Cooperative Federated Learning-Based Task Offloading Scheme for Tactical Edge Networks

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ABSTRACT In this study, we focus on the federated learning (FL) based tactical edge network platform to cooperatively operate computation-hungry tasks as efficiently as possible. Based on the incentive of FL model training, each individual device makes offloading decisions for their tactical tasks in resource-constrained network environments. According to the ideas of two different bargaining solutions - weighted average solution and constant elasticity substitution solution - edge server and IoT devices work together in a coordinated manner to approximate a well-balanced system performance. Therefore, we can reach an agreement while exploring the mutual benefits to leverage a reciprocal consensus between different viewpoints. The main novelty of our approach is to investigate the dual-interactive bargaining process based on the interdependent relationship between IoT devices and the tactical edge server. To the best of our knowledge, this is the first work that jointly considers different bargaining solutions to handle tactical edge-assisted task offloading services. Based on the numerical simulation, it is demonstrated that the proposed approach can increase the system throughput, device payoff and device fairness up to 10%, 15% and 20%, respectively, in comparison with existing protocols.

INDEX TERMS Tactical edge network, federated learning, mobile edge computing, weighted average solution, constant elasticity substitution solution.

I. INTRODUCTION
Information at the tactical level is becoming increasingly critical in today’s conflicts. Situational awareness is critical in tactical operations in domains such as battlefields and disaster areas. However, successful tactical operations require efficient information sharing among the network agents involved. In addition, another important challenge in the tactical network environment is timeliness, in which the mission should be accomplished by continuously providing a tactical system even with constrained network resources. To satisfy these requirements, recent studies have been proposed to introduce mobile edge computing (MEC) technology. It is emerging as a new compelling computing paradigm by pushing cloud computing capabilities closer to end agents, underpinning a variety of computation-intensive yet latency-sensitive service applications. In such a challenging and hostile tactical edge environment, MEC technology is necessary to support seamless operation tasks even if a tactical edge is isolated [1], [2].

In recent years, mobile Internet of Things (IoT) devices have been equipped with increasingly advanced sensing, communication, and computing capabilities that allow them to perform more complex tasks in addition to their inherent calling features. Coupled with the advancement of 5G network technologies, IoT devices can be deployed for various tactical tasks, which can collaboratively sense information in different contexts and submit these sensing data. Such tasks are based on large amounts of data, data analysis, and model training. In addition, the increasing emphasis on privacy and security of personal information brings difficulties to the sharing and integration of data. Motivated by the
above discussion, the proposal of federated learning (FL) has partially solved the problem of tactical network operations. Many individual IoT devices have their private data and update the model parameters through local training [3], [4].

As a distributed collaborative artificial intelligent (AI) approach, the FL method is emerging to transform edge intelligence architectures. Conceptually, it is a distributed AI approach that enables the training of high-quality AI models by averaging local updates aggregated from multiple IoT devices. Without the need for direct access to the local data, individual IoT devices can collaboratively work with the MEC server to perform neural network training, where devices only exchange the parameters, while raw data sharing is not needed. In particular, the FL method caters to the growing trend that a massive amount of real-world data is generated at multiple IoT devices, and the combination of growing storage and computational power of devices and the increasing concern over transmitting private information to a server has made it attractive to store data and train learning models locally on each device. However, there may be different IoT devices with varying computational resource capabilities. This may lead to an implementation challenge for FL resource rationing issues [5], [6].

In a tactical edge computing environment, the resource allocation process is crucial for cooperative computational offloading at the edge. Usually, there is a trade-off between various performance parameters. Therefore, these control decisions across heterogeneous platforms require a new control paradigm. In particular, the MEC-assisted FL platform needs to consider multiple internal and external constraining factors such as network dynamics, awareness of network constraints, the huge volume of data, and tactical task coordination. To implement such an optimal computing control process, previous work includes AI techniques, machine learning, and heuristic and optimization algorithms to improve the computational efficiency of platforms in constrained environments. However, this is an extremely challenging task. Therefore, finding a new control paradigm has given top priority to design future FL-based tactical edge computing algorithms [7].

Despite the aforementioned benefits, FL is still facing a critical challenge. Most of all, traditional FL studies assume that all IoT devices contribute their computing resources unconditionally without any incentives to motivate FL participation. Such an assumption may not be practical in the real world because of the resource costs incurred by model training. From the viewpoint of the MEC server, providing incentives is necessary for stimulating IoT devices to become available workers in the FL process. From the viewpoint of IoT devices, the major concern is to complete their tactical tasks by considering the task offloading mechanism. Based on different characteristics, MEC servers and IoT devices have different control strategies. However, they work together to achieve an optimal network performance. Therefore, in this study, we adopted a cooperative bargaining game paradigm to design a fine-grained control scheme for an MEC-assisted FL platform [8].

