Game-Theoretic Power Control for Energy Constrained Machine Type Communications

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***Abstract*—Machine type communications (MTC) unleashes a broad range of applications ranging from mission-critical services to massively connected autonomous nodes. The cellular systems will help in enabling such nodes to play a critical role in future networks. A coexisting cellular scenario for traditional and MTC devices is considered and the need for an energy efficient power control mechanism for MTC nodes is investigated. Reliability is a major requirement for MTC devices (MTCDs) which is the prime utility to be considered along with the power consumed by each user device. For a dense network environment, the MTC power control problem is modeled as a mean field game (MFG) and system utility is modeled in terms of the interference and reliability condition. The proposed MFG is solved using the finite difference method to obtain an optimal power control policy for MTCDs. Simulation results identify the considered scheme a low complexity alternative for a transmit power control mechanism for MTC devices in the coexisting network.**

***Index Terms*—machine type communications, game theory, mean field games, power control, cellular MTC.**

I. Introduction

THE development of next-generation cellular networks has seen a rapid expansion from new algorithms to modified network architectures in the recent past. This has largely been driven by the emergence of new user requirements and use cases as defined by ITU-R [1]. Fifth generation (5G) networks must meet new challenges in terms user capacity, increased costs, energy starvation and dense network deployments due to diverse service demands. MTC emphasizes a communication paradigm with user devices producing, exchanging and analyzing data without any human intervention. MTC can be categorized based on application requirements as either massive MTC (mMTC) or ultra-reliable low latency MTC (uRLLC) [2]. mMTC usually requires a larger user base consisting of low-complexity as well as having low power requirements with a varying quality of service (QoS). Some examples include smart agriculture, surveillance systems, smart metering, sensor networks, and remote control & diagnostics [3]. On the other hand, uRLLC devices are very sensitive to transmission delays and require high reliability with moderate service rates. Remote healthcare, traffic management, autonomous vehicles/drones, and automated cyber-physical systems are some examples of uRLLC device scenarios [3].

MTCDs are expected to reach numbers of 4.1 billion by 2024 presenting a huge potential for research, development and understanding of MTC traffic in future networks. Efficient resource management is critical to accommodate the huge influx of new devices into the network. A distributed resource management approach will be more suitable for a massive number of users to avoid overloading the network in terms of traffic as well as processing demands. Each user device will be responsible to select its own resource based on the available resource pool considering the spectrum and energy efficiency, which are important design parameters in MTC design. Prime considerations while designing a distributed approach include the ability to handle random deployment of devices, scalability, minimal signaling overhead, limited energy supply to devices, inhomogeneity amongst devices and uncertainty as well as incompleteness of information available about these devices.

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The need for a coexisting network framework is becoming a reality with the evolution of services offered to the cellular subscribers. In this context, the primary aim of traditional human type communication (HTC) devices is to improve data throughput due to increasingly data consuming services like telepresence, HD video and virtual reality services. A highly energy and spectrally efficient service architecture is required to enable user devices for improved data rates. Similarly, different classes of MTC devices have diverse service requirements as described with power consumption minimization having prime importance. Remote sensing MTCDs require efficient design and control of power consumption to enhance life expectancy and operational time. The lack of a recharging infrastructure for MTCDs makes the energy efficient design of a transmit power control mechanism for these devices is an area worth studying to cope with the growing demands of future wireless networks.

Mean field game (MFG) is proposed as a candidate approach for an energy efficient power control scheme for MTC networks. The concept of the mean field for MTC power control networks is explored and power consumption along with reliability is considered for multi-dimensional state dynamics of users. Mean field existence for a dense MTC environment is only viable if the MTCDs meet certain conditions [5]. Hamilton-Jacobi-Bellman (HJB) and Fokker-Planck-Kolmogorov (FPK) equations for our proposed game design are formulated and then solved using a finite difference technique [6]. The contributions of this paper can be summarized as follows:

- Interference and power consumption modeling for a coexisting HTC and MTC is performed for MTC nodes.
- A mean field game framework for MTC network is formulated successfully with an ability to handle a massive number of nodes.
- Energy and interference aware state dynamics is proposed for the MFG along with the design of the utility function to complement the proposed framework.

- A solution to the proposed MFG framework is proposed using the finite difference method. Lax-Freidrichs technique is utilized to solve the coupled FPK and HJB equations.
- Performance analysis of the proposed power control policy using MFG is done and energy consumption analysis is performed.

The structure of the remaining paper is described as follows. In Section II, a survey of the related works is done. In Section III, a system model is formulated for the coexisting HTC/MTC network and state space modeling is performed. In Section IV, a mean field game is formulated for obtaining an optimal power control policy for energy efficient transmit power allocation design for MTCDs. An iterative algorithm for achieving a converged solution to formulated MFG is proposed and game equilibrium conditions are discussed. In Section V, simulations and numerical analysis of the proposed power control design are performed.

II. Related Work

Provision of scalable connectivity, as well as a scheduling design which is also energy efficient, is a key requirement for efficient operation of MTCDs in cellular networks. Network congestion is most likely to occur when a large number of MTCDs try to seek access to BS simultaneously. MTC metric measure considered in previous works include delay, throughput, transmit power, and impact on QoS of HTC devices. Energy efficiency of machine-to-machine (M2M) communications over LTE networks has been studied in [7], where it is shown that the LTE physical layer is not suitable for an energy efficient design. Investigation of a power-efficient uplink scheduler design for delay-sensitive traffic over LTE systems has been done in [8], where the considered delay models and traffic characteristics are not applicable to MTCDs.

The concept of the