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A Game Theoretic Framework for Quality of Experience Enhancement in Dense Stadia

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ABSTRACT In crowded venues, such as sports stadia, maintaining an acceptable network quality of experience (QoE) is hard to achieve. Installing small cells, distributed antenna systems or high-density WiFi in every stadium is too expensive for mobile network operators. Hence, we propose a novel distributed low-cost solution based on user coordination to improve the average QoE when the network capacity cannot be enhanced. Specifically, fans take turns in disabling their cellular connectivity, such that the connected users utilize the relaxed network to obtain then share common match data with the disconnected users via Peer-to-Peer (P2P) connectivity. To eliminate a free-riding behavior, a limited punishment strategy in a large repeated game is proposed and shown to yield an approximate subgame-perfect Nash equilibrium. In addition, we model human irrationality as game noise incorporated into the proposed equilibria. A proposed application-oriented QoE model is first obtained via SimuLTE, an extension of OMNET++, then used in MATLAB simulations to verify the proposed solution. The results show tangible gains realized by the proposed solution under realistic scenarios and parameters.

INDEX TERMS Stadium connectivity, QoE, QoS, repeated games, symmetric Nash equilibrium, large games.

I. INTRODUCTION

Despite the recent advancements in wireless technology, there are still many inevitable scenarios where the traffic demand exceeds the network capacity degrading the QoE. These situations either occur because of extreme number and density of users, as in sports stadia, or due to a sudden compromise of the network infrastructure as a result of electrical faults, natural disasters or wars [1]. As such events are generally infrequent, it would be infeasible to design the network capacity to account for these rare circumstances. Hence, alternative solutions such as spectrum slicing, resource sharing and cooperative strategies have been proposed in the literature [2], [3].

In a football stadium, fans experience poor cellular connectivity due to many reasons [4], [5]. First, the network resources, when shared by a huge number of users, will result in extremely low per-user throughput. Due to limited number of resource blocks, the cellular base station (BS) may only serve a limited number of users at a time extending the delay and latency [6], [7]. Additionally, packet collision and interference in the multiple access channel further reduce the capacity in the dense network. Besides the above, we believe that fans' correlated usage behavior will cause traffic spikes during certain moments, such as the half-time break.

To improve cellular coverage and capacity, distributed antenna systems (DAS), small cells [5], Cell on Wheels (COW) [8], and high-density (HD) Wi-Fi [9] may be installed in the stadium. In [10], the optimal distributed antenna selection problem is studied. A novel DAS design is proposed in [4] and shown to outperform legacy DAS in both indoor and outdoor stadia. On the other hand, an HD-WiFi benefits from the many non-overlapping channels in the 5 GHz band to mitigate interference and maximize the capacity in the dense stadium [11]. Due to high cost and complexity, the aforementioned techniques may turn infeasible for many network operators and club owners. Alternatively, a P2P network created by the fans' smartphones to share match-specific application data, such as match statistics and video replays, may improve user satisfaction [12]. The InCrowd *app* [13] allows fans who opportunistically experience good connectivity to forward text-based match data to the disconnected devices using a delay tolerant protocol. In [14], a P2P scheme is proposed to reduce the communication cost where a proxy, elected by a server, distributes multimedia contents

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to nearby peers. The main disadvantage of InCrowd is its limitation to text based applications, whereas the solution in [14] imposes a security risk as fans join untrusted hotspots.

Recently, QoE, defined as the user's perceived quality of service (QoS), has gained more interest as a new metric for evaluating network performance, since QoS may not reflect the exact quality perception [15]. However, quantifying QoE and its relation to QoS is not trivial due to external factors and the subjective nature of the user experience [16], [17]. Hence, many QoE-QoS correlation models and metrics have been investigated in the literature [15] (and references therein). A survey of quality assessment models for video applications is presented in [18] with more emphasis on subjective and objective models and tests. In [19], a real-time QoE prediction model for 5G video streaming is proposed. More tools and methods for QoE prediction for online video streaming applications are studied in [20], whereas assessment techniques for VoIP QoE are surveyed in [21]. Each QoE model above considered a single application category, such as voice or video services, based on system, context and human factors, which are difficult to predict.

Game theory has been recently adopted to model incentives and selfishness of users in P2P networks. In [22], the authors propose a QoE game to optimize the network diversity gain. In [23], users in a VoIP application reduce their data rates in a symmetric behavioral game to maximize the aggregate performance and ultimately the QoE. Reference [24] proposes a non-cooperative game to model the user contribution in heterogeneous P2P networks. A behavioral-based scheme with imperfect monitoring is analyzed in [25] for packet-forwarding in self-organizing networks. As the number of players grows, stable and approximate Nash equilibria can be efficiently computed motivating the application of large games in stadium networks [26], [27].

In this paper,[1] we propose a novel cooperative strategy to enhance the average QoE over the football match duration. We first define a generic QoE-QoS mapping scheme of the overall Internet service quality in which a higher QoE level is realized whenever the QoS metrics meet certain recommended values defined by the applications. Then, we propose a coordination strategy whereby a random group of the fans disable their cellular connectivity at a time such that the cellular enabled (CE) users acquire the common match data at a faster rate and then share them with the cellular disabled (CD) users via P2P connectivity. Since the user has to control the cellular enable state manually due to smartphone operating system constraints, the free-riding behavior will be inevitable as with many file sharing applications [29]. To counteract the selfish behavior, obtain the optimal CE percentage, and ensure fairness, incentives in the form of reward and punishment are required. Thus, we propose a repeated game theoretic model with symmetric mixed strategies and analyze its properties. Additionally, we model the irrational behavior of users by including the strategy error into the game equilibrium [30]. The performance of the proposed scheme, named CrowdConnect (CC), is then verified using MATLAB and SimuLTE, an extension of the OMNET++ [31] simulator. Specifically, SimuLTE [32] is used to define a mapping function from the number of simultaneously active users to discrete QoE levels. Based on the obtained model, MATLAB is used to compute the gains of the proposed game solution under different scenarios and parameters. The results show substantial improvements in average QoE when a significant proportion of the fans adopt the proposed scheme and the strategy error is moderate. Remarkably, the application of CC in the stadium also benefits non-CC users. Our contributions along with the motivations behind them are summarized as follows:

- Proposed an application-oriented QoE-QoS model for the overall Internet service quality based on the achievable throughput and latency.
- Developed a novel software-based coordination scheme to enhance the average QoE in sports stadia given the fact that a range of QoS values can yield the same QoE level. Adopting the QoE instead of the QoS improves the stability and complexity of the solution, as will be shown in the sections to follow.
- Modeled the fans' behavior as a large game with stable and efficient equilibria computed with low complexity. The proposed large game theoretic model is a robust tool for future dense wireless networks, such as the Internet of Things (IoT) in which the number of interacting users becomes very large.
- Proposed a novel limited punishment strategy to maintain cooperation and support efficient equilibria in a finitely repeated interaction.
- Modeled the player irrationality as game noise integrated into the proposed game equilibria. This detailed implementation verifies its practicality when deployed in a real scenario.
- Simulated the proposed QoE model using a realistic LTE simulator. Since the proposed scheme is application-oriented, it was necessary to verify it by considering the whole network stack.

To our best knowledge, the proposed QoE-QoS model, the CE coordination scheme, and the game theoretic analysis have never been discussed in the literature. The remaining sections of this paper can be summarized as follows. The network and QoE models are discussed in section II. Section III explains the game theoretic model used to implement the proposed strategy. Simulation results and analysis are presented in section IV. Then, a discussion on practicality issues is provided in Section V before concluding remarks and future work are outlined in section VI.