Game theory is the study of the ways in which interacting choices of game players produce outcomes with respect to the preferences of those players, where the outcomes in question might have been intended by none of the players. The importance of game theory is evident in the fact that it is now widely applied in various fields, such as economics, biology, political science, social psychology, sociology, and anthropology. A branch of game theory is the cooperative bargaining category. It deals with how coalitions or cooperative groups interact when only payoffs are known. Usually, the surplus created by players’ cooperation can be shared in many ways. Therefore, one of the main research questions in bargaining theory is how to share the created surplus among players in a fair way. The answer to this question is related to the solution concepts. Different solution concepts based on different notions of fairness have been proposed in the bargaining theory literature. In this study, the inter-relationship between the MEC server and IoT devices is modeled as a dual-interactive cooperative bargaining game, and we chose two bargaining solution concepts to develop our resource rationing algorithms for FL and tactical task operations [9].

A. TECHNICAL CONCEPTS

Almost seventy years ago, J. Nash published his pioneered seminal paper on what is now known as the axiomatic theory of bargaining; his model has been one of the most successful paradigms of cooperative game theory. It concerns directly with normative principles that players in bargaining situations might adopt to decide how to share the benefits of cooperation. The Nash bargaining solution has become one of the most fruitful paradigms in bargaining theory and inspired a large body of literature on axiomatic solutions and applications. However, even though Nash’s idea is the founding stone of the bargaining process, some features have been criticized in subsequent years. Since then, several new bargaining solutions have been introduced. These are important challenges to the original Nash solution [9], [10].

With the Nash solution, two other known bargaining solutions are egalitarian and utilitarian. The egalitarian solution selects the weakly efficient agreement under which both players receive identical payoffs, and the utilitarian solution selects an agreement under which the sum of the players’ utilities is maximized. For any bargaining problem, the Nash solution lies on the Pareto boundary of the utility space between egalitarian and utilitarian solutions. One of the solutions to create a compromise between egalitarianism and utilitarianism is the average bargaining solution; it considers the maximization of a convex combination of utilitarian and egalitarian objectives in the context of intergenerational equity. A generalization of the average bargaining solution is the maximization of the weighted average, which is called the weighted average bargaining (WAB) solution. In bridging the gap between utilitarianism and egalitarianism, a stronger
idea is favored in terms of having augmented weight in the bargaining process [11].

Another way to unify different bargaining solutions is to design the constant elasticity substitution (CES) function, and a new bargaining solution is obtained by maximizing the CES function. This solution is referred to as the CES solution, which includes the Nash and egalitarian solutions as special cases. Originally, the CES function is a neoclassical production function that displays constant elasticity of substitution. In other words, production technology has a constant percentage change in factor proportions due to a percentage change in the marginal rate of technical substitution. The CES function is characterized by efficiency, distribution, and substitution parameters. In the CES solution, the elasticity of substitution specifies how two factors substitute each other as a result of a change in the ratio of their prices. It has many appealing technical properties useful for the analysis of utility functions [10].

B. MAIN CONTRIBUTIONS

According to the WAB and CES solutions, we can effectively handle FL and tactical task operations. In the MEC infrastructure with different IoT devices, we design a novel dual-interactive bargaining game model that can play a significant role in determining system performance. In a distributed online fashion, individual IoT devices adaptively decide their FL contributions based on the idea of the WAB solution. By considering the current information, the MEC server distributes the incentives to participate in IoT devices for their offloading services. This distribution process was developed by adopting the concept of the CES solution. During the interactive and iterative processes, control decisions are coupled to approximate the optimized system performance. The major contributions of this study are, i) to study the fundamental concepts of the WAB and CES solutions to design our dual-interactive bargaining model, ii) FL contributions are adjusted using the WAB solution, and incentives for the offloading service are decided according to the CES solution, iii) control decisions are coupled with each other for FL and task offload operations, iv) to reach a desirable solution while leveraging a reciprocal consensus in a coordinated manner.

II. RELATED WORK

The FL-based edge computing paradigm is a new concept that has the potential to play a key role in meeting the requirements of 5G networks. With the rapid development of edge computing and distributed learning techniques, many studies have explored related platforms. The paper [14] surveys the existing studies which optimize the task offloading in edge networks with mobility management. This paper formulates taxonomy of the research domain for classification of research works. In addition, it compares the listed state-of-the-art research works based on the components identified from taxonomy. The future research directions are debated for mobility, security, and scalability aware MEC offloading [14].

The paper [15] presents an in-depth study and analysis of offloading strategies for lightweight user mobile edge computing tasks using a machine learning approach. Based on the analysis of the concave-convex properties of this optimization model, this paper uses variable relaxation and nonconvex optimization theory to transform the problem into a convex optimization problem [15]. The article [16] encapsulates the state of art work in methodologies of offloading in MEC and wireless power transfer (WPT) to end nodes. It considers MEC offloading techniques with WPT and real time application requirements while summarizing related studies. In addition, this study formulates a taxonomy of joint WPT and offloading in MEC, and compares the state-of-the-art studies based on parameters identified from taxonomy [16].

