TANDEM: Trust-aware Sustainable Data Offloading in Multi-access Edge Computing

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***Abstract*—The need to maintain efficient and environmentally responsible data processing at the network edge has introduced a new research field in the area of edge computing sustainability. This paper introduces a novel social-aware, trust-based data offloading framework, named TANDEM, in Multi-access Edge Computing (MEC) environments. TANDEM is designed to jointly optimize the user' data offloading strategies and the MEC providers' dynamic pricing policies. TANDEM incorporates a social-aware trust model based on direct and indirect interactions of the users with the MEC servers, and is based on a Stackelberg game-theoretic approach to optimize the data offloading and pricing. TANDEM significantly outperforms existing methods by reducing carbon emissions in MEC systems and ensuring a sustainable edge computing environment.**

***Index Terms*—Sustainable Computing, Social-aware Trust, Game Theory, Network Economics, Edge Computing.**

I. Introduction

Nowadays, the Multi-Access Edge Computing (MEC) servers' energy demands and carbon footprint increase rapidly due to the increased demand for computing resources and the plethora of data processing services. *Sustainable data offloading and processing* practices, e.g., the integration of renewable energy source, can mitigate this phenomenon [1]. Complementary, the appropriate consideration of the *trust risks* associated with the MEC servers' Quality of Service (QoS) can substantially improve the sustainable computing and accommodate the users' computing demands [2].

In this paper, the TANDEM framework is introduced to support the users' optimal data offloading and MEC servers' pricing policies toward improving the carbon emissions. TANDEM proposes a novel social-aware trust model, where the users exploit their direct and indirect interactions with the MEC servers, exploring their social ties with other peers to build their personal trust scores to the MEC servers. A Stackelberg game-theoretic approach is proposed to optimize the users' data offloading strategies and the MEC providers' pricing policies in order to achieve a more sustainable MEC computing environment with reduced carbon emissions.

A. Related Work

Carbon-aware sustainable computing has recently attracted the interest of the research community to mitigate the problem of global warming and improve the utilization of renewable energy sources. A carbon-aware data offloading approach is introduced in [3] by integrating carbon emission rights purchasing and task management using a two-timescale Lyapunov optimization technique, towards minimizing the accuracy loss and managing the costs effectively despite uncertainties. Aiming at improving the energy efficiency in data processing, the authors in [4] present a cross-layer cooperative scheme for optimizing resource allocation in cloud-edge environments based on a deep reinforcement learning (DRL)-enabled task offloading strategy. A similar DRL-based approach is analyzed in [5] to optimize the providers' profit in integrated space-air-ground networks powered by green energy, while considering the user requirements and green energy dynamics.

Recent research works have increasingly focused on *trust-aware data offloading* in MEC environments to provide users with informed decision-making support throughout the data offloading process [6]. A reward model for local and re-offloaded tasks and an efficient trust acquisition method are introduced in [7] to improve the data offloading process in MEC systems by enhancing the data offloading rate. A multi-feedback trust mechanism and trust weight k-means clustering are proposed in [8] to facilitate the data offloading in order to enhance the reliability, efficiency, and responsiveness of task allocation in MEC systems. A trust mechanism for efficient data offloading in Unmanned Aerial Vehicles-enabled (UAVs) MEC systems is designed in [9] to improve the task completion rates and delays, and optimize the UAVs' trajectories.

Moreover, the problem of *optimizing the MEC servers' pricing strategies* is an ongoing research effort in the research community [10]. A game-theoretic computation offloading and resource pricing scheme for blockchain-enabled MEC is introduced in [11] aiming at improving the trust in resource transactions, the users' experience, and the MEC providers' revenue. The optimization of the pricing, data offloading distribution among MEC servers, and social welfare is achieved in [12] based on a double auction mechanism. A game-theoretic algorithm is designed in [13] to determine the optimal pricing and resource allocation strategies that maximize the benefits for both the MEC servers and the users.

B. Contributions and Outline

Despite the significant research efforts made in the existing literature regarding the carbon-aware and trust-aware data offloading strategies in MEC environments, the problem is

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addressed in a fairly isolated manner. The existing research efforts either address the carbon-aware strategies without considering the trust levels between MEC providers and users or focus on trust-aware models without fully integrating the MEC providers' sustainability or their dynamic pricing strategies.

In this paper, we introduce TANDEM, i.e., a social-aware trust-based data offloading framework, which jointly optimizes the users' data offloading and the MEC servers' personalized pricing, aiming at supporting a sustainable edge computing environment. TANDEM contributions are summarized as follows.

1) A social-aware trust model is introduced to enable the users to exploit their direct and indirect trust, as it is derived from their direct interaction with the MEC providers and the feedback provided by their peers, respectively.
2) Novel utility functions are introduced to capture the users' QoS benefits and costs, accounting for the trust scores, data processing capacities, personalized pricing associated with the MEC providers, and the servers' profit.
3) A Stackelberg game-theoretic approach determines the users' optimal data offloading strategies and the MEC providers' pricing policies, while considering the social-aware trust model. The existence of a Stackelberg equilibrium is shown via detailed mathematical analysis.
4) Detailed numerical results demonstrate the pure operation of the TANDEM framework, as well as its superiority compared to alternative data offloading mechanisms proposed in the state of the art, in terms of substantially reducing the MEC environment's carbon emissions.

