therefore, the subproblem (16) of power allocation can finally be formulated as

$$\begin{aligned} \min_{\mathbf{q},\mathbf{f},\mathbf{F},\boldsymbol{\Theta}} \quad & \sum_{m=1}^{M} \lambda_m (E_m^{\text{loc}} + E_m^{\text{tra}}(q_m) + E_m^{\text{ser}}) \\ \text{s.t.} \quad & (10f) - (10i), (14), (19), (22). \end{aligned} \tag{23}$$

Since problem (23) is convex, it can be directly solved by some optimization tools, such as CVX [14]. After obtaining the solution, the transmit power at the UE p_m can be computed by

$$p_m = \frac{1}{\chi_m}\left(2^{\frac{1-\vartheta_{m,0}}{q_m}} - 1\right), \forall m \in \{m|\vartheta_{m,0} = 0\}. \tag{24}$$

By iteratively optimizing offloading strategy and power allocation, we can obtain a joint resource allocation algorithm for ILAC in edge-intelligent networks as follows.

Algorithm 1 : Joint Resource Allocation for ILAC in Edge-intelligent Networks

Input: $N, M, K, L, B, \sigma_w^2, P_m^{\max}, \lambda_m, D_m, C_m, \tau_m, F_m^U, \kappa_m^U, F_n^M, \kappa_n^M, \eta_l, \forall m, n, l$
Output: $\boldsymbol{\vartheta}, \mathbf{p}, \mathbf{f}, \mathbf{F}$

1: **Initialize** Outer iteration index $i = 0$, $p_m^{(i)} = P_m^{\max}$, $f_m^{\text{loc}(i)} = F_m^U$, $f_{m,n}^{\text{ser}(i)} = F_n^M/M, \forall m, n$;
2: **repeat**
3: Obtain $\boldsymbol{\vartheta}^{(i+1)}$ based on the BnB algorithm according to the relaxed problem (15) with fixed $\mathbf{p}^{(i)}$, $\mathbf{f}^{(i)}$ and $\mathbf{F}^{(i)}$;
4: **Initialize** Inner iteration index $j = 0$, Taylor series expansion point $\tilde{q}_m^{(j)} = \frac{1-\vartheta_{m,0}}{\log(1+P_m^{\max}\chi_m)}$;
5: **repeat**
6: Obtain $\mathbf{q}^{(j+1)}$, $\mathbf{f}^{(j+1)}$ and $\mathbf{F}^{(j+1)}$ by solving problem (23) with fixed $\tilde{\mathbf{q}}^{(j)}$ and $\boldsymbol{\vartheta}^{(i+1)}$;
7: $\tilde{\mathbf{q}}^{(j+1)} = \mathbf{q}^{(j+1)}$;
8: $j = j + 1$;
9: **until** Inner loop convergence
10: Obtain $\mathbf{f}^{(i+1)} = \mathbf{f}^{(j+1)}$, $\mathbf{F}^{(i+1)} = \mathbf{F}^{(j+1)}$, and $\mathbf{p}^{(i+1)}$ based on $\mathbf{q}^{(j+1)}$ according to (24).
11: $i = i + 1$;
12: **until** Outer loop convergence

Remark: It is seen that the proposed joint resource allocation algorithm is composed of offloading strategy and power allocation in an iterative way. Due to the space limited, we only give a brief analysis of computational complexities for the proposed offloading strategy $I_2 C_2^{\text{cost}}$ and power allocation $I_2 C_2^{\text{cost}}$, where I_1 is the number of BnB tree nodes traversed for finding the optimal solution and I_2 is the required iteration number to convergence. Moreover, C_1^{cost} and C_2^{cost} are the worst-case complexities of solving problem (15) and problem (23) by a standard inter-point method (IPM), respectively. Specifically, $C_i^{\text{cost}} = \sqrt{\Xi_i + 9L}\ln(i/\varepsilon_i)\left[(\Xi_i + 243L)n_i + (\Xi_i + 45L)n_i^2 + n_i^3\right]$ for a given accuracy $\varepsilon_i > 0$, $i \in \{1, 2\}$, where $\Xi_1 = MN + 2M + N$ and $\Xi_2 = 3M + N$, the decision variables $n_1 = \mathcal{O}(MN)$ and $n_2 = \mathcal{O}(2M + 9L)$.