In [12], the FL-based computation offloading (FLCO) scheme was proposed for an edge-computing-supported IoT platform. To supplement the limited capacity of IoT devices, this scheme offloads intensive computing tasks from IoT devices to edge nodes. In particular, computational offload decisions are determined in real time by involving complex resource management issues. In addition, to reduce the transmission costs between the IoT devices and edge nodes, the FL mechanism is used to train the learning agents in a distributed fashion. To adapt dynamic workloads and system environments, the FLCO scheme is responsible for system load balancing while maintaining the quality of the services. Finally, the performance evaluation results show the effectiveness of the FLCO scheme and FL in a dynamic IoT system [12].

Y. Ye et al. proposed the FL-based edge computing (FLEC) scheme, which separates the process of updating the local model that is supposed to be completed independently by mobile devices [4]. The global aggregation process was conducted in the cloud server. Mobile IoT devices can focus on the training of low layers, and more computation-intensive tasks are assigned to the MEC server with richer computational resources. After obtaining the initial model parameters, the mobile devices start dividing the local data into several batches of a fixed size. In each batch, the output from the low layers of multiple IoT devices and the corresponding data labels are transferred to the MEC server for aggregation. Finally, simulation experiments demonstrate that the FLEC scheme has advantages in different FL-based MEC environments [4].

In [13], the edge-assisted FL computation (EFLC) scheme was designed to reduce the computational burden in the FL process. In this scheme, IoT devices offload partial computation to the MEC server, and this server participates in the model training together with all devices. To leverage the MEC server’s idle computing power, the offloading data size is optimized to minimize the learning delay of the system, and a delay minimization problem is formulated to select an efficient offloading strategy. To assist multiple IoT devices in model training, the EFLC scheme solves this minimization problem using a threshold-based offloading strategy. This approach can be extended to a dynamic scenario; the EFLC scheme can derive the corresponding offloading strategy by
dynamically grouping them into different device sets. Finally, the simulation results demonstrate that the EFLC scheme is superior to the original federated learning protocols [13].

Previous research has focused on the control algorithms in the MEC-assisted FL platform while adjusting the key parameter values, whereas in the proposed scheme, the dual-interactive bargaining process is investigated based on the interdependent relationship between IoT devices and the MEC server. To the best of our knowledge, this is the first work that jointly considers different bargaining solutions to handle MEC-assisted task offloading services.

III. THE PROPOSED DUAL-INTERACTIVE BARGAINING SCHEME

In this section, we present the MEC-assisted FL infrastructure and explain our dual-interactive bargaining game model. Then, the main ideas of the WAB and CES solutions are presented to design the proposed task offloading algorithm. Finally, we explain the main steps of our dual-bargaining-based approach.

A. MEC ASSISTED FL PROCESS PLATFORM AND DUAL GAME MODEL

In this study, a system model in the FL environment with an MEC server was used for analysis. There are several types of IoT devices, that is, \( \mathbb{D} = \{D_1, \ldots, D_n\} \); they are smartphones, laptops, surveillance cameras, smartwatches, etc., and their computational abilities are limited. MEC server \( (\varepsilon) \) is mainly deployed at the edge of the backbone network, and it is composed of large amounts of computation resources as well as a stable power supply. The \( \varepsilon \) provides a distributed computing environment by running applications and performing related processing tasks closer to IoT devices. Simultaneously, individual devices can offload computation-intensive tasks to their nearby MEC server. Task offloading can speed up the task execution time and reduce the battery lifetime of mobile IoT devices. To effectively handle offloading services, the MEC resource allocation algorithm plays a major role in the edge computing paradigm. For the quantitative analysis of computing resources, the time horizon is discretized into time epochs with equivalent duration in seconds [4], [12], [13].

FL is a collaborative machine learning framework that enables the participating devices to periodically update the model parameters based on their local datasets. While keeping all the local training data, IoT devices upload their model parameters to the MEC server. The server aggregates these updated parameters to obtain a global model and then broadcasts it back to the IoT devices for the next local update. Before parameter aggregation, each local device may perform one or multiple epochs of model training during the local update phase. In the MEC-assisted FL scenario, the process of local IoT devices is divided into two parts: i) FL-based distributed model training and ii) tactical task computation. With the local computing process, individual devices can focus on task offloading to the MEC server. From the fine-grained task offloading strategy, IoT devices may become lighter and faster, which is more practical. These observations motivated us to propose a novel MEC-assisted FL control scheme that achieves a tradeoff between the task offloading service and the FL process [4], [13].