In the rest of the paper, Section II presents the social-aware trust model, while the trust-aware sustainable data offloading is analyzed in Section III. The Stackelberg game-theoretic approach is analyzed in Section IV. Experimental results are presented in Section V, and Section VI concludes the paper.

II. Social-aware Trust Model

A MEC system consists of a set of users $\mathcal{N} = \{1, \dots, n, \dots, N\}$ and servers $\mathcal{K} = \{1, \dots, k, \dots, K\}$. Each user has a total amount of data $B_n^{\max}$ [bits] that need to be processed in the MEC environment. Also, each MEC server is characterized by a maximum amount of data $B_k^{\max}$ [bits] that can be processed in parallel based on its computing capacity. Each MEC server announces a personalized price $P_{k,n}\left[\frac{\$}{\text{bits}}\right]$ to each user regarding the processing of its offloaded data and has a data processing cost $c_k\left[\frac{\$}{\text{bits}}\right]$. Each user offloads $b_{n,k}$ [bits] data to each MEC server k, with $\sum_{k\in\mathcal{K}} b_{n,k} = B_n^{max}$.

The users' preference to a MEC server is captured based on the data that they offload to the server, the server's carbon emissions sustainability, and its capacity to handle data. Thus, the user's server preference is quantified as follows:

$$S_{n,k} = \frac{b_{n,k}}{\sum_{\forall n\in\mathcal{N}} b_{n,k}} \text{Zipf}(x_k) \frac{B_k^{\max}}{\sum_{\forall k\in\mathcal{K}} B_k^{\max}} \quad (1)$$

where $\text{Zipf}(x_k) = \frac{\gamma}{x_k^\beta}, X = \{x_1, \dots, x_k, \dots X_K\}, x_k, \gamma, \beta \in \mathbb{R}^+$ is the Zipf distribution capturing the level of carbon emissions of an MEC server, where for presentation purposes and without loss of generality, MEC servers with higher ID are characterized by decreased environmental sustainability.

A. Direct Trust

Each user establishes direct trust in a MEC server based on the QoS delivered by the server. A user positively values the provided service if the server's performance meets or exceeds a certain preference threshold S_{thr}, i.e., $\delta_{n,k}^{\lambda_{n,k}} = 1$, if $S_{n,k} \geq S_{\text{thr}}$. If the server's performance falls below this threshold, the user perceives the service quality as unsatisfactory, i.e., $\delta_{n,k}^{\lambda_{n,k}} = 0$. In both scenarios, the user's perception of the server's service quality decays over time. Based on this understanding, the user's appreciation of both good (Eq. 2) and bad (Eq. 3) services can be formulated as follows:

$$GS_{n,k} = \sum_{\lambda=1}^{\lambda_{n,k}} \delta_{n,k}^{\lambda} \log_2\left(\frac{b}{T - t_{n,k}^{\lambda}} + 1\right) \quad (2)$$

$$BS_{n,k} = \sum_{\lambda=1}^{\lambda_{n,k}} (1 - \delta_{n,k}^{\lambda}) \log_2\left(\frac{b}{T - t_{n,k}^{\lambda}} + 1\right) \quad (3)$$

where $\lambda_{n,k}$ is the number of times that user n selected to offload $b_{n,k}$ bits to the MEC server k, T is the total time that we examine the data offloading process, $t_{n,k}^{\lambda}$ is the time instance that user n selected server k at the $\lambda_{n,k}$ interaction, and $b > 0$ is the decay factor. It is noted that small values of b indicate a quicker rate of forgetting past interactions.

Each user n develops a direct trust with each server k based on the provided services that is derived as follows.

$$\begin{aligned} DT_{n,k} &= \mathbb{E}\left(\text{beta}(GS_{n,k} + 1, BS_{n,k} + 1)\right) \\ &= \frac{GS_{n,k} + 1}{GS_{n,k} + BS_{n,k} + 2} \end{aligned} \quad (4)$$

B. Indirect Trust

The users may not frequently interact directly with some MEC servers, thus, their direct trust may not reflect the provided QoS. The users can leverage the peers' experiences, with whom they maintain social connections and they have similar computing demands. This approach allows the users to form a more accurate perception of the MEC server services, even in cases where their own interaction is limited. Also, each user seeks to identify the peers whose direct experiences are most similar to their own (implying similar computing demands), thus assigning greater trust to those peers compared to others. The most trusted user $\hat{n}$ for each server k is determined as follows.

$$\hat{n}_k = \arg\min_{\hat{n}_k\in\mathcal{N}} \left[\sum_{\forall n\in\mathcal{N}, n'\neq n} |DT_{n',k} - DT_{n,k}|\right] \quad (5)$$