II. SYSTEM MODEL AND ASSUMPTIONS

A. CELLULAR NETWORK MODEL

We consider a football stadium with a total capacity of N^C seats uniformly occupied by N^F fans each carrying a single

[1] A conference version of the this paper [28] has been published in IEEE GLOBECOM Proceedings, 2018, Abu Dhabi, UAE.

smartphone with a cellular data subscription with one of O network operators. Without loss of generality, we assume $N^O = \frac{N^F}{O}$ fans per operator, out of which $N^U = \Upsilon N^O$ fans will adopt the proposed solution, where $\Upsilon \in [0, 1]$ is the degree of participation. Additionally, let $N^{SU} = \tau N^U$ be the proportion of N^U users simultaneously requesting cellular resources with $\tau \in [0, 1]$. Next, we divide the match duration of T_M minutes into N_T periods, each of length $T_P = \frac{T_M}{N_T}$ minutes. At the beginning of each period $t \in \{1, \ldots, N_T\}$, the cellular connectivity status $a_n^t \in \{0, 1\}$ is set by user $n \in \{1, \ldots, N^U\}$ of a given operator then remains fixed for the duration of t. Only upon selecting $a_n^t = 1$, the fan gains Internet access via cellular data, henceforth denoted by $Service - A$, with a throughput of $\mathcal{C}^A(\mathcal{C}, \mathbf{a}^t)$ and a latency of $\mathcal{T}^A(\mathbf{a}^t)$, where $\mathbf{a}^t = \{a_1^t, \ldots, a_{N^U}^t\}$ is a vector of the CE states in period t, and $\mathcal{C}$ is the cell capacity. The functions $\mathcal{C}^A(\cdot)$ and $\mathcal{T}^A(\cdot)$ are empirically obtained via realistic simulations, as will be explained in Section IV. A summary of the network parameters and symbols are listed in Table 1.

TABLE 1. Network parameters.

N^F	No. of users in the stadium
O	No. operators
T_M	Match length (min)
N_T	Total periods
N_{pun}	Punishment periods
$\mathcal{C}$	Cell capacity
N^U	No. CC users per operator
N^O	No. users per Operator
CE	Cellular Enabeled
L	QoE levels
τ	Simultaneous users %
Υ	Percentage of CC users
η	Game noise
ρ_{self}	Self punishment
y^{P2P}	Minimum CE
N^C	Stadium capacity
T_P	Period duration (min)
N^{SU}	No. Simultaneous users
CD	Cellular Disabled

B. PEER-TO-PEER NETWORK MODEL

A hierarchical cluster-based P2P network[2] is assumed to be established between the fans' devices using WiFi-Direct [33] or Bluetooth [34]. As such, the cellular disabled (CD) fans (selecting $a_n^t = 0$) will obtain common match data, henceforth denoted by $Service - B$, through the Internet connection of CE fans (across different operator networks) acting as cluster heads (CH) in the P2P network. Due to the higher capacity and lower latency of the WiFi-Direct based P2P network compared to the stadium's congested cellular network and due to the broadcast nature of in-match application data, it will be assumed that the P2P network brings no additional capacity bottleneck [13], [35]. Thus, the average per-user throughput of $Service - B$, denoted $\mathcal{C}^B(\mathbf{a}^t)$, will be assumed equal to that of $Service - A$ whenever $y(\mathbf{a}^t) = \sum_{i=1}^{N} a_i^t$ is greater than y_{min}^{P2P}, the minimum number of CE fans required to establish full P2P connectivity. On the other hand, the latency of $Service - B$ is given as $\mathcal{T}^B(\mathbf{a}^t) = \mathcal{T}^A(\mathbf{a}^t) + \mathcal{T}^{P2P}(\mathbf{a}^t)$, where $\mathcal{T}^{P2P}(\cdot)$ is the latency caused by the P2P network as a function of the number of CEs (CHs). In this work, $\mathcal{T}^{P2P}(\cdot)$ will be assumed a constant value much smaller than $\mathcal{T}^A(\mathbf{a}^t)$ only when $y(\mathbf{a}^t) > y_{min}^{P2P}$. However, for $y(\mathbf{a}^t) \leq y_{min}^{P2P}$, the capacity $\mathcal{C}^B(\mathbf{a}^t)$ will be zero and the latency will be infinite. The proposed network model is illustrated in Fig. 1.

[2] The details of the P2P network are out of the scope of this paper and will be considered in future work.

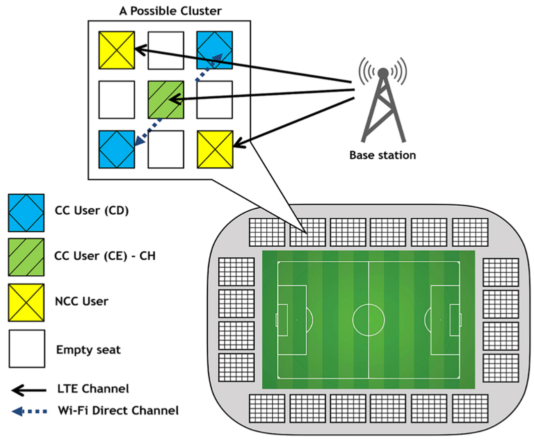

FIGURE 1. Network model.

C. QUALITY OF EXPERIENCE MODEL

Due to human perception and application constraints, the QoE remains nearly constant over a range of throughput and latency values. For instance, a VoIP call will not be established if the data rate is too low or the latency is too high, while the voice quality will be perfect for any data rate above a given high value [36]. Thus, we propose a quantized QoE-QoS mapping function, where a QoE level $l \in \mathcal{L} = \{1, \ldots, L\}$, s.t. $L \leq N$, corresponds to a capacity range $[\mathcal{C}_l^x, \mathcal{C}_{l+1}^x)$ and a latency range $(\mathcal{T}_{l+1}^x, \mathcal{T}_l^x]$ for $Service - x$, $x \in \{A, B\}$, such that $l = 1$ indicates a non-usable service. In turn, the range of CE users associated with level l will be $(Y_{l+1}^x, Y_l^x]$, where $Y_l^x = \min(Y_l^{\mathcal{C},x}, Y_l^{\mathcal{T},x})$. Also, $Y_l^{\mathcal{C},x}$ and $Y_l^{\mathcal{T},x}$ are the maximum number of CE users to yield $\mathcal{C}_l^x$ and $\mathcal{T}_l^x$ respectively. It is assumed that $\mathcal{C}_l^x$ and $\mathcal{T}_l^x$ have been obtained using QoE-QoS correlation models, such as those outlined in [16].

III. NETWORK RESOURCE SHARING AS A REPEATED GAME

In light of the above model, we propose a cooperative strategy whereby users will occasionally switch-off their cellular connectivity during the football match. Thus, instead of obtaining poor QoE continuously, a user may be better off, on average, obtaining useful throughput and latency that support higher QoE levels only in certain periods of the match, while being completely disconnected in the remaining periods. The user satisfaction can be further improved by the sharing of common match-specific application data through the P2P network, such that the CE users forward the common match data to the CD users. Since each fan controls his own CE status, and due to the absence of binding agreements, we model the above scenario as a repeated coordination game, wherein each period a stage game is played as follows.

A. STAGE GAME DESCRIPTION

A stage game is represented by the tuple $\mathcal{G} = \{\mathcal{N}, \mathcal{A}, \mathcal{U}^{\mathcal{G}}\}$, where $\mathcal{N}$ is the set of $N = N^U$ players (CC users per operator), $\mathcal{A} = \{0, 1\}$ is the action space indicating the player's CE status, and $\mathcal{U}^{\mathcal{G}} = \{U_1^{\mathcal{G}}, \ldots, U_N^{\mathcal{G}}\}$ is a vector of player utilities. The utility of a player $n \in \mathcal{N}$, realized at the end of the stage game, is expressed as:

$$U_n^{\mathcal{G}}(a_n, \mathbf{a_{-n}}) = \begin{cases} \pi^A(a_n, \mathbf{a_{-n}}) & a_n = 1 \\ \pi^B(a_n, \mathbf{a_{-n}}) & a_n = 0 \end{cases} \tag{1}$$

where $\mathbf{a_{-n}} = \mathbf{a} \setminus a_n$ is a vector of actions of all players except n. Upon selecting $a_n = 1$, a CE player n obtains a payoff given by the function $\pi^A(\cdot)$ which maps the number of CE users to a payoff value π_l^x corresponding to the achievable QoE level l of $Service - A$ applications. Similarly, by disabling the cellular data ($a_n = 0$), the player obtains $\pi^B(\cdot)$, the payoff of $Service - B$, such that $\pi_l^x < \pi_{l+1}^x \; \forall l \in \mathcal{L}$ and $\pi_1^x = 0 \; \forall x \in \{A, B\}$. For simplicity of notation, the superscript t has been omitted in the stage game analysis.