IV. Simulation Results

In this section, we provide simulation results to verify the effectiveness of the proposed algorithm. Without loss of generality, all UEs, BSs and targets are assumed being randomly distributed in 3D range of 300 m × 300 m × 300 m. The pass loss is modeled as $\text{PL}_{\text{dB}} = 128.1 + 37.6\log_{10}(d)$ [15], where d (km) is the propagation distance. Unless otherwise stated, we set $M = 10, N = 3, K = 64, L = 2$, $\lambda_m = 1$, $\tau_m = \tau_0 = 50$ ms, $\eta_l = \eta_0 = 0.05\ \text{m}^2$, $\kappa_0^U = \kappa_0^M = 5\times10^{-29}$, $F_m^U = F_0^U = 1$ GHz, $F_n^M = F_0^M = 20$ GHz, $D_m \in [40, 60]$ KB, $C_m \in [100, 150]$ cycles/bit, $\sigma_w^2 = -110$ dBm, $B = 10$ MHz, and $P_k^{\max} = P_0 = 30$ dBm.

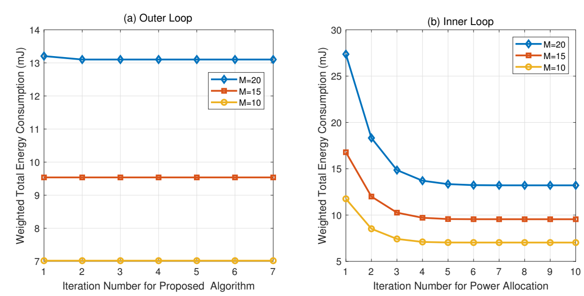

Fig. 2. Convergence behavior of the proposed algorithm.

Firstly, we present the convergence of the proposed algorithm (outer loop) and the power allocation sub-algorithm (inner loop) with different numbers of UEs. It is seen from Fig. 2 that the proposed algorithm requires almost only one or two iterations to converge and the proposed power allocation sub-algorithm converges within 10 iterations, which means the implementation cost of the proposed algorithm is bearable in practical systems. Secondly, we show the performance of the proposed algorithm over three baseline algorithms in Fig. 3, i.e., *Fixed Transmit Power Algorithm* with fixed transmit power at the UE $p_m = P_m^{\max}/2$, *Fixed Computing Power Algorithm* with fixed local computing power $f_m^{\text{loc}} = f_m^U$ and fixed MEC computing power allocation $f_{m,n}^{\text{ser}} = f_n^U/M$, and *Random Offloading Algorithm* with all offloading by randomly selecting the BS. It is clearly seen that the proposed algorithm performs best among all algorithms, the random offloading algorithm performs moderately, and the fixed power

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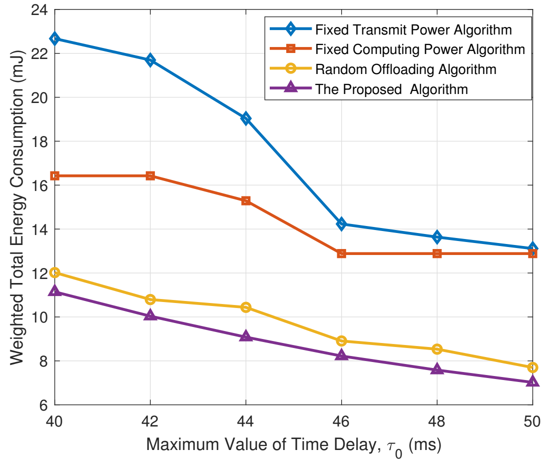

Fig. 3. The performance comparison of different algorithms.

allocation (including transmit power and computing power) algorithms perform worst, which verifies the effectiveness of the proposed algorithm. Moreover, it also indicates that power allocation has a significant impact on the performance of energy consumption, while the offloading strategy has a relatively small but non-negligible impact. Finally, we investigate the impacts of the number of BS antennas K and the performance requirements τ_0 and η_0 on the weighted total energy consumption in Fig. 4. As is expected, the smaller the threshold of the performance requirements, the more the total energy consumption. Moreover, it is seen that the total energy consumption decreases as the number of BS antennas increases. This is because more BS antennas can improve both localization accuracy for target tracking and transmission rates for data computing. Besides, it is found that the gain by adding the BS antennas is limited. Hence, it makes sense to select a proper number of BS antennas for improving the overall performance.

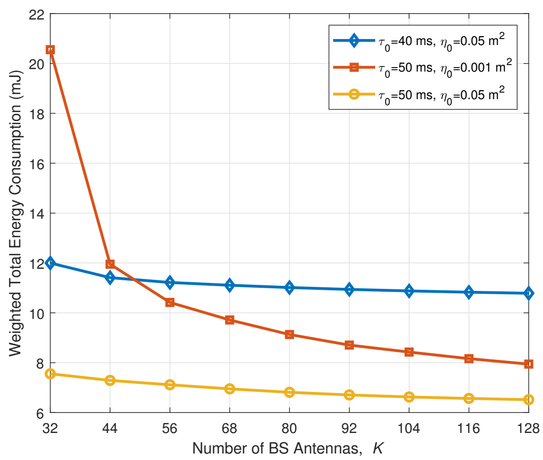

Fig. 4. Weighted total energy consumption versus number of BS antennas for different performance requirements.