Based on the identified most trusted peers $\hat{n}_k$ for each server $k, k \in \mathcal{K}$, each user is aware of the set of the most trusted peers $\mathcal{N}^{\text{tr}}$. The user incorporates the opinions of its trusted users $|\mathcal{N}^{\text{tr}}|$ (second terms of Eq. 6 and Eq. 7) along with its personal direct trust (first terms of Eq. 6 and Eq. 7) in order to establish its own overall trust to a server k to provide good (Eq. 6) or bad (Eq. 7) services.

$$OGS_{n,k} = w_1 GS_{n,k} + w_2 \sum_{n'=1}^{|\mathcal{N}^{\text{tr}}|} GS_{n',k} \tag{6}$$

$$OBS_{n,k} = w_1 BS_{n,k} + w_2 \sum_{n'=1}^{|\mathcal{N}^{\text{tr}}|} BS_{n',k} \tag{7}$$

The user's n overall trust to a MEC server k is given below.

$$\begin{aligned} \tau_{n,k} &= \mathbb{E}\left(\text{beta}(OGS_{n,k}+1, OBS_{n,k}+1)\right) \\ &= \frac{OGS_{n,k}+1}{OGS_{n,k}+OBS_{n,k}+2} \end{aligned} \tag{8}$$

III. Trust-aware Sustainable Data Offloading

Each user experiences a utility by offloading its data to the MEC servers while considering the trust established during their interactions and the personalized pricing by the MEC servers. Therefore, the user's utility is formulated as follows:

$$U_n(\mathbf{b}_n, \mathbf{b}_{-n}) = a_n \ln\left(1 + \sum_{k\in\mathcal{K}} \tau_{n,k} b_{n,k}\right) - \sum_{k\in\mathcal{K}} P_{k,n} b_{n,k} \tag{9}$$

where $\alpha_n \in \mathbb{R}^+$ denotes the satisfaction factor from processing the data to the servers, $\mathbf{b}_n = \{b_{n,1}, \ldots, b_{n,k}, \ldots, b_{n,\mathcal{K}}\}$ denotes the user's data offloading vector to the K servers, and $\mathbf{b}_{-n} = \{\mathbf{b}_1, \ldots, \mathbf{b}_{n-1}, \mathbf{b}_{n+1}, \ldots, \mathbf{b}_N\}$ is the data offloading vector of all other users except for user n. The logarithmic function is adopted to model the user's satisfaction, as it increases with the processing of the user's data. However, due to the bounded nature of the user's maximum data volume $B_n^{\max}$, the utility experiences diminishing returns and results in a slower rate of increase beyond a certain threshold, i.e., $B_n^{\max}$. The second term of Eq. 9 captures the user's cost from processing its data to the MEC servers.

Focusing on the MEc server's side, the profit of the MEC server from processing the users' data is formulated as follows:

$$U_{k,n}(P_{k,n}) = P_{k,n} b_{n,k} - c_k b_{n,k} \tag{10}$$

where the first term captures the MEC server's revenue and the second term represents the data processing cost.

IV. A Stackelberg Game-theoretic Approach

The goal of each user (leader) is to determine its optimal data offloading vector $\mathbf{b}_n$ to the MEC servers in order to maximize its utility. Similarly, the goal of each MEC server (follower) is to determine the optimal personalized pricing $P_{k,n}$ announced to each user in order to maximize its profit. The decisions of the users and the MEC servers are tightly connected to each other, thus, they can be formulated as a *multi-leader multi-follower Stackelberg game*.

Stage II: Leaders – Users: Each user's goal is to maximize its utility (Eq. 11a), while considering the data offloading feasibility constraints (Eq. 11b – 11c) and the MEC servers' personalized pricing policies, i.e., $P_{k,n}, \forall k \in \mathcal{K}$. The optimization problem for each user $n \in \mathcal{N}$ is formulated as follows.

$$\max_{b_n} U_n(\mathbf{b}_n, \mathbf{b}_{-n}) \tag{11a}$$

$$\text{s.t. } 0 \le b_{n,k} \le B_n^{max} \tag{11b}$$

$$\sum_{k\in\mathcal{K}} b_{n,k} = B_n^{max} \tag{11c}$$

Theorem 1: (Optimal Data Offloading Strategy) Each user's n optimal data offloading strategy to a MEC server k is:

$$b^*_{n,k} = \frac{a_n}{P_{k,n}} - \frac{\left(1 + \sum_{k'\in\mathcal{K},k'\neq k} \tau_{n,k'} b_{n,k'}\right)}{\tau_{n,k}}. \tag{12}$$