B. STAGE GAME EQUILIBRIA

According to Nash [37], a symmetric game must have a symmetric Nash equilibrium (NE) in mixed strategies, in which all players choose $a_n = 1$ with the same probability $p \in [0, 1]$. Precisely, when $N-1$ players adopt p, the remaining player will be indifferent between choosing any value of p as in the following equation:

$$\Pi^A(N, p) = \Pi^B(N, p), \tag{2}$$

$$\Pi^A(N, p) = \pi_1^A \sum_{i=Y_2^A}^{N-1} \mathcal{X}_N^{i,p} + \cdots + \pi_L^A \sum_{i=0}^{Y_L^A - 1} \mathcal{X}_N^{i,p}, \tag{3}$$

$$\Pi^B(N, p) = \pi_1^B \sum_{i=Y_2^B+1}^{N} \mathcal{X}_N^{i,p} + \cdots + \pi_L^B \sum_{i=y^{P2P}}^{Y_L^B} \mathcal{X}_N^{i,p}, \tag{4}$$

$$\mathcal{X}_N^{i,p} = \binom{N-1}{i} p^i (1-p)^{N-1-i}, \tag{5}$$

where (3) and (4) represent the expected payoffs of a player deviating from p to $a_n = 1$ and $a_n = 0$ respectively while the remaining players adopt p. Also, $\mathcal{X}_N^{i,p}$ is the probability that exactly i players will select $a_n = 1$ upon playing the symmetric mixed strategy p. Since the solution of (2) is complex and that the number of players is large, we approximate (2) using the law of large numbers to become:

$$\pi^A(1, p(N-1)) = \pi^B(0, p(N-1)). \tag{6}$$

As a result, for any $l \in \mathcal{L}$ for which $\pi_l^A = \pi_l^B$, there exists a continuum of equilibria in the interval $(\frac{\max(Y_{l+1}^A, Y_{l+1}^B)}{N}, \frac{\min(Y_l^A, Y_l^B)}{N}]$ yielding the same approximate payoffs. In addition, boundary strategies $p = \frac{Y_l^x}{N}$ yield equilibria if $\pi_l^A > \pi_l^B$ and $\pi_{l-1}^A < \pi_l^B \; \forall l \in \mathcal{L}$ or $\pi_l^A < \pi_l^B$ and $\pi_l^A > \pi_{l+1}^B \; \forall l \in \mathcal{L}$. These approximate equilibria are *near* NE according to the following definition.

Definition 1 ($\epsilon -$ **NashEquilibrium**): A symmetric mixed strategy p^* is an $\epsilon - NE$ [38] if $\forall n \in \mathcal{N}$ and $\epsilon \geq 0$:

$$U_n^{\mathcal{G}}(p^*, \mathbf{p}_{-n}^*) \geq U_n^{\mathcal{G}}(p, \mathbf{p}_{-n}^*) - \epsilon, \tag{7}$$

In words, the deviation gain from the $\epsilon - NE$ is limited by ϵ which is the magnitude of the difference between the exact and the approximate utility gains resulting from a deviation to $a_n = 1$ or $a_n = 0$. Hence, ϵ is given as:

$$\begin{aligned} \epsilon &= \text{abs}(p^* \Pi^A(N, p^*) + (1-p^*)\Pi^B(N, p^*) \\ &\quad - \Pi^A(N, p^*)) \qquad (8) \\ &= \text{abs}((1-p^*)(\Pi^B(N, p^*) - \Pi^A(N, p^*))). \qquad (9) \end{aligned}$$

Such equilibria have the following properties:

Lemma 2: ϵ approaches 0 as N approaches infinity.

Proof: Assuming a symmetric equilibrium p^* in the middle of the interval $(\frac{Y_{l+1}^x}{N}, \frac{Y_l^x}{N}]$, applying *Chebyshev's inequality* results in the following [39]:

$$Pr(|X - Np^*| \geq \frac{N}{2L}\sqrt{(1-p^*)Np^*}) \leq \frac{4L^2}{N^2}, \tag{10}$$

where Np^* and $\sqrt{(1-p^*)Np^*}$ are the mean and the standard deviation of the binomial random variable X respectively. Hence, for fixed L and p^*, increasing N reduces the probability of X (the actual number of fans choosing $a = 1$) falling outside the range $(\frac{Y_{l+1}^x}{N}, \frac{Y_l^x}{N}]$ which in turn reduces the expected gain from payoffs $\{\pi_1^A, \ldots, \pi_{l-1}^A, \pi_{l+1}^A, \ldots, \pi_L^A\}$ and $\{\pi_1^B, \ldots, \pi_{l-1}^B, \pi_{l+1}^B, \ldots, \pi_L^B\}$ while increasing the gain from the payoffs π_l^A and π_l^B. Thus, the term $\Pi^B(N, p^*) - \Pi^A(N, p^*)$ in (9) diminishes and ϵ approaches zero. ■

Remark 3: It follows from lemma 2 that ϵ is minimized for an equilibrium point in the middle of the interval $(\frac{\max(Y_{l+1}^A, Y_{l+1}^B)}{N}, \frac{\min(Y_l^A, Y_l^B)}{N}]$.

Remark 4: The approximate equilibria above are $ex - post$ $\epsilon - NE$ [26]. That is, no player will revise his action after all actions have been revealed. Hence, the stage game $\epsilon - NE$ is stable.

C. REPEATED GAME MODEL

To sustain cooperative behavior that enforces efficient (QoE maximizing) strategies (not necessarily NE), and since the fans interact over a finite period (the match duration), we propose a finitely repeated game denoted by $\mathcal{G}^R$ wherein each period $t \in \{1, \ldots, N_T\}$, the stage game $\mathcal{G}_t^R$, described in Section III-A, is played and the utility to player n, in the repeated game, is the average utility received over all the periods given by $U_n^{\mathcal{G}^R} = \frac{1}{N_T}\sum_{t=1}^{N_T} U_n^{\mathcal{G}_t^R}(a_n^t, \mathbf{a}_{-n}^t)$. Also, a public signal l^t indicating the QoE level achieved in period t becomes common knowledge at the beginning of period $t+1$, leading to a game of *imperfect monitoring* [40]. Moreover, the strategy vector $s_n = \{a_n^1, \ldots, a_n^{N_T}\}$ represents the action

Algorithm 1 Limited Punishment Strategy

1: **if** $U(p_{NNE})>U(p_{HNE})$ & $U(p_{HNE})>U(p_{LNE})$ **then** %Play $\mathbf{s^{pun}}$
2:   **for** $t \in \{1, \ldots, N_T\}$ **do**
3:     **if** $t = 1$ **then**
4:       $a_n^t \leftarrow p_{NNE}$
5:     **else**
6:       **if** $l^{t-1} < l^{thr}$ **then**
7:         **if** $t > N_T - 2N_{pun}$ **then**
8:           $a_n^{t,\ldots,N_T} \leftarrow p_{LNE}, t \leftarrow N_T$
9:         **else**
10:           $a_n^{t,\ldots,t+N_{pun}-1} \leftarrow p_{LNE}$,
11:           $a_n^{t+N_{pun}} \leftarrow p_{NNE}, t \leftarrow t + N_{pun}$
12:         **end if**
13:       **else**
14:         **if** $t = N_T - N_{pun} + 1$ **then**
15:           $a_n^{t,\ldots,N_T} \leftarrow p_{HNE}, t \leftarrow N_T$
16:         **else**
17:           $a_n^t \leftarrow p_{NNE}$
18:         **end if**
19:       **end if**
20:     **end if**
21:   **end for**
22: **else**
23:   $a_n^{t,\ldots,N_T} \leftarrow p_{HNE}$ %Play $\mathbf{s^{HNE}}$
24: **end if**

plan of player n in the repeated game given all possible histories of play up to any stage t, denoted as $\mathbf{h^t} = \{\mathbf{a^1}, \ldots, \mathbf{a^t}\}$. Finally, the strategy profile of all players in the game is denoted by $\mathbf{s} = \{s_1, \ldots, s_N\}$.

Next, we propose a symmetric strategy $\mathbf{s^{pun}}$, based on a limited punishment described in Algorithm 1, by utilizing the highest and the lowest utility stage game $\epsilon - NE$ strategies p_{HNE} and p_{LNE}, respectively [41]. However, if only a single stage game NE exists or if p_{HNE} yields lower utility than p_{LNE}, (line 1), the trivial strategy of playing p_{HNE} in every period of the game denoted by $\mathbf{s^{HNE}}$ will be adopted instead of $\mathbf{s^{pun}}$ (line 23).