The interactive mechanism in the MEC-assisted FL control scheme has become an increasingly important and challenging topic. In this study, we assume that each individual IoT has several tactical tasks while processing the FL. In this context, we should consider how to allocate the computational resources for these two different operations while striking an appropriate system performance. To solve this problem, we have developed a new dual-interactive bargaining game model \( (G) \), which consists of the MEC’s bargaining game \( (G_e) \) and the \( D_i \)’s bargaining game \( (G_{D_i}) \). In the \( G_e \) and \( G_{D_i} \) games, the computation resources of \( \varepsilon \) and \( D_i \) are distributed and divided, respectively. In an interactive and sequential manner, \( G_e \) and \( G_{D_i} \) work together and act cooperatively with each other to enhance conflicting performance criteria. Formally, we define our dual-interactive bargaining game entities, that is, \( G = \{G_e, G_{D_i \leq i} \} = \{G_e, M_e, U_{D_i \leq i}(), \mathcal{M}_{D_i}, v_e\}, G_{D_i} = \{\mathcal{N}_{D_i}, (R^{T}_{D_i}, R^{FL}_{D_i}), (\mathcal{U}^{T}_{D_i}, R^{T}_{D_i}), (\mathcal{U}^{FL}_{D_i}, R^{FL}_{D_i})\}; \)

- Our dual bargaining game \( (G) \) consists of \( G_e \) and \( G_{D_i \leq i} \), they are mutually and reciprocally interdependent in an interactive manner.
- In the \( G_e \), \( M_e \) is the total computation capacity of \( \varepsilon \); it is distributed into multiple \( D_{i \leq i \leq} \), \( U_{D_i}() \) is the utility function of \( D_i \), and \( \mathcal{M}_{D_i} \) is the assigned computation resource for the \( D_i \)’s offloading service where \( \sum_{D_{i \leq i \leq}} \mathcal{M}_{D_i} \leq M_e \).
- In the \( G_{D_i} \), \( M_{D_i} \) is the strategy of \( \varepsilon \), and \( v_e = [\mathcal{M}_{D_1}, \ldots, \mathcal{M}_{D_n}] \) is the vector of strategy profiles.
- In the \( G_{D_i} \), \( N_{D_i} \) is the total computation capacity of \( D_i \), and \( R^{T}_{D_i}, R^{FL}_{D_i} \) are the assigned computation resources for the tactical task operation and FL process, respectively.
- In the \( G_{D_i} \), \( R^{T}_{D_i}, R^{FL}_{D_i} \) are the \( D_i \)’s strategies where \( R^{T}_{D_i} + R^{FL}_{D_i} \leq \mathcal{N}_{D_i} \), and \( \mathcal{U}^{T}_{D_i}(R^{T}_{D_i}) \) and \( \mathcal{U}^{FL}_{D_i}(R^{FL}_{D_i}) \) are their utility functions, respectively.
- \( T = \{t_1, \ldots, t_c, t_{c+1}, \ldots\} \) denotes the time period, which is represented by a sequence of time steps.

B. THE BASIC IDEA AND CONCEPT OF WAB AND CES SOLUTIONS

To characterize the basic ideas of the WAB and CES solutions, we first start with some definitions. Let \( N = \{1, \ldots, i, \ldots, n\} \) denote the set of players and let \( \mathbb{R}^n \) denote the \( n \)-dimensional Euclidean space. Given vectors \( x, y \in \mathbb{R}^n, x \geq y \) and \( x \gg y \) if \( x_i \geq y_i \) and \( x_i > y_i \) for all \( i \), respectively. We use \( x \ast y = ((x_1 \cdot y_1), (x_2 \cdot y_2), \ldots, (x_n \cdot y_n)) \) to denote the Hadamard product of \( x \) and \( y \). For \( \lambda \in \mathbb{R}^n \) and \( S \subseteq \mathbb{R}^n \) where \( S \) is the choice set in payoff space, \( \lambda \ast S = \{\lambda \ast x | x \in S\} \). Set \( \mathbb{R}^n_+ = \{x \in \mathbb{R}^n | x \geq 0\}, \mathbb{R}^n_{++} = \{x \in \mathbb{R}^n | x > 0\} \),
\( \Delta_n = \{ x \in \mathbb{R}_+^n \mid x_1 + \cdots + x_n = 1 \} \), and \( \Delta_{n+} = \Delta_n \cap \mathbb{R}_{n+} \).

Elements in \( S \) are payoff allocations that players can achieve with agreements, whereas a disagreement point \( d \) specifies payoffs the players end up getting in case of disagreement where \( d \in S \). By a hyperplane problem, a bargaining problem is given by [10]:

\[
S = \{ x \in \mathbb{R}_+^n \mid [(p_1 \cdot x_1) + \cdots + (p_n \cdot x_n)] \leq B \} \tag{1}
\]

for some vectors \( p \in \mathbb{R}_{n+} \), and number \( B > 0 \). We denote by \( \gamma \) the elasticity of substitution, which measures the percentage change in the ratio of any two variables with respect to the change in the marginal rate of substitution between these two variables. With the distribution parameter \( \delta \in \Delta_{n+} \) and \( \gamma \in (0, 1) \cup (1, \infty) \), the \( n \)-variable CES function over \( \mathbb{R}_+^n \) is given by [10]:

\[
H (x | \delta, \gamma) = \left[ \left( \delta_1 \cdot x_1^{\frac{\gamma-1}{\gamma}} \right) + \left( \delta_2 \cdot x_2^{\frac{\gamma-1}{\gamma}} \right) + \cdots + \left( \delta_n \cdot x_n^{\frac{\gamma-1}{\gamma}} \right) \right]^{\frac{1}{\gamma}}.
\]

s.t. \( \lim \gamma \to \gamma \)

\[
\begin{align*}
\min \{ x_1, x_2, \ldots, x_n \}, & \quad \text{if } \gamma = 0 \\
\{ x_1^{\delta_1}, x_2^{\delta_2}, \ldots, x_n^{\delta_n} \}, & \quad \text{if } \gamma = 1 \\
\delta_1 \cdot x_1 + \delta_2 \cdot x_2 + \cdots + \delta_n \cdot x_n, & \quad \text{if } \gamma = \infty
\end{align*}
\]

Based on the class of bargaining problems, a single-valued function \( C \{ S ; \delta, \gamma \} \) is defined as the CES solution. Note that the CES solution coincides with the Nash bargaining solution when \( \gamma = 1 \) and with the egalitarian solution when \( \gamma = 0 \) [10]:

\[
C \{ S ; \delta, \gamma \} = \arg \max_{x \in S} H (x | \delta, \gamma) \tag{3}
\]

For \( x \in S \), the egalitarian solution is the unique maximizer of \( \min \{ x_i \} \), and the utilitarian solution is the unique maximizer of the utility sum, that is, \( \sum_{i \in N} x_i \). For any bargaining problem \( S \), the Nash bargaining solution lies on \( S \)’s Pareto boundary between the egalitarian and utilitarian solutions. The paper [11] shows that whenever the Nash bargaining solution coincides with the egalitarian solution, this common solution is also a utilitarian solution. Therefore, the Nash bargaining solution is more utilitarian than it is egalitarian. The Nash solution can be generalized by considering players’ weights; the weighted Nash bargaining solution lies between the weighted utilitarian and egalitarian solutions. To bridge the gap between weighted utilitarianism and egalitarianism, the WAB solution is given by [11]

\[
WAB \{ S ; \alpha \} = \max_{x \in S} \left[ \alpha \times \sum_{i \in N} x_i + \left( 1 - \alpha \right) \times \min_{i \in N} \{ x_i \} \right].
\]

s.t. \( \alpha \in [0, 1] \) \tag{4}

\[\text{C. THE DUAL-INTERACTIVE BARGAINING GAME IN TACTICAL NETWORKS}\]

In this study, each individual \( D_i \) operated its tactical task while processing the FL. To coordinate the FL training process among multiple IoT devices, the MEC server distributes its offloading computation capacity as an incentive; it guides selfish devices toward a socially optimal outcome. From the MEC server’s viewpoint, the \( D_i \)’s utility function, that is, \( U_{D_i} (\cdot) \), is defined based on the \( D_i \)’s FL contribution and its incentive. Commonsensically, the FL contribution and incentive of \( D_i \) are proportional to the \( R^{FL}_{D_i} \) and \( M_{D_i} \), but, they are properly adjusted according to their respective characteristics. Therefore, the \( U_{D_i} (\cdot) \) is given by:

\[
U_{D_i} (R^{FL}_{D_i}, M_{D_i}, \theta_{D_i}) = \left( \eta + \left( \frac{R^{FL}_{D_i} M_{D_i}}{\delta_{D_i}} \right)^{\theta_{D_i}} \right) \times \left( \frac{1}{1 + \exp \left( -\frac{M_{D_i}}{\theta_{D_i}} \right)} - \varphi \right) \tag{5}
\]

where \( \eta \) and \( \varphi \) are control parameter for \( U_{D_i} (\cdot) \), and \( \theta_{D_i} \) is the \( D_i \)’s characteristic value of FL contribution. In the \( G_x \), multiple IoT devices, that is, \( D_{1 \leq i \leq n} \), are assumed as game players, and the \( \varepsilon \) distributes its \( M_i \) to game players in a fair-efficient manner. According to the \( R^{FL}_{D} \) values, our bargaining approach can solve the \( M_i \) distribution problem. If the difference in \( R^{FL}_{D} \) values is larger, the axiom of scale invariance is important. In this case, the Nash solution is suitable. Otherwise, an egalitarian solution was appropriate. Therefore, in this study, we adopt the concept of the CES solution for the \( G_x \). According to (2) and (5), the CES solution is obtained as follows:

\[
\begin{align*}
&\text{CES}_e (\psi | \delta, \gamma) = \left[ \sum_{D_i \in I} \left( \delta_{D_i} \times U_{D_i} (R^{FL}_{D_i}, M_{D_i}, \theta_{D_i}) \right) \right]^{\frac{1}{\gamma}} \\
\text{s.t. } \gamma &\text{, if } \gamma = 0 \\
&\left( \max_{D_i \in \{1 \leq i \leq n\}} \frac{R^{FL}_{D_i}}{M_{D_i}}, \min_{D_i \in \{1 \leq i \leq n\}} \frac{R^{FL}_{D_i}}{M_{D_i}} \right), \phi, \beta \text{ and } \\
&\delta_{D_i} = \frac{1}{||I||}
\end{align*}
\]

where \( \phi \), \( \beta \) are the lower and upper bounds of \( \gamma \). \( ||I|| \) is the cardinality of \( I \) and the distribution parameter \( \delta \) is set to be evenly distributed. In each individual device, the \( G_{D_{1 \leq i \leq n}} \) games are operated in a dispersive and parallel manner. In the \( G_{D_{n}} \), the tactical task operation and FL process are assumed as game players, and the decisions of \( R^{FL}_{D_{n}} \) and \( M_{D_{n}} \) values are their strategies. Therefore, the \( M_{D_{n}} \) is divided to operate the tactical tasks and the FL process. For these two different
In this paper, we propose a novel dual-interactive bargaining approach to address the resource allocation problem in a MEC-assisted FL infrastructure. Based on the concepts of \(WAB\) and \(CES\) solutions, we design two different bargaining games, \(G_e\) and \(G_{D_i}\), to ensure the tradeoff among conflicting control perspectives. According to the \(CES\) solution, the MEC server distributes incentives to induce selfish IoT devices to participate in the FL process. Based on the \(WAB\) solution, individual IoT devices dynamically adjust their FL contributions toward the optimal system performance. Based on real-time online monitoring, our proposed step-by-step interactive feedback process continues until an efficient bargaining solution is obtained while ensuring good global properties. Owing to the desirable characteristics of the \(WAB\) and \(CES\) solutions, we can maximize the system throughput, normalized payoff and fairness of FL contributions. The main steps of the proposed algorithm can be described as follows, and they are described by the following flowchart.

**D. MAIN STEPS OF OUR DUAL-INTERACTIVE BARGAINING GAME**

In this paper, we propose a novel dual-interactive bargaining model to address the resource allocation problem in an MEC-assisted FL infrastructure.

For the \(\mathbb{D}_i\)'s point of view, utilitarian and egalitarian objectives should be considered fairly. Therefore, the idea of the \(WAB\) solution was chosen for the \(\mathbb{D}_i\). According to (4) and (7), the \(WAB\) solution is obtained as follows:

\[
WAB\left(\mathcal{R}_{\mathbb{D}_i}^T, \mathcal{R}_{\mathbb{D}_i}^{FL}\right) | \alpha = \max_{(\mathcal{R}_{\mathbb{D}_i}^T, \mathcal{R}_{\mathbb{D}_i}^{FL})} \left(\alpha \times \mathbb{H}_U + (1 - \alpha) \times \mathbb{H}_E\right) \quad \text{s.t.,} \quad \mathcal{R}_{\mathbb{D}_i}^T + \mathcal{R}_{\mathbb{D}_i}^{FL} \leq \mathbb{M}_{\mathbb{D}_i}; \alpha = \frac{\min \left\{ \mathcal{P} \left( \mathcal{M}_{\mathbb{D}_i} \right), \mathcal{P} \left( \mathcal{R}_{\mathbb{D}_i}^{FL} \right) \right\}}{\max \left\{ \mathcal{P} \left( \mathcal{M}_{\mathbb{D}_i} \right), \mathcal{P} \left( \mathcal{R}_{\mathbb{D}_i}^{FL} \right) \right\}} \chi \right)
\]

Table 1. System parameters used in the simulation experiments.

| Parameter | Value | Description |
|-----------|-------|-------------|
| \(n\)     | 10    | the total number of IoT devices |
| \(\eta, \vartheta\) | 1, 0.5 | control parameter for \(U_R(\cdot)\) |
| \(\vartheta\) | 1 ≤ | the \(D\)'s characteristic value of FL contribution |
| \(\vartheta\leq3\) | | |
| \(\phi, \beta\) | 0.1, 0.9 | the lower and upper bounds of \(\gamma\) |
| \(\mu, \psi\) | 1, 1.5 | control parameter for \(U_L(\cdot)\) |
| \(\lambda\) | 1.5 | the modification factor for the offloading service |
| \(\chi\) | 0.1 | the lower bound of \(\alpha\) value |

**Step 1:**
- To implement our proposed task offloading algorithm, the values of the adjustment parameters and control factors are listed in Table 1, and the simulation setup is given in Section IV.
- At each time epoch, multiple IoT devices generate their tactical tasks, and operate the FL process in the MEC-assisted FL platform.

**Step 3:**
- The \(G_e\) game is operated on the MEC server. Initially, \(\mathcal{R}_{\mathbb{D}_i}^{FL}\) value of each device is set equally, and the \(U_R(\cdot)\) is defined according to (5).