Proof: Toward determining the user's optimal data offloading strategy $b_{n,k}$ to each MEC server k, we calculate: $\frac{\partial U_n}{\partial b_{n,k}} = \frac{a_n \tau_{n,k}}{1+\sum_{k\in\mathcal{K}} \tau_{n,k} b_{n,k}} - P_{k,n}$ and $\frac{\partial^2 U_n}{\partial b^2_{n,k}} = -\frac{a_n \tau^2_{n,k}}{\left(1+\sum_{k\in\mathcal{K}} \tau_{n,k} b_{n,k}\right)^2} < 0$, which implies that $U_n(\mathbf{b}_n, \mathbf{b}_{-n})$ is concave with respect to $b_{n,k}$. Thus, $U_n(\mathbf{b}_n, \mathbf{b}_{-n})$ has a maximum point, which can be derived as follows: $\frac{\partial U_n}{\partial b_{n,k}} = 0 \implies 1 + \sum_{k'\in\mathcal{K},k'\neq k} \tau_{n,k'} b_{n,k'} + \tau_{n,k} b_{n,k} = \frac{a_n \tau_{n,k}}{P_{k,n}} \implies b^*_{n,k} = \frac{a_n}{P_{k,n}} - \frac{\left(1+\sum_{k'\in\mathcal{K},k'\neq k} \tau_{n,k'} b_{n,k'}\right)}{\tau_{n,k}}$. ■

Stage II: Followers - MEC Servers: The goal of each MEC server is to maximize its profit, considering the users' data offloading strategies (Eq. 12). Each MEC server's profit (Eq. 10) can be rewritten by utilizing Eq. 12 as follows:

$$U_k\left(P_{k,n}, \mathbf{P}_{-k,n}\right) = \left(P_{k,n} - c_k\right)\left[\frac{a_n}{P_{k,n}} - \frac{1 + \sum_{\substack{k'\in\mathcal{K} \\ k'\neq k}} \tau_{n,k'} b_{n,k'}}{\tau_{n,k}}\right] \tag{13}$$

where $\mathbf{P}_{-k,n} = (P_{1,n}, \ldots, P_{k-1,n}, P_{k+1,n}, \ldots, P_{K,n})$ denotes the prices of all other servers except for server k.

Thus, the corresponding optimization problem for each MEC server k is formulated as follows:

$$\max_{P_{k,n}} U_k\left(P_{k,n}, \mathbf{P}_{-k,n}\right) \tag{14a}$$

$$\text{s.t. } 0 \le P_{k,n} \le P_k^{\max} \tag{14b}$$

$$0 \le \sum_{n\in\mathcal{N}} b_{n,k} \le B_k^{\max} \tag{14c}$$

where Eq. 14b captures the market constraint with respect to the maximum allowed price $P_k^{\max}$ based on the regulations for edge computing services per region that the MEC server k resides, and Eq. 14c reflects the feasible bounds of the MEC server's data processing capacity.

The MEC servers actively compete to attract users for offloading their data by offering customized pricing $P_{k,n}$ based on individual user requirements. Thus, a non-cooperative game $\mathcal{G}_K = \{\mathcal{K}, \{A_k\}_{k\in\mathcal{K}}, \{U_{k,n}\}_{\forall k\in\mathcal{K},\forall n\in\mathcal{N}}\}$ is formulated, where $\mathcal{K}$ is the set of players, i.e., MEC servers, $A_k = [0, P_k^{\max}]$ denotes their strategy set of pricing policies, and $U_{k,n}$ captures their profit from serving the users.

Theorem 2: (Existence of Nash Equilibrium) A Nash Equilibrium (NE) $\mathbf{P}^*_n = [P^*_{1,n}, \ldots, P^*_{k,n}, \ldots, P^*_{\mathcal{K},n}]$ exists in the non-cooperative game $\mathcal{G}_\mathcal{K}$.

Proof: The strategy set $A_k = [0, P_k^{\max}]$ is a non-empty, convex, and compact set. Also, the MEC server's profit function (Eq. 10) is continuous in $\mathbf{P}_n$. We examine the concavity of the profit function with respect to $P_{k,n}$ as follows $\frac{\partial U_{k,n}}{\partial P_{k,n}} = \left[\frac{a_n}{P_{k,n}} - \frac{1+\sum_{k'\neq k}\tau_{n,k'}b_{n,k'}}{\tau_{n,k}}\right] - (P_{k,n} - c_k)\frac{a_n}{P_{k,n}^2}$ given that $\frac{\partial b_{n,k'}}{\partial P_{k,n}} = 0$ and $\frac{\partial^2 U_{k,n}}{\partial P_{k,n}^2} = -\frac{2c_k a_n}{P_{k,n}^3} < 0$. Thus, $U_{k,n}$ is concave in $P_{k,n}$, and the non-cooperative game $\mathcal{G}_{\mathcal{K}}$ has at least one Nash Equilibrium, derived as follows [14].

$$P_{k,n}^* = \sqrt{\frac{\tau_{n,k}c_k a_n}{1+\sum_{k'\neq k}\tau_{n,k'}b_{n,k'}}} \tag{15}$$

■

Theorem 3: (Uniqueness of Nash Equilibrium) The non-cooperative game $\mathcal{G}_{\mathcal{K}}$ has a unique NE.