In the first period of $\mathbf{s^{pun}}$ (line 3), all players adopt the cooperative and efficient non-NE mixed strategy p_{NNE}. In the following periods, if the QoE level of the last period (l^{t-1}) falls below a common threshold l^{thr} (the level associated with p_{NNE}) (line 6) a finite punishment is triggered as follows. If the number of remaining periods is more than $2N_{pun}$ (line 7), where N_{pun} is the number of punishment periods, the players will defect from cooperation by selecting p_{LNE} for the next N_{pun} periods (line 10) before returning to play p_{NNE} at $t+N_{pun}$ (line 11). Otherwise, they will play p_{LNE} up to the last period of the game (line 8). In case the threshold is not violated, players will cooperate by choosing p_{NNE} in the current period (line 17) and consider the punishment in the following period as above, except in the last $N_{pun} + 1$ period (line 14), where p_{HNE} is selected until the end of the game (line 15). In addition to the collective punishment of playing p_{LNE}, a deviating player incurs a cost of ρ_{self}, which reflects the fan's negative emotions from cheating the system or the penalties imposed by the CC app. An illustrative example of $\mathbf{s^{pun}}$ is shown in Fig. 2, in which the players cooperate until stage $t = 2$, after which the punishment is triggered until stage $t = 5$. In the last N_{pun} periods, p_{HNE} is played since the users cooperate at $t = N_T - N_{pun}$.

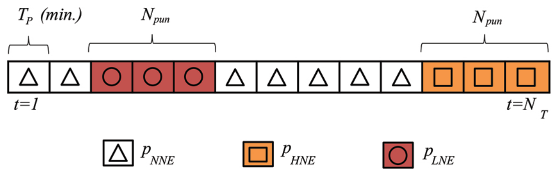

FIGURE 2. $\mathbf{s^{pun}}$ **strategy.**

D. EXISTENCE OF SUB-GAME PERFECT NASH EQUILIBRIA

The strategy profile $\mathbf{s^{pun}}$ described above yields a near sub-game perfect Nash equilibrium ($\epsilon - SPNE$) of $\mathcal{G}^R$ if it constitutes an $\epsilon - NE$ in every sub-game $\mathcal{G}_t^R$ $\forall t \in \{1, \ldots, N_T\}$, the continuation play following each possible history $\mathbf{h^t}$, as in the following theorem [42].

Theorem 5: Strategy profile $\mathbf{s^{pun}}$ constitutes an $\epsilon - SPNE$ of $\mathcal{G}^R$ for sufficiently large ρ_{self} and N_{pun}.

Proof: We first prove, using backward induction, that every sub-game in $\mathcal{G}^R$ forms an $\epsilon - NE$. Starting at $t = N_T - N_{pun} + 1$, for which $N_T \geq N_{pun}$, any sub-game will form an $\epsilon - NE$, since either p_{HNE} or p_{LNE} will be played from $t = N_T - N_{pun} + 1$ to $t = N_T$. Considering the sub-games at the preceding period $t = N_T - N_{pun}$ (if $N_T > N_{pun}$), for all histories ending with $l^{t-1} \geq l^{thr}$ or has all of $l^{t-N_{pun}-1}, \ldots, l^{t-1} < l^{thr}$ (signaling end of

$$U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{NNE}) = p_{NNE}\Pi^A(N, p_{NNE}) + (1 - p_{NNE})\Pi^B(N, p_{NNE}), \tag{11}$$

$$U_n^{\mathcal{G}_t^R}(1, \mathbf{a_{-n}}^{NNE}) = \Pi^A(N, p_{NNE}), \tag{12}$$

$$\mathcal{P}_t^p = Pr(l^t \leq l^{thr}|a_n = p) = \sum_{i=0}^{Y_{l^{th}}^A} \mathcal{X}(N, i, p) \tag{13}$$

$$U_n^{\mathcal{G}_t^R}(1, \mathbf{a_{-n}}^{NNE}) - U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{NNE}) \leq ((1 - \mathcal{P}_t^1)U_n^{\mathcal{G}_{t+1}^R}(\mathbf{a_n}^{LNE}) + \mathcal{P}_t^1 U_n^{\mathcal{G}_{t+1}^R}(\mathbf{a_n}^{HNE}) - (1-\mathcal{P}_t^{p_{NNE}})U_n^{\mathcal{G}_{t+1}^R}(\mathbf{a_n}^{LNE}) - \mathcal{P}_t^{p_{NNE}} U_n^{\mathcal{G}_{t+1}^R}(\mathbf{a_n}^{HNE}))N_{pun} + \rho_{self}, \tag{14}$$

a punishment), playing p_{NNE} is an equilibrium of the continuation play if a unilateral deviation is non-profitable as in the inequality (14), where the payoffs and probabilities are specified in (11) to (13), as shown at the bottom of the previous page. Now, for any history, in which $l^{t-1} < l^{thr}$, at $t = N_T - N_{pun}$, playing the punishment strategy p_{LNE} until the last period is clearly an $\epsilon - NE$. Next, we show that adopting p_{NNE} at $t = N_T - N_{pun} - k$ starting with $k = 1$ ($k < N_T - N_{pun}$) and working recursively until $t = 1$, given the equilibrium play above, is a best response if the conditions (16) and (17), as shown at the bottom of this page, are satisfied for $k > N_{pun}$ and $k \leq N_{pun}$ respectively. Since every sub-game is $\epsilon - NE$, $\mathbf{s^{pun}}$ constitutes an $\epsilon - SPNE$ of $\mathcal{G}^R$ for sufficiently large ρ_{self} and N_{pun}. In these inequalities, $U_n^{\mathcal{G}_t^{Sub}}(\mathbf{a_n}^{\mathbf{NNE}})$ is the expected utility of the sub-game equilibrium starting at period t, given as:

$$U_n^{\mathcal{G}_t^{Sub}}(\mathbf{a_n}^{NNE}) = \begin{cases} \mathcal{I}_1 : & t = N_T - T_{pun} \\ \mathcal{I}_2 : & N_T - 2T_{pun} \leq t < N_T - T_{pun} \\ \mathcal{I}_3 : & 1 \leq t < N_T - 2T_{pun} \end{cases}, \quad (15)$$

where $\mathcal{I}_1$, $\mathcal{I}_2$ and $\mathcal{I}_3$ are expressed (18) to (20), as shown at the bottom of this page. Hence, for a given N_{pun}, there is always a finite value for ρ_{self} that makes the deviations non-profitable and sustain the above equilibrium. This is the maximum value of ρ_{self} that satisfies the inequalities (14), (16) and (17) simultaneously. ■

The simple strategy $\mathbf{s^{HNE}}$ can be easily shown to form an $\epsilon - SPNE$, since a stage game $\epsilon - NE$ is played in every period of the game.

E. IRRATIONALITY AND GAME NOISE

Since the proposed game will be played by humans instead of machines, the CC *app* installed on the fan's device will compute the optimal strategy in each period of the game and implement the randomization of p on behalf of the user. However, mistakes in adopting the equilibrium strategy may still occur due to human error in manually updating the CE status or the irrationality of the user. Specifically, the fan may simply forget to set the recommended CE status at the beginning of each period or may not believe in the optimality of the recommended strategy. We model this error as game noise with a factor of $\eta \in [0, 0.5]$ being symmetric and common knowledge among the fans. When η is combined with strategy p, the expected number of CE devices becomes $pN(1-\eta)+(1-p)\eta N$. That is, the number of players actually selecting $a = 1$ after their realizations of p happens to be $a = 1$, plus erroneous players who were supposed to choose $a = 0$. In turn, the stage game NE in (6) becomes:

$$\pi^A(1, p(N-1)(1-\eta) + (1-p)(N-1)\eta) = \pi^B(0, p(N-1)(1-\eta) + (1-p)(N-1)\eta). \quad (21)$$

Accordingly, the repeated noisy game equilibrium strategies are updated as follows. As for $\mathbf{s}^{HNE}$, the noisy stage game $\epsilon - NE$ with highest utility is played in all periods of the repeated game. In the finite punishment strategy, the cooperative action p_{NNE} is adjusted to $p^{\eta}_{NNE} = (p_{NNE} - \eta)/(1 - 2\eta)$ in order to compensate for the noise η. Thus, playing p^{η}_{NNE} by all players results in the original average CE count of $p_{NNE}N$ despite the noise. However, this entails that p_{NNE} must be greater than η.

F. CONVERGENCE AND COMPLEXITY

The convergence and complexity properties of the proposed game are shown using the following lemmas:

Lemma 6: For arbitrary payoff functions, a stage game symmetric near-Nash equilibrium is guaranteed to emerge following an iterative search over the L QoE levels.