**Step 4:**
- For the \(G_e\) game, the concept of the \(CES\) solution is adopted, and the \(\nu_v\) values are determined using (6).

**Step 5:**
- In each individual device, the \(G_e\) game is operated in a dispersive and parallel manner. For the tactical task operation and FL process, the \(U_R(\cdot)\) and \(U_{FL}(\cdot)\) are defined according to (7).
Step 6: For the $G_D$ game, the idea of the WAB solution is chosen, and the values of $R_D^L$ and $R_D^{FL}$ are determined using (8).

Step 7: Based on an integrated dual bargaining game model, the proposed scheme explores the sequential interaction of $G_ε$ and $G_D$ games to achieve mutual advantages in a coordinated manner.

Step 8: Constantly, each individual game entity self-monitors the current MEC-assisted tactical network environments, and proceed to Step 2 for the next dual bargaining game process.

IV. PERFORMANCE EVALUATION

In this section, we provide simulation results to evaluate the performance of our proposed scheme and the existing FLCO, FLEC, and EFLC protocols in [4], [12], [13]. For the performance comparison, we built a simulation environment using MATLAB. To validate the contributions of this study, we adopted the simulation scenario and environment setup as follows:

- The simulated MEC-assisted FL platform consisted of one MEC server ($ε$) and 10 IoT devices, where $|I| = 10$. They are located in the neighboring area of $ε$.
- The total computation capacity of $ε$ ($Ω_ε$) was 300 GHz, and the total computation capacity of each IoT device ($Ω_D$) was 45 GHz.
- Tactical tasks were generated in each individual device. At each time epoch, the generation process for tasks is Poisson with rate $Λ$ (services/t), and the range of offered workload was varied from 0 to 3.0.
- $θ_D$ value is chosen randomly in the distribution range from 1.0 to 3.0.
- Six different tactical tasks were assumed based on their computation requirements and service duration times.
- System performance measures obtained on the basis of 100 simulation runs were plotted as a function of the offered task request load.

Fig. 1 shows the system throughput of our proposed scheme and the existing FLCO, FLEC and EFLC protocols based on different tactical workload rates. In our simulation model, the system throughput was defined as the normalized task amount of successfully serviced. From the viewpoint of the platform operator, the system throughput is a main concern. First, we find that the system throughput of all protocols increases when the workload rate increases, which is intuitive. However, the throughput of the proposed scheme is higher than that of the other existing schemes, from low to heavy workload intensities. That proves that our dual bargaining game approach can capture the dynamics of the MEC-assisted tactical network environment and makes control decisions adaptively based on a step-by-step interactive feedback mechanism. The simulation results clearly confirm the performance gain of the proposed scheme.

Fig. 2 compares the normalized device payoffs of all the protocols. In general, the performance trends of the system throughput and device payoff were almost the same. As shown in the resulting curves, we can observe that the proposed scheme maintains superior payoff outcomes for widely different and diversified task workload situations. This is because the idea of the WAB solution is applied to each individual device to effectively share its constrained computing resources. Thus, each device can strike an appropriate balance between the tactical task operation and the FL process. The simulation results once again prove that our approach has a better device payoff than the other protocols.

Fairness comparisons among IoT devices regarding the FL contribution are plotted in Fig. 3. Traditionally, the major challenge in developing a new bargaining game is ensuring
a relevant tradeoff between efficiency and fairness. From the viewpoint of individual devices, fairness is a desirable property and an interesting control issue. The major characteristic of the WAB and CES solution combination is the provision of a fair-efficient solution while ensuring the trade-off among conflicting control issues. This feature directly implies a fairness problem in the MEC-assisted FL infrastructure. Therefore, our proposed scheme can achieve the best fairness compared to the existing FLCO, FLEC and EFLC protocols for the range of offered workload rates.

V. SUMMARY AND CONCLUSION

In this paper, we study the fine-grained tactical task offloading mechanism while leveraging the FL process. First, we begin with an introduction to the motivation for our dual-interactive bargaining game model to adaptively handle the resource-constrained MEC-assisted FL process platform. Then, we explain the basic ideas of WAB and CES solutions; they are important to study how different bargaining approaches can be combined with each other to further improve the performance. Next, we provide the $\mathcal{G}_E$ and $\mathcal{G}_D_i$ games to distribute and divide the $\Omega_i$ and $\Omega_D$, respectively. To strike an appropriate system performance, the $\mathcal{G}_E$ and $\mathcal{G}_D_i$ games work cooperatively in an interactive and sequential manner while ensuring good global properties. Under dynamically changing tactical network environments, our dual-interactive bargaining approach can leverage a reciprocal consensus from complicated control issues in FL and tactical task operations. Finally, we discuss the simulation results to prove that our proposed scheme has improved the system throughput, normalized payoff, and fairness of the device’s FL contribution up to 10%, 15% and 20%, respectively, compared to the existing FLCO, FLEC and EFLC protocols.