Proof: We need to show that the NE (Eq. 15) is a best response standard function, i.e., the conditions of positivity, monotonicity, and scalability hold true [15]. The best response strategy of $\mathcal{G}_{\mathcal{K}}$ is derived from Eq. 15, as follows.

$$BR_{k,n}\left(\mathbf{P}_{-k,n}^*\right) = P_{k,n}^* \tag{16}$$

Based on Eq. 16, we have $BR_{k,n}\left(\mathbf{P}_{-k,n}^*\right) > 0, \forall \mathbf{P}_{-k,n}^* > 0$, thus, the condition of positivity holds true. Focusing on the monotonicity, we analyze Eq. 16, as follows: $BR_{k,n}\left(\mathbf{P}_{-k,n}^*\right) = \sqrt{\frac{\tau_{n,k}c_k a_n}{1+\sum_{k'\neq k}\tau_{n,k'}\left(\frac{a_n}{P_{k',n}} - \frac{1+\sum_{\kappa''\neq\kappa'}\tau_{n,\kappa''}b_{n,\kappa'}}{\tau_{n,\kappa'}}\right)}}$. Thus, we observe that $BR_{k,n}\left(\mathbf{P}_{-k,n}^*\right)$ has a proportional relationship to $P_{k',n}$. Therefore, if $\mathbf{P}_{-k,n}^* \geq \mathbf{P'}_{-k,n}^*$, $\implies BR_{k,n}\left(\mathbf{P}_{-k,n}^*\right) \geq BR_{k,n}\left(\mathbf{P'}_{-k,n}^*\right)$, and the condition of monotonicity holds true. Focusing on the scalability, the following condition should hold true: $\lambda BR_{k,n}\left(\mathbf{P}_{-k,n}^*\right) > BR_{k,n}\left(\lambda\mathbf{P}_{-k,n}^*\right)$, $\lambda > 1$. Based on Eq. 16, we have:

$$\frac{\lambda BR_{k,n}\left(\mathbf{P}_{-k,n}^*\right)}{BR_{k,n}\left(\lambda\mathbf{P}_{-k,n}^*\right)} = \sqrt{\frac{\lambda^2+\sum_{k'\neq k}\lambda\tau_{n,k'}b_{n,k'}}{1+\sum_{k'\neq k}\tau_{n,k'}b_{n,k'}}} > 1 \tag{17}$$

Thus, the condition of monotonicity also holds true. We conclude that the best response $BR_{k,n}\left(\mathbf{P}_{-k,n}^*\right)$ is a standard function, and the game $\mathcal{G}_{\mathcal{K}}$ has a unique Nash Equilibrium. ■

Based on Theorems 1 and 3, we conclude that a unique Stackelberg Equilibrium $\left\{b_{n,k}^*, P_{k,n}^*\right\}_{\forall n\in\mathcal{N},\forall k\in\mathcal{K}}$ exists and a Best Response Dynamics algorithm can be adopted to determine it [15].

V. Experimental Results

In this section, detailed experimental results are presented based on real datasets to demonstrate: (i) the pure performance and operation of the TANDEM framework (Section V-A), (ii) its applicability in real-world scenarios (Section V-B), (iii) its scalability (Section V-C), and (iv) its superiority compared to the state of the art in terms of supporting a sustainable MEC environment (Section V-D). In the rest of the analysis, the following dataset

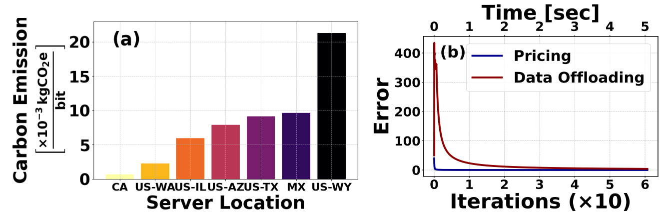

Fig. 1: (a) MEC servers' carbon emissions and (b) TANDEM framework's convergence.

has been adopted, $N = 15$, $K = 7$, the convergence threshold of the TANDEM framework is set equal to $1e^{-5}$, $\text{Zipf}(x_k) = \frac{1}{x_k^{1.5}}$, $\mathbf{x} = [1, 2.48, 5.86, 7.64, 8.82, 9.27, 20]$, $b = 0.7$, $S_{\text{thr}} = 0.05$, $w_1 = w_2 = 0.5$, $c_k = 2$, $a_n = 1200$, $B_k^{\max} = [450, 350, 250, 200, 80, 20, 1][Ebits]$, $B_n^{\max} = [160, 150, \ldots, 30, 20][Ebits]$, $\mathbf{P}^{\max} = [10, 9, 8, 7, 6, 5, 4][\frac{1\$}{Pbit}]$, unless otherwise explicitly stated. A real dataset from Microsoft Azure is used for our experiments, as described below. The users' processing tasks resemble the training of a moderate-scale Large Language Model (LLM), such as GPT-Neox-20B. GPT-Neox-20B shares a similar architecture with GPT-3, and its training dataset primarily consists of English texts. The MEC servers are equipped with NVIDIA V100 Tensor Core GPUs, recognized as state-of-the-art in GPU technology. With a memory bandwidth of 900 GB/s, these GPUs are theoretically capable of transferring and processing up to 900 gigabytes of data per second under optimal conditions[1]. By using the Microsoft Azure, we derived the total training time of GPT-Neox-20B and the corresponding carbon emissions across various server locations in North America. Based on Eq. 18, we can accurately calculate the carbon emissions per bit, as follows:

$$\frac{CE_k}{BW_{GPU}(\text{GB/s}) \times T(\text{s}) \times 8\,\text{bits}} \tag{18}$$

where $BW_{GPU} = 900$ GB/sec, and CE_k reflects the carbon emissions per MEC server k residing in a corresponding location in North America and processing computing tasks for a time period T sec, where the values for the latter are directly derived by the Microsoft Azure (Fig. 1a). It is noted that the carbon emissions (CE_k) differ across regions where the servers reside, primarily due to the variations in the local energy mix, with regions relying on fossil fuels generating higher emissions. Also, differences in the efficiency of the smart grid system, cooling requirements, and regional regulations further contribute to the variability in carbon emissions.

A. Pure Operation and Performance

In this section, the pure operation and the performance of the TANDEM framework are presented. Fig. 1b – 3b demonstrate the convergence of the TANDEM framework with respect to the pricing policies and data offloading strategies, the MEC servers' mean price, mean trust, mean profit, and the users' utility as a function of the TANDEM iterations.

[1]https://www.nvidia.com/en-us/data-center/v100/

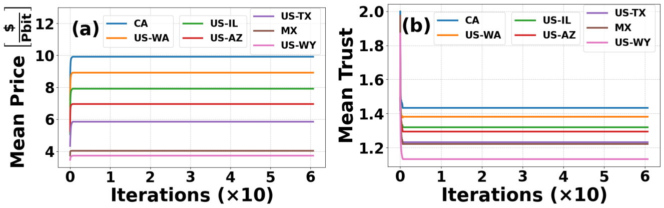

Fig. 2: MEC servers' (a) mean price, and (b) mean trust levels.

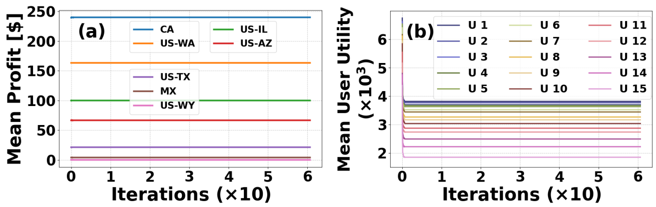

Fig. 3: (a) MEC servers' profit and (b) users' utility.

The results reveal that the TANDEM framework converges fast to the Stackelberg Equilibrium (Fig. 1b), i.e., less than 5sec. The MEC servers' pricing policies demonstrate minimal variation and converge more quickly than the users' data offloading strategies. Considering the same convergence criterion, the users adapt their decisions to the MEC servers' pricing and the multiple available choices to offload their data. Moreover, the results show that the more environmentally friendly servers (Fig. 1a), result in higher pricing policies (Fig. 2a), as eco-friendly servers typically follow more costly protocols to minimize their environmental impact. Also, since the more eco-friendly servers are capable of processing a larger volume of data, they gain increased trust among the users (Fig. 2b). Given that the more environmentally friendly servers attract a larger amount of offloaded data at a higher data processing price, they achieve a higher profit (Fig. 3a). Furthermore, the results confirm that users with higher data processing demands, i.e., those handling larger volumes of data, achieve a greater utility, as they invest more in accessing premium and resource-intensive computing services (Fig. 3b).

B. A Real-world Scenario

In this section, we analyze a real-world application of the TANDEM framework considering a set of 7 MEC servers with same data processing capacity ($B_k^{\max} = 400[Ebits]$) and 15 users with similar data processing requests ($B_n^{\max} = 90[Ebits]$). The objective is to evaluate the influence of both the servers' and users' eco-friendliness on the MEC servers' pricing strategies and the users' data offloading decisions. Fig. 4 illustrates the MEC servers' and users' optimal decisions at the Stackelberg Equilibrium. The heatmap captures the MEC servers' pricing, while the yellow circles represent the users' offloaded data to a corresponding server. A brighter color and larger circle correspond to a higher volume of offloaded data. Also, the first 7 users are behaving in a more eco-friendly manner ($a_n = 1200$), compared to the last 8 users ($a_n = 1$). he MEC servers' maximum price vector is $\mathbf{P}^{\max} = [15, 15, 15, 10, 3, 3, 3][\frac{1\$}{Pbit}]$. The results indicate that the environmentally conscious users, i.e., users 1-7, prefer to offload a greater volume of data to environmentally sustainable servers, willingly incurring higher data processing costs to reduce carbon emissions. On the other hand, the price-sensitive users, i.e., users 8-15, prioritize offloading their data to lower-cost servers, with little regard for the environmental impact.