Proof: By iterating through the finite L QoE levels, a continuum of equilibria is obtained for each level where the payoffs of both services are identical. Since the payoffs are identical for $l = 1$ by definition and since $L \leq N$, there will always be a stage game near-Nash equilibrium obtained with a complexity bounded by L. ■

Lemma 7: The repeated game strategy outlined in Algorithm 1 converges in a finite number of iterations.

Proof: According to Lemma 6, the $\mathbf{s^{HNE}}$ strategy is directly obtained from p^{HNE} at no additional computational burden. On the other hand, given the condition in line 2 of Algorithm 1 is satisfied and that ρ_{self} and N_{pun} satisfy the existence property of Theorem 5, playing $\mathbf{s^{pun}}$ requires computing the optimal p^{NNE} by searching all possible values of p starting from the fully cooperative mixed-strategy

$$U_n^{\mathcal{G}_t^R}(1, \mathbf{a_{-n}}^{NNE}) - U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{NNE}) \leq (\mathcal{P}_t^{p_{NNE}} - \mathcal{P}_t^1) U_n^{\mathcal{G}_{t+1}^{Sub}}(\mathbf{a_n}^{NNE}) + (\mathcal{P}_t^{p_{NNE}} - \mathcal{P}_t^1) U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{LNE})(N_T - t) + \rho_{self}, \quad (16)$$

$$U_n^{\mathcal{G}_t^R}(1, \mathbf{a_{-n}}^{NNE}) - U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{NNE}) \leq (\mathcal{P}_t^{p_{NNE}} - \mathcal{P}_t^1)(U_n^{\mathcal{G}_{t+1}^{Sub}}(\mathbf{a_n}^{NNE}) - U_n^{\mathcal{G}_{t+T_{pun}}^{Sub}}(\mathbf{a_n}^{NNE})) + (\mathcal{P}_t^{p_{NNE}} - \mathcal{P}_t^1) U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{LNE}) T_{pun} + \rho_{self}. \quad (17)$$

$$\mathcal{I}_1 = U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{NNE}) + (\mathcal{P}_t^{p_{NNE}} U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{HNE}) + (1 - \mathcal{P}_t^{p_{NNE}}) U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{LNE})) T_{pun}, \quad (18)$$

$$\mathcal{I}_2 = U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{NNE}) + \mathcal{P}_t^{p_{NNE}} U_n^{\mathcal{G}_{t+1}^{Sub}}(\mathbf{a_n}^{NNE}) + ((1 - \mathcal{P}_t^{p_{NNE}}) U_n^{\mathcal{G}_{t+1}^{Sub}}(\mathbf{a_n}^{LNE}))(N_T - t), \quad (19)$$

$$\mathcal{I}_3 = U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{NNE}) + ((Pr(l^t \leq l^{thr} | a_n = p_{NNE})(U_n^{\mathcal{G}_{t+1}^{Sub}}(\mathbf{a_n}^{NNE}) - U_n^{\mathcal{G}_{t+T_{pun}}^{Sub}}(\mathbf{a_n}^{NNE})) + (Pr(l^t > l^{thr} | a_n = p_{NNE}) U_n^{\mathcal{G}_t^R}(\mathbf{a_n}^{LNE})) T_{pun}. \quad (20)$$

TABLE 2. Network parameters.

N^F	100,000	L	7
O	4	τ	0.2
T_M	100 mins	Υ	0.6
N_T	25	η	0.1
N_{pun}	4	ρ_{self}	3
$\mathcal{C}$	300 Mpbs	y_{min}^{P2P}	$0.02N^U$
$\mathcal{T}^{P2P}$	20 ms		

$p = y_{min}^{P2P}/N$ to the value associated with l^{thr}. The optimal value that satisfies equations (14), (16), and (17) simultaneously yields p^{NNE}. Since computing this value is bounded by N, Algorithm 1 converges in a finite number of steps bounded by $N_T N$. ■

G. UNIQUENESS OF THE GAME EQUILIBRIUM

Apparently, the proposed game can enforce multiple $\epsilon - SPNE$ equilibria. This is generally not preferred, since the players may not agree on a single equilibrium. However, since the smartphone *app* will compute the most efficient equilibrium on behalf of the fans, the *app* can be programmed to search for a unique optimal strategy then instruct each fan on the best response action in each period of the game.

IV. NUMERICAL EVALUATION

The proposed solution (CC) was jointly simulated using MATLAB and OMNET++. First, an LTE cellular network scenario was created using SimuLTE, an extension of OMNET++, to obtain the QoE-QoS model shown in Table 3. Specifically, for each application category (QoE level l), a test user adopts this level by receiving the application packets generated at a server connected to the single eNodeB base station. All the other users are made to request constant traffic from the server being packets of size 500 bytes at intervals of 0.002s. These are mean values in a typical cellular network. The number of active users (except the test user) is then incremented from 0 to the maximum value and the test user's application performance (throughput and latency) is compared against the threshold values for each level to determine the maximum CE users Y_l^x. The parameters were specified to simulate a 20 MHz LTE network with 100 resource blocks (RB) in the downlink, a Round Robin scheduling policy, and a 4X4 MIMO yielding a cell capacity of 300 Mbps. The remaining parameters were set to the SimuLTE default settings. The fans were divided into 20 seating areas each being a square of size $20 \times 20\ m^2$ with an LTE small cell

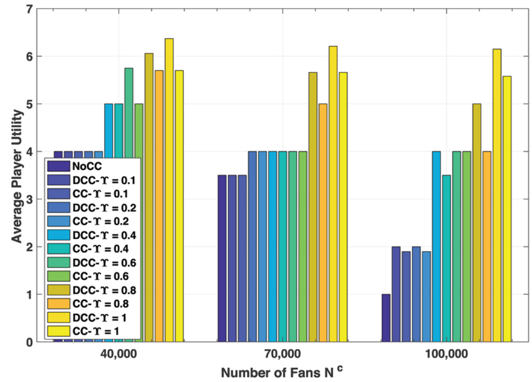

FIGURE 3. Average player utility vs. number of fans.

positioned in the middle of the square at a height of $20m$. Due to the limited computational resources and capabilities of the simulator, we have only simulated a single area then multiplied the outcome by the total number of areas.

Using the obtained QoE model, a MATLAB simulation was then performed to evaluate the performance of the proposed game solution (CC) that implements Algorithm 1 above. In addition, two benchmarks were simulated: (1) a centralized version of CC with dedicated players (DCC), in which the fans always fulfil the network optimal CE frequency, and (2) NoCC, the situation without CC being deployed. Since DAS, HD-WiFi and COW works through capacity enrichment and given that CC is not intended to replace the aforementioned techniques, we opted not include them in the comparisons. Without loss of generality, we assumed the QoE payoff vectors π^A and π^B in Table 3, where $Service - B$ yields higher payoffs at lower data rates, as most of the proposed in-match applications are text-based. Unless specified otherwise, the game parameters listed in Table 2 were used in all simulation scenarios, which were averaged over 1000 iterations.

Figures 3, 4, and 5 depict the performance of the above schemes for different number of fans and CC participants in terms of average user utility, average peak throughput, and CE percentage. In all schemes, the average QoE drops with more attendees and CC participants in the case of CC and DCC, where non-CC fans are assumed to continuously enable cellular data. It is seen that CC and DCC yield higher QoE levels (utility) than NoCC when $\Upsilon \geq 0.2$ or when the stadium is fully occupied, in which case the gain ranges from 100% to 600% as the degree of participation increases from

TABLE 3. QoE-QoS model.

l	Service A	Service B	Min. Throughput	Max. Latency	π_l^A	π_l^B	Y_l^x
1	No Service	No Service	0 Kbps	∞	0	0	>5000
2	Messaging	Statistics	30 Kbps	500 ms	1	2	5000
3	Low Quality VoIP	Low Quality Commentary	64 Kbps	150 ms	3.5	3.5	3750
4	High Quality VoIP	High Quality Commentary	80 Kbps	50 ms	4	4	3100
5	Browsing	Match Photos	200 Kbps	1s	5	5	1350
6	SD Video	SD Replays	300 Kbps	5 s	7	5.6	1000
7	HD Video	HD Replays	1 Mbps	4 s	9	6	250

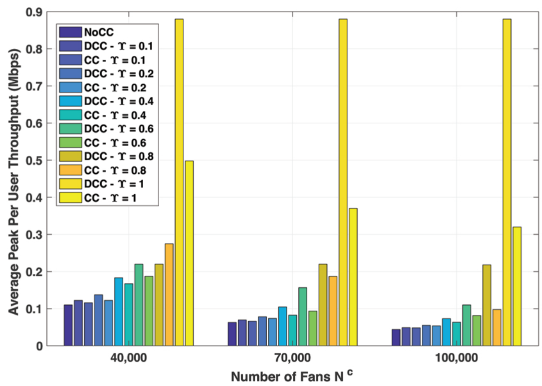

FIGURE 4. Average throughput vs. number of fans.

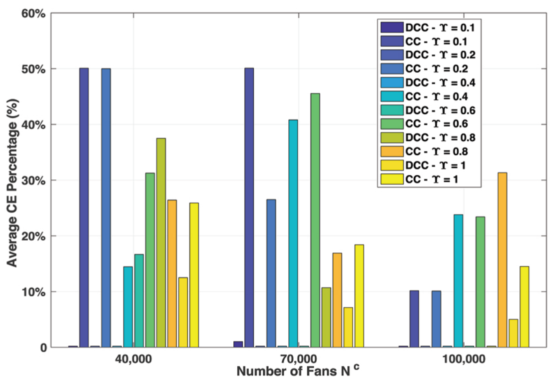

FIGURE 5. Average CE percentage vs. number of fans.

0.1 to 1. This gain is realized through the increase in peak throughput which in turn demands for lower CE percentages compared to NoCC. It is also observed that DCC outperforms CC in average player utility by enforcing an optimal combination of CE percentage and throughput that maximizes the utility while assuming users always agree on this optimal CE percentage. Conversely, CC only permits the values that constitute Nash equilibria. Besides, CC suffers from game noise which limits the minimum possible CE percentage p_{NNE} as pointed out in Section III-E. This QoE degradation is more obvious with higher number of fans and participation levels. As such, DCC generally entails higher throughput and lower CE percentage (higher cooperation) than CC, but may occasionally select lower throughput/higher CE percentage values that achieve the highest utility, as indicated by the scenario $N^c = 40,000$ and $\Upsilon = 0.8$.

In Fig. 6, the average per-user traffic, downloaded over the course of the match, is computed for different occupancy and participation levels. In terms of aggregate traffic, CC always outperforms NoCC, particularly at high occupancy and participation levels. However, CC trades-off Internet traffic ($Service - A$) for $Service - B$ coverage, such that the overall user's experience is enhanced. For example, an average of 60 MB per user traffic is achieved in a full stadium with 60% participation rate compared to 30 MB in the case of NoCC. However, only 15 MB of CC traffic is due to Internet access, while the rest is obtained as in-match data.

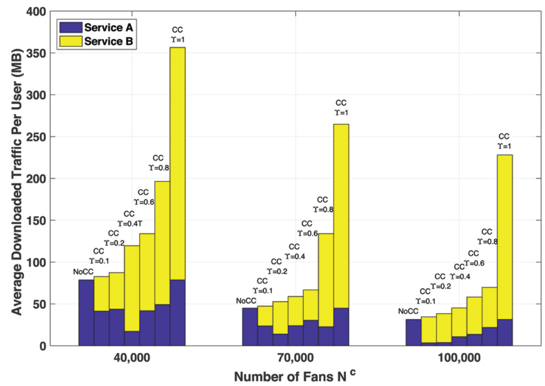

FIGURE 6. Downloaded traffic vs. number of fans.

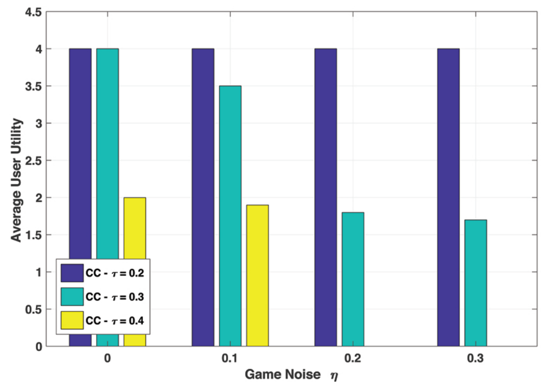

FIGURE 7. Average utility vs. game noise.

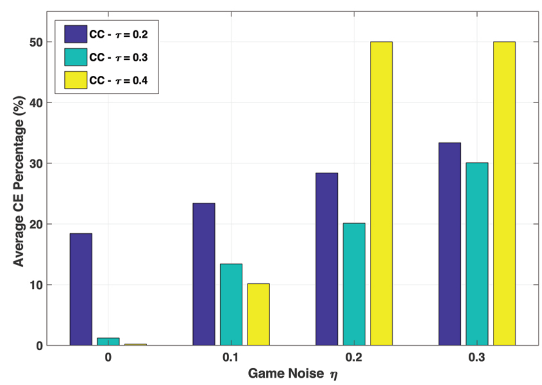

FIGURE 8. Average CE percentage vs. game noise.

The effect of varying the game noise on the performance of CC is illustrated in figures 7 and 8 for different values of τ. At low traffic ($\tau = 0.2$), the noise has no significant effect on the utility but results in higher CE ratios. By increasing τ, the QoE sharply falls with the noise factor since the required CE percentages can no longer be supported.

Next, the impact of the number of simultaneous connections is depicted in figures 10 and 11. Increasing τ demonstrates the effectiveness of CC and DCC over NoCC under a highly constrained network scenario. Particularly, CC brings

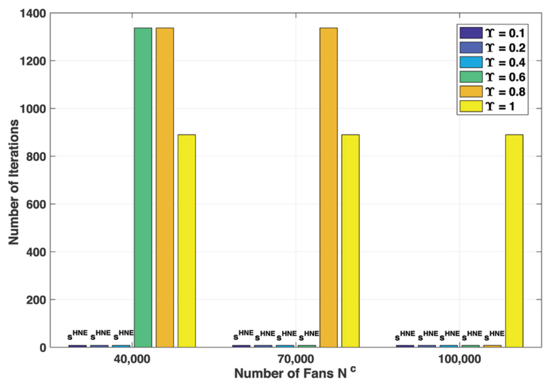

FIGURE 9. Number of iterations vs. number of fans.

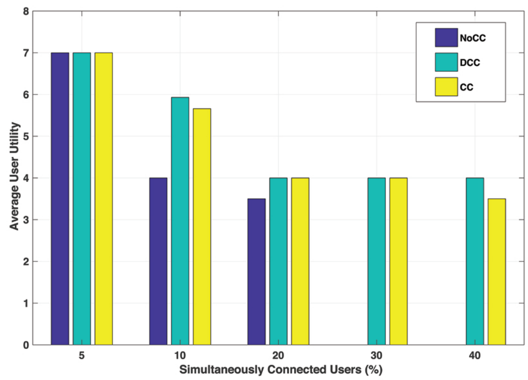

FIGURE 10. Average utility vs. simultaneous users.

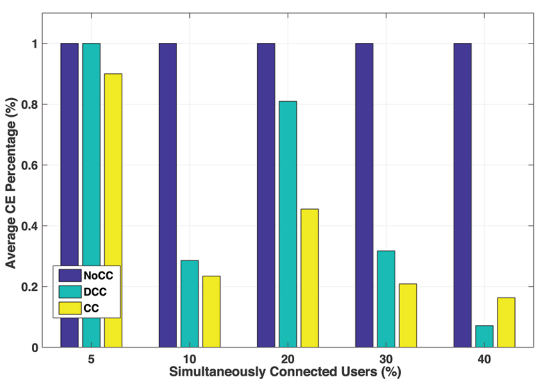

FIGURE 11. Average CE percentage vs. simultaneous users.

an average QoE of 4 whereas NoCC yields a virtually non-functional cellular network when τ is 0.3 or above.

In Fig. 9, we examine the convergence performance of the proposed solution for different N^c and Υ values. Apparently, $\mathbf{s^{pun}}$ requires much more iterations than $\mathbf{s^{HNE}}$. It is also seen that $\mathbf{s^{pun}}$ requires higher Υ values as the number of fans increases since higher QoE levels $l > 5$ can be achieved with p^{NNE}. This additional complexity is justified by the increased utility as depicted in Fig. 3. It is also noteworthy that the proposed strategy can be computed prior to the start of the football match since the number of fans, cellular capacity, percentage of CC users, usage patterns, and the rest of the the parameters can be predicted in advance.

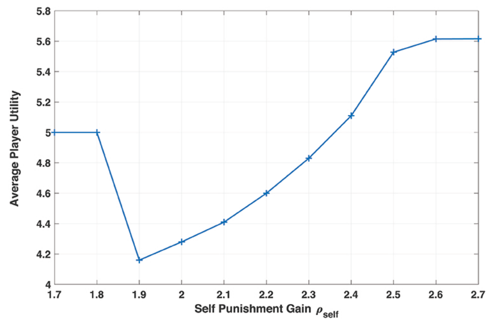

FIGURE 12. Average utility vs. self-punishment gain.

Fig. 12 shows the effect of varying the self punishment gain ρ_{self} on the performance of CC given $N^F = 70,000$, $\eta = 0$, and $\Upsilon = 0.8$. Because the values 1.7 and 1.8 are too low to sustain an $\epsilon - SPNE$ for $\mathbf{s^{pun}}$, strategy $\mathbf{s^{HNE}}$ is played yielding a utility of 5 in every period of the game. Although the value 1.8 sustains an equilibrium for $\mathbf{s^{pun}}$, it requires p_{NNE} to be very close to the threshold value, increasing the probability of triggering the punishment and hence reducing the expected utility. As ρ_{self} is increased, p_{NNE} can be shifted away from l^{thr}, which explains the gradual improvement in utility.

Finally, the advantages of adopting CC were demonstrated under a real match scenario, whereby the match duration is divided into periods with different game and network parameters as shown in Table 4. Each match period was simulated as a separate repeated game with different number of periods. For instance, ''Crowds In'' represents the 30 minutes prior to kick-off, in which the crowds are filling up the stadium seats with an average of 60% occupancy. At this time, more fans will be using their phones, as the game has not yet started, and the game noise will be relatively low. In contrast, during injury time, the stadium is nearly full but τ is low since the fans are more engaged with the more important match events. However, this will induce more errors explaining the high value of η. In general, CC is seen to maintain an average QoE of 4 throughout the event, whereas the cellular network may be occasionally useless in the absence of CC.

V. DISCUSSION

A. EFFECTS OF NON-CC USERS

In the proposed scenario, the non-CC users, omitted from the set of players, are those fans who have not been introduced to the CC *app* nor had the chance to install it before attending the event. Interestingly, those users will experience the same *Service−A* improvement brought by CC while being continuously connected to cellular data. This may seem to discourage participation in CC. However, once a fan is introduced to the CC app, he becomes part of the coordination game and hence participating in the scheme while adopting the equilibrium play will be the rational choice, noting that irrational decisions are accounted for by the game noise discussed above.

TABLE 4. NoCC vs. CC in a match scenario.

Match Period	N^C	$N_T T_P$	τ	η	U^{NoCC}	U^{CC}	$\mathcal{C}^{A^{NoCC}}$ Kbps	$\mathcal{C}^{A^{CC}}$ Kbps	p^{CC}
Crowds In	60K	30	0.3	0.1	1	4	49	85	0.29
First 5 mins	80K	5	0.3	0.1	0	4	36.6	75	0.15
First Half	100K	35	0.2	0.2	1	4	44	77	0.28
Injury Time	90K	5	0.1	0.4	4	4	100	140	0.5
Break	60K	15	0.4	0.1	0	4	37	75	0.15
First 5 mins	90K	5	0.3	0.1	0	3.5	33	64	0.18
Second half	100K	35	0.2	0.2	1	4	44	77	0.284
Injury Time	80K	5	0.05	0.3	7	6.4	220	290	0.6
Crowds Out	50K	10	0.4	0.1	1	4	44	81	0.234
Average					1.66	4.06	67	87	0.278

Therefore, the success of the proposed solution will highly depend on the effectiveness of the accompanying marketing strategy.

On the other hand, the non-CC users negatively affect the performance of CC as they continuously connect to the cellular network leaving CC users with a smaller margin for cooperation as the peak instantaneous per-user capacity will be approximately $\mathcal{C}/(N^O - N^U)$. Meanwhile, the non-CC users degrades $Service - B$ in two ways. In one aspect, the more non-CC users the more segmented the P2P network will be. In another aspect, the non-CC users may cause interference to the P2P network when they join other WiFi/Bluetooth networks. In the above analysis, the former issue has been accounted for by assuming a minimum threshold on the number CC fans above which the P2P can be assumed fully connected. However, P2P interference have not been considered as a detailed P2P network is left for future research. However, this interference may be considered insignificant.

B. ACCURACY OF THE PROPOSED QOE-QOS MODEL

The payoff values and number of levels in Table 3 were arbitrarily selected to demonstrate the proposed game equilibria, whereas the QoS requirements were obtained from specification documents of service providers as well as literature on QoS measurements, such as [43] and [44]. More realistic payoff values can be obtained from Mean Opinion Score (MOS) measurements as described in [16] and references therein. The fans' preferences over the services were assumed to be identical, which may not be the case in reality. However, since the player's contribution is negligible in the large game, the average user preference and hence the average payoff has been adopted.

VI. CONCLUSION

In this paper, a novel strategy to leverage QoE gains in capacity-limited wireless networks was analyzed using the theory of large games. It was shown through realistic simulations that the proposed technique can significantly improve the average QoE over the football match duration only when a significant proportion of the fans adopt the scheme. The proposed solution has shown tolerance against moderate noise in the adopted symmetric strategy demonstrating the practicality of the solution. It is noteworthy that CC can co-exist with DAS, HD-WiFi, the upcoming 5G system, or even InCrowd, to achieve further QoE gains. It is also important to emphasize that the proposed game is not limited to the proposed QoE-QoS model. Besides sports stadia, the proposed technique can be applied to other dense and capacity limited scenarios, such as music halls and shopping mall after tuning the game parameters and the QoE model appropriately. Despite the promising results shown in the simulations, an actual implementation of CC using smartphones is necessary to verify its feasibility though this is a cumbersome task which may be considered in future work.

REFERENCES

[1] T. Sakano, Z. M. Fadlullah, T. Ngo, H. Nishiyama, M. Nakazawa, F. Adachi, N. Kato, A. Takahara, T. Kumagai, H. Kasahara, and S. Kurihara, ''Disaster-resilient networking: A new vision based on movable and deployable resource units,'' *IEEE Netw.*, vol. 27, no. 4, pp. 40–46, Jul. 2013.

[2] A. K. Bairagi, S. F. Abedin, N. H. Tran, D. Niyato, and C. S. Hong, ''QoE-enabled unlicensed spectrum sharing in 5G: A game-theoretic approach,'' *IEEE Access*, vol. 6, pp. 50538–50554, 2018.

[3] M. S. Bahbahani, M. W. Baidas, and E. Alsusa, ''A distributed political coalition formation framework for multi-relay selection in cooperative wireless networks,'' *IEEE Trans. Wireless Commun.*, vol. 14, no. 12, pp. 6869–6882, Dec. 2015.

[4] D. Calin, A. Ö. Kaya, B. H. Kim, K. Yang, and S. Yiu, ''On the high capacity lightradio metro cell design for stadiums,'' *Bell Labs Tech. J.*, vol. 18, no. 2, pp. 77–97, Sep. 2013.

[5] A. Ö. Kaya, D. Calin, and H. Viswanathan, ''On the performance of stadium high density carrier Wi-Fi enabled LTE small cell deployments,'' in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, New Orleans, LA, USA, Mar. 2015, pp. 855–860.

[6] G.-Y. Lin, S.-R. Chang, and H.-Y. Wei, ''Estimation and adaptation for bursty LTE random access,'' *IEEE Trans. Veh. Technol.*, vol. 65, no. 4, pp. 2560–2577, Apr. 2016.

[7] V. Kulkarni, S. Tripathi, and A. Kumar, *LTE E-UTRAN and Its Access Side Protocols*. Hillsboro, OR, USA: Radisys, 2011.

[8] L. Rabieekenari, K. Sayrafian, and J. S. Baras, ''Autonomous relocation strategies for cells on wheels in environments with prohibited areas,'' in *Proc. IEEE Int. Commun. Conf. (ICC)*, Paris, France, May 2017, pp. 1–6.

[9] M. N. Islam, S. Subramanian, A. Partyka, and A. Sampath, ''Coverage and capacity of 28 GHz band in indoor stadiums,'' in *Proc. IEEE Wireless Commun. Netw. Conf.*, Doha, Qatar, Apr. 2016, pp. 1–7.