V. Conclusion

This paper provided a unified ILAC framework for edge-intelligent networks. To improve the overall performance, a joint resource allocation design was proposed to minimize the weighted total energy consumption while meeting the requirements of the localization task and the computing task. The design was formulated as a complicated MINLP problem by jointly optimizing the computing offloading choice and power allocation. To solve this problem, we turned to some approximation techniques for convex transformation and proposed an AO-based algorithm to obtain a feasible sub-optimal solution. Numerical results validated the effectiveness of the proposed algorithm.

Appendix A
Derivation of FIM

The FIM for the unknown parameter vector $\mathbf{u}_l = [x_l, y_l, z_l]$ is given by [6]

$$\mathbf{J}_l\left(\mathbf{u}_l\right) = \mathbb{E}\left\{\frac{\partial}{\partial \mathbf{u}_l} \ln f\left(\mathbf{r}_l|\mathbf{u}_l\right)\left(\frac{\partial}{\partial \mathbf{u}_l} \ln f\left(\mathbf{r}_l\,|\mathbf{u}_l\,\right)\right)^T\right\}, \tag{25}$$

with the conditional probability density function (pdf)

$$f\left(\mathbf{r}_l|\mathbf{u}_l\right) \propto \exp\left\{-\frac{1}{\sigma_w^2}\sum_{m=1}^{M}\sum_{n=1}^{N}\int_{\mathcal{T}_m}\left|w_{m,l,n}(t)\right|^2 dt\right\}, \tag{26}$$

where $w_{m,l,n}(t) = r_{m,l,n}(t) - \sum_{k=1}^{K}\sqrt{p_m}h_{m,l,n,k}s_m\left(t-\tau_{m,l,n}\right)$. Since the conditional pdf (26) is a function of the propagation delay $\tau_{m,l,n}$, we can compute the FIM $\mathbf{J}_l\left(\boldsymbol{\tau}_l\right)$ with respect to the vector $\boldsymbol{\tau}_l = \left[\tau_{1,l,1},\ldots,\tau_{M,1,N}\right]^T$, and use the chain rule to obtain $\mathbf{J}_l\left(\mathbf{u}_l\right)$ as belows

$$\mathbf{J}_l\left(\mathbf{u}_l\right) = \mathbf{Q}_l\mathbf{J}_l\left(\boldsymbol{\tau}_l\right){\mathbf{Q}_l}^T, \tag{27}$$

where the Jacobian matrix $\mathbf{Q}_l = \frac{\partial \boldsymbol{\tau}_l}{\partial \mathbf{u}_l}$ is given by

$$\mathbf{Q}_l = \frac{1}{c}\begin{bmatrix} \bar{x}_{1,l,1} & \ldots & \bar{x}_{M,l,N} \\ \bar{y}_{1,l,1} & \ldots & \bar{y}_{M,l,N} \\ \bar{z}_{1,l,1} & \ldots & \bar{z}_{M,l,N} \end{bmatrix}, \tag{28}$$

where $\bar{x}_{m,l,n} = \sin\psi_{m,l}^T\cos\varphi_{m,l}^T + \sin\psi_{n,l}^R\cos\varphi_{n,l}^R$, $\bar{y}_{m,l,n} = \sin\psi_{m,l}^T\sin\varphi_{m,l}^T + \sin\psi_{n,l}^R\sin\varphi_{n,l}^R$, and $\bar{z}_{m,l,n} = \cos\psi_{m,l}^T + \cos\psi_{n,l}^R$. Then, the elements of the FIM $\mathbf{J}_l\left(\boldsymbol{\tau}_l\right)$ can be computed by $\mathbf{J}_l\left(\boldsymbol{\tau}_l\right)[i,j] = \frac{\partial^2[\ln f(\mathbf{r}_l|\mathbf{u}_l)]}{\partial\tau_{m,l,n}\partial\tau_{z,l,q}}$, where $i = (n-1)+m$ and $j = (q-1)+z$. Thus, the FIM $\mathbf{J}_l\left(\boldsymbol{\tau}_l\right)$ can be expressed as

$$\mathbf{J}_l\left(\boldsymbol{\tau}_l\right) = \mathrm{diag}\left[\Upsilon_{1,l,1},\ldots,\Upsilon_{M,l,N}\right]^{MN\times MN}, \tag{29}$$

where $\Upsilon_{m,l,n} = 8\pi^2B^2p_m\sum_{k=1}^{K}\left|h_{m,l,n,k}\right|^2/\sigma_w^2$ is the elements on the main diagonal of diagonal matrix $\mathbf{J}_l\left(\boldsymbol{\tau}_l\right)$ [6]. Finally, based on (27) with (28) and (29), we can obtain the FIM $\mathbf{J}_l$.

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