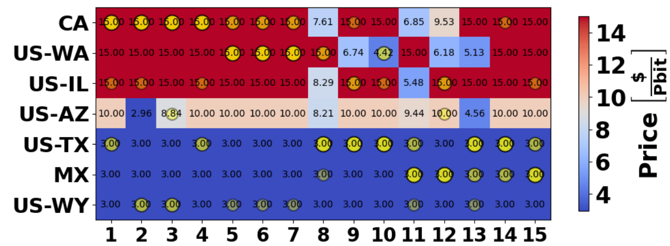

Fig. 4: Data offloading and pricing heatmap.

C. Scalability Analysis

In this section, a scalability analysis is performed to demonstrate the efficiency and robustness of TANDEM framework for a large-scale setup. The number of users requesting concurrently services from the 7 MEC servers ranges from 15 to 50 users, and the rest of the parameters are $a_n = 3000$, $B_k^{\max} = [600, 600, 600, 500, 500, 500, 500][Ebits]$, $B_n^{\max} = 60[Ebits]$, $\mathbf{P}^{\max} = [100, \ldots, 100][\frac{1\$}{Pbit}]$, $S_{thr} = 0.1$, $w_1 = 0.7$, and $w_2 = 0.3$. Fig. 5a – 5c show the MEC servers' mean price, profit, and the users' mean utility, as a function of the increasing number of users in the system. The results show that an increasing number of users results in higher computing service demand from the MEC servers, driving the MEC servers to increase their prices (Fig. 5a), and in turn, increase their profit (Fig. 5b). Given the higher computing prices, the users' mean utility decreases (Fig. 5c). Also, it is observed that the users' trust remains relatively constant across different scenarios, as it is unaffected by the number of users and depends on the MEC servers' provided services and data processing capacity.

D. Comparative Scenarios

In this section, a thorough comparative evaluation of the TANDEM framework to existing data offloading mechanisms from the state of the art is performed to demonstrate its benefits in terms of reducing the servers' carbon emissions, while serving the users' computing demands. The following comparative mechanisms are considered: (i) **Green**: The users proportionally offload their data to the MEC servers based on the servers' environmental sustainability and prioritizing greener options; (ii) **Cost-driven**: the users offload their data in proportion to the pricing policies of the MEC servers and favoring the most cost-effective options as determined by the TANDEM framework for fairness in the comparison; (iii) **Eco-Agnostic**: the users make data offloading decisions without considering the MEC servers' environmental impact, i.e., $S_{n,k} = \frac{b_{n,k}}{\sum_{\forall n \in \mathcal{N}} b_{n,k}} \cdot \frac{B_k^{\max}}{\sum_{\forall k \in \mathcal{K}} B_k^{\max}}$; and (iv) **Social-Ignorance**: the users disregard their social interactions with their peers when determining their optimal data offloading strategies, i.e., $\tau_{n,k} = 1, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}$. For the comparative evaluation, we consider $a_n = 3000$, $B_k^{\max} =$

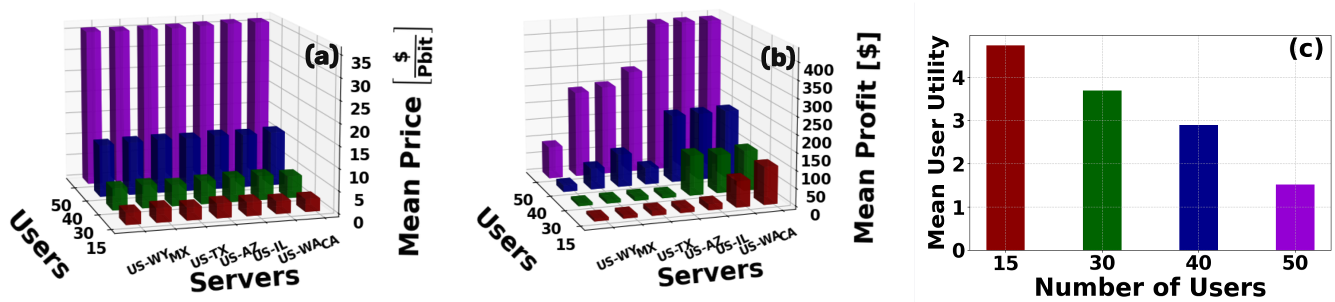

Fig. 5: Scalability analysis: MEC servers' (a) mean price, (b) mean profit, and (c) users' mean utility.

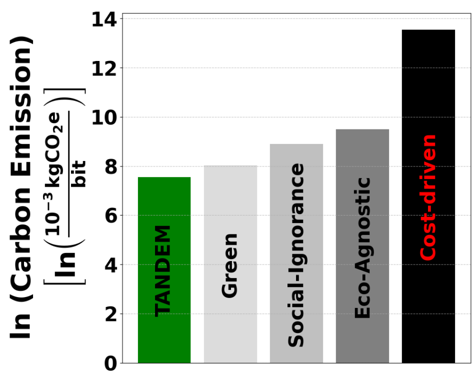

Fig. 6: Comparative evaluation.

$[600, 600, 600, 500, 500, 500, 500][Ebits]$, $B_n^{\max} = 60[Ebits]$, and $\mathbf{P}^{\max} = [100, \dots, 100][\frac{1\$}{Pbit}]$.