[10] Y. Li and J. Zhang, ''Hot-spot wireless access exploiting shadowing diversity of distributed antennas,'' in *Proc. IEEE Int. Symp. Broadband Multimedia Syst. Broadcast.*, Mar./Apr. 2008, pp. 1–5.

[11] *Cisco StadiumVision*. Cisco Syst. Inc., San Jose, CA, USA, 2013. [Online]. Available: http://www.cisco.com/c/en/us/products/video/stadiumvision/index.html

[12] FINALOGIC Business Technologies AG. *FanPlay*. Accessed: Apr. 18, 2018. [Online]. Available: https://www.fanplay.eu/index.html

[13] *TibeHive Connect—InCrowd Sports*. Accessed: Jul. 29, 2019. [Online]. Available: https://incrowdsports.com/wp-content/uploads/2016/11/InCrowd-TribeHive-Connect-Explanation.pdf
[14] S.-S. Kang and M. W. Mutka, "A mobile peer-to-peer approach for multimedia content sharing using 3G/WLAN dual mode channels," *Wireless Commun. Mobile Comput.*, vol. 5, no. 6, pp. 633–645, Sep. 2005.
[15] T. Zhao, Q. Liu, and C. W. Chen, "QoE in video transmission: A user experience-driven strategy," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 1, pp. 285–302, 1st Quart., 2017.
[16] M. Yang, S. Wang, R. N. Calheiros, and F. Yang, "Survey on QoE assessment approach for network service," *IEEE Access*, vol. 6, pp. 48374–48390, 2018.
[17] U. Engelke, D. P. Darcy, G. H. Mulliken, S. Bosse, M. G. Martini, S. Arndt, J. Antons, K. Y. Chan, N. Ramzan, and K. Brunnström, "Psychophysiology-based QoE assessment: A survey," *IEEE J. Sel. Topics Signal Process.*, vol. 11, no. 1, pp. 6–21, Feb. 2017.
[18] Y. Chen, K. Wu, and Q. Zhang, "From QoS to QoE: A tutorial on video quality assessment," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 2, pp. 1126–1165, 2nd Quart., 2015.
[19] J. Nightingale, J. M. A. Calero, Q. Wang, and P. Salva-Garcia, "5G-QoE: QoE modelling for ultra-HD video streaming in 5G networks," *IEEE Trans. Broadcast.*, vol. 64, no. 2, pp. 621–634, Jun. 2018.
[20] P. Juluri, V. Tamarapalli, and D. Medhi, "Measurement of quality of experience of video-on-demand services: A survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 1, pp. 401–418, 1st Quart., 2016.
[21] S. Jelassi, G. Rubino, H. Melvin, H. Youssef, and G. Pujolle, "Quality of experience of VoIP service: A survey of assessment approaches and open issues," *IEEE Commun. Surveys Tuts.*, vol. 14, no. 2, pp. 491–513, 2nd Quart., 2012.
[22] Z. Du, Q. Wu, P. Yang, Y. Xu, J. Wang, and Y.-D. Yao, "Exploiting user demand diversity in heterogeneous wireless networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 8, pp. 4142–4155, Aug. 2015.
[23] E. H. Watanabe, D. S. Menasche, E. de Souza e Silva, and R. M. M. Leao, "Modeling resource sharing dynamics of VoIP users over a WLAN using a game-theoretic approach," in *Proc. IEEE 27th Conf. Comput. Commun. INFOCOM*, Phoenix, AZ, USA, Apr. 2008, pp. 915–923.
[24] C. Buragohain, D. Agrawal, and S. Suri, "A game theoretic framework for incentives in P2P systems," in *Proc. 3rd Int. Conf. Peer-Peer Comput. (P2P)*, Sep. 2003, pp. 48–56.
[25] V. Srivastava and L. A. DaSilva, "Equilibria for node participation in ad hoc networks—An imperfect monitoring approach," in *Proc. IEEE Int. Conf. Commun.*, Istanbul, Turkey, vol. 8, Jun. 2006, pp. 3850–3855.
[26] H. Yu, M. A. Khan, K. P. Rath, and Y. Sun, "Strategic uncertainty and the ex post Nash property in large games," *Theor. Econ.*, vol. 10, no. 1, pp. 103–129, 2015.
[27] M. A. Khan and Y. Sun, "Non-cooperative games with many players," in *Handbook of Game Theory with Economic Applications*, vol. 3, R. Aumann and S. Hart, Eds. Amsterdam, The Netherlands: Elsevier, 2002, ch. 46, pp. 1761–1808. [Online]. Available: https://ideas.repec.org/h/eee/gamchp/3-46.html
[28] M. S. Bahbahani and E. Alsusa, "CrowdConnect: A quality of experience enhancement solution for dense stadium networks," in *Proc. IEEE Global Commun. Conf. (Globecom)*, Dec. 2018, pp. 1–7.
[29] B. Cohen. (May 2013). *Incentives Build Robustness in BitTorrent*. [Online]. Available: http://bittorrent.org/bittorrentecon.pdf
[30] M. Mäs and H. H. Nax, "A behavioral study of 'noise' in coordination games," *J. Econ. Theory*, vol. 162, pp. 195–208, Mar. 2016.
[31] A. Varga and R. Hornig, "An overview of the OMNeT++ simulation environment," in *Proc. 1st Int. Conf. Simulation Tools Techn. Commun., Netw. Syst. Workshops (Simutools)*, 2008, pp. 60-1–60-10.
[32] T. Ören, M. S. Obaidat, J. Kacprzyk, and J. Filipe, *Simulation and Modeling Methodologies, Technologies and Applications*, vol. 402. Springer, 2016, pp. 83–105.
[33] D. Camps-Mur, A. Garcia-Saavedra, and P. Serrano, "Device-to-device communications with Wi-Fi Direct: Overview and experimentation," *IEEE Wireless Commun.*, vol. 20, no. 3, pp. 96–104, Jun. 2013.
[34] F. Mazzenga, D. Cassioli, A. Detti, I. Habib, P. Loreti, and F. Vatalaro, "Performance evaluation in Bluetooth dense piconet areas," *IEEE Trans. Wireless Commun.*, vol. 3, no. 6, pp. 2362–2373, Nov. 2004.
[35] Q. Gong, Y. Guo, Y. Chen, Y. Liu, and F. Xie, "Design and evaluation of a WiFi-direct based LTE cooperative video streaming system," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2016, pp. 1–6.
[36] Y. Chen, T. R. Farley, and N. Ye, "QoS requirements of network applications on the Internet," *Inf.-Knowl.-Syst. Manage.*, vol. 4, pp. 55–76, 2004.
[37] Y. Vorobeychik, S.-F. Cheng, D. M. Reeves, and M. P. Wellman, "Notes on equilibria in symmetric games," in *Proc. 6th Int. Workshop Game Theoretic Decis. Theoretic Agents GTDT*, 2004, pp. 71–78.
[38] E. Cartwright, "Learning to play approximate Nash equilibria in games with many players," Milan, Italy, FEEM Working Paper 85.04, May 2004.
[39] G. Alsmeyer, *Chebyshev's Inequality*. Berlin, Germany: Springer, 2011, pp. 239–240.
[40] A. K. Charles, N. Pissinou, A. Busovaca, and K. Makki, "Belief-free equilibrium of packet forwarding game in ad hoc networks under imperfect monitoring," in *Proc. 29th Int. Perform. Comput. Commun. Conf.*, Albuquerque, NM, USA, Dec. 2010, pp. 315–324.
[41] M. J. Osborne, *An Introduction to Game Theory*. New York, NY, USA: Oxford Univ. Press, 2004.
[42] J. Flesch and A. Predtetchinski, "On refinements of subgame perfect ϵ-equilibrium," *Int. J. Game Theory*, vol. 45, no. 3, pp. 523–542, Aug. 2016.
[43] Y. Chen, T. R. Farley, and N. Ye, "QoS requirements of network applications on the Internet," *Inf., Knowl., Syst. Manage.*, vol. 4, no. 1, pp. 55–76, 2004.
[44] *RF Design for the Mobile Devices Explosion*, Cisco Syst. Inc., San Jose, CA, USA, 2013. [Online]. Available: https://www.cisco.com/c/dam/global/cs_cz/assets/ciscoconnect/2013/pdf/T-VT1-HighDensity-RF-design-Alex_Zaytsev.pdf

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