Research on the FL process in the MEC-assisted tactical network infrastructure is still in its infancy. An interesting continuation of our study presented in this paper can be extended in a number of ways. One future direction is to investigate an optimal robust control model for the fuzzy-logic-based cooperative game theory. Another potential direction for future research is to apply high-order control to a dynamic system with uncertainty. In addition, we will develop an optimal distributed control protocol for multi-agent systems with an unknown switching communication graph.

COMPETING OF INTERESTS

The author declares that there are no competing interests regarding the publication of this paper.

AUTHOR’ CONTRIBUTION

The author is a sole author of this work and ES (i.e., participated in the design of the study and performed the statistical analysis).

AVAILABILITY OF DATA AND MATERIAL

The data used to support the findings of this study are available by contacting the corresponding author at swkim01@sogang.ac.kr.

REFERENCES

[1] K. Sun and Y. Kim, “LISP-based hierarchical service mobility management for the tactical edge computing,” in Proc. Int. Conf. Inf. Commun. Technol. Convex. (ICTC), Oct. 2020, pp. 1–3.
[2] Y. Li, X. Wang, X. Gan, H. Jin, L. Fu, and X. Wang, “Learning-aided computation offloading for trusted collaborative mobile edge computing,” IEEE Trans. Mobile Comput., vol. 19, no. 12, pp. 2833–2849, Dec. 2020.
[3] W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y.-C. Liang, Q. Yang, D. Niyato, and C. Miao, “Federated learning in mobile edge networks: A comprehensive survey,” IEEE Commun. Surveys Tuts., vol. 22, no. 3, pp. 2031–2063, 3rd Quart., 2020.
[4] Y. Ye, S. Li, F. Liu, Y. Tang, and W. Hu, “EdgeFed: Optimized federated learning based on edge computing,” IEEE Access, vol. 8, pp. 209191–209198, 2020.
[5] D. C. Nguyen, M. Ding, P. N. Pathirana, A. Seneviratne, J. Li, D. Niyato, O. Dobre, and H. V. Poor, “6G Internet of Things: A comprehensive survey,” IEEE Internet Things J., early access, Aug. 9, 2021, doi: 10.1109/JIOT.2021.3103320.
[6] C. Shen, J. Xu, S. Zheng, and X. Chen, “Resource rationing for wireless federated learning: Concept, benefits, and challenges,” IEEE Commun. Mag., vol. 59, no. 5, pp. 82–87, May 2021.
[7] R. V. Dasari, E. B. Geerhart, M. D. Alexander, and R. D. Shires, “Distributed computation offloading framework for the tactical edge,” in Proc. IEEE INFOCOM, Apr. 2019, pp. 1–6.

[8] S. Kim, “Incentive design and differential privacy based federated learning: A mechanism design perspective,” IEEE Access, vol. 8, pp. 187317–187325, 2020.

[9] S. Kim, Game Theory Applications in Network Design. Hershey, PA, USA: IGI Global, 2014.

[10] C.-J. Haakea and C.-Z. Qin, “On unification of solutions to the bargaining problem,” CIE Working Paper Series, Paderborn Univ., Paderborn, Germany, Tech. Rep. SSRN 3184007, 2018.

[11] S. Rachmilevitch, “The Nash solution is more utilitarian than egalitarian,” Theory Decis., vol. 79, no. 3, pp. 463–478, Nov. 2015.

[12] J. Ren, H. Wang, T. Hou, S. Zheng, and C. Tang, “Federated learning-based computation offloading optimization in edge computing-supported Internet of Things,” IEEE Access, vol. 7, pp. 69194–69201, 2019.

[13] Z. Ji, L. Chen, N. Zhao, Y. Chen, G. Wei, and F. R. Yu, “Computation offloading for edge-assisted federated learning,” IEEE Trans. Veh. Technol., vol. 70, no. 9, pp. 9330–9344, Sep. 2021.

[14] S. K. U. Zaman, A. I. Jehangiri, T. Maqsood, Z. Ahmad, A. I. Umar, J. Shuja, E. Alanazi, and W. Alasmary, “Mobility-aware computational offloading in mobile edge networks: A survey,” Cluster Comput., vol. 1, no. 1, pp. 1–22, Apr. 2021.

[15] S. Zhou, W. Jadoon, and J. Shuja, “Machine learning-based offloading strategy for lightweight user mobile edge computing tasks,” Complexity, vol. 2021, pp. 1–11, Jun. 2021.

[16] E. Mustafa, J. Shuja, S. K. U. Zaman, A. I. Jehangiri, S. Din, F. Rehman, S. Mustafa, T. Maqsood, and A. N. Khan, “Joint wireless power transfer and task offloading in mobile edge computing: A survey,” Cluster Comput., vol. 2021, pp. 1–20, Aug. 2021.

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