The results reveal that the TANDEM framework concludes to the lowest carbon emissions compared to all the comparative scenarios (Fig. 6) while the scenarios where the users are solely driven by the cost result in the worst environmental impact, i.e., cost-driven scenario. Also, the results show that as the users either become eco-agnostic or socially ignorant, the resulting carbon emissions increase in the system. Finally, the results demonstrate that the simple consideration of the MEC servers' carbon emissions in the data offloading decision-making process, results in worse outcomes than the TANDEM framework, as the latter also exploits the users' social interaction with their peers in order to gain rich information and ultimately shape their data offloading decisions.

VI. Conclusion

In this paper, a novel social-aware trust-based data offloading framework for MEC environments, named TANDEM, is introduced to jointly optimize the users' data offloading strategies and MEC servers' dynamic pricing policies. TANDEM integrates a social trust model that leverages both the direct interactions of the users with the MEC servers, as well as their peers' feedback to guide their offloading decisions. TANDEM is based on a Stackelberg game-theoretic approach to optimize the MEC servers' and the users' strategies. Detailed experimental results confirm TANDEM's ability to outperform existing methods while significantly reducing the carbon emissions in MEC environments. Part of our current and future work is the extension of the TANDEM framework to accommodate also the MEC servers' energy consumption and jointly improve the edge computing sustainability.

References

[1] Y. Yang, Y. Chen, K. Li, and J. Huang, "Carbon-aware dynamic task offloading in noma-enabled mobile edge computing for iot," *IEEE Internet of Things Journal*, vol. 11, pp. 15 723–15 734, 2024.

[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. on Mobile Computing*, vol. 19, no. 12, pp. 2833–2849, 2020.

[3] H. Ma, Z. Zhou, X. Zhang, and X. Chen, "Toward carbon-neutral edge computing: Greening edge ai by harnessing spot and future carbon markets," *IEEE Int. of Things Jour.*, vol. 10, pp. 16 637–16 649, 2023.

[4] C. Fang, X. Meng, Z. Hu, X. Yang, F. Xu, P. Li, and M. Dong, "Drl-based green task offloading for content distribution in noma-enabled cloud-edge-end cooperation environments," in *IEEE International Conference on Communications*, 2023, pp. 6126–6131.

[5] X. Huang, R. R. Liu, B. Lei, W. Xing, and X. Zhang, "Platform profit maximization for space-air-ground integrated computing power network supplied by green energy," in *IEEE International Conference on Communications*, 2024, pp. 2507–2512.

[6] Z.-L. Chang, C.-Y. Wang, and H.-Y. Wei, "Flat-rate pricing and truthful offloading mechanism in multi-layer edge computing," *IEEE Transactions on Wireless Communications*, vol. 20, no. 9, pp. 6107–6121, 2021.

[7] P. Zeng, A. Liu, C. Zhu, T. Wang, and S. Zhang, "Trust-based multi-agent imitation learning for green edge computing in smart cities," *IEEE Trans. on Green Comm. and Net.*, vol. 6, no. 3, pp. 1635–1648, 2022.

[8] W. Kong, X. Li, L. Hou, J. Yuan, Y. Gao, and S. Yu, "A reliable and efficient task offloading strategy based on multifeedback trust mechanism for iot edge computing," *IEEE Int. of Things Jour.*, vol. 9, no. 15, pp. 13 927–13 941, 2022.

[9] J. Bai, Z. Zeng, T. Wang, S. Zhang, N. N. Xiong, and A. Liu, "Tanto: An effective trust-based unmanned aerial vehicle computing system for the internet of things," *IEEE Int. of Things Jour.*, vol. 10, no. 7, pp. 5644–5661, 2023.

[10] J. Zhang, Y. Wu, and G. Min, "System revenue maximization for offloading decisions in mobile edge computing," in *IEEE International Conference on Communications*, 2021, pp. 1–6.

[11] B. Lin, X. Chen, X. Chen, Y. Ma, and N. N. Xiong, "Sgcs: An intelligent stackelberg-game-based computation offloading and resource pricing scheme in blockchain-enabled mec for iiot," *IEEE Internet of Things Journal*, vol. 11, no. 16, pp. 26 727–26 740, 2024.

[12] H.-J. Hong, W. Fan, C. E. Chow, X. Zhou, and S.-Y. Chang, "Optimizing social welfare for task offloading in mobile edge computing," in *2020 IFIP Networking Conference (Networking)*, 2020, pp. 524–528.

[13] T. Lyu, H. Xu, and Z. Han, "Multi-leader multi-follower stackelberg game based resource allocation in multi-access edge computing," in *IEEE Int. Conference on Communications*, 2022, pp. 4306–4311.

[14] J. B. Rosen, "Existence and uniqueness of equilibrium points for concave n-person games," *Econometrica: Journal of the Econometric Society*, pp. 520–534, 1965.

[15] R. D. Yates, "A framework for uplink power control in cellular radio systems," *IEEE Journal on selected areas in communications*, vol. 13, no. 7, pp. 1341–1347, 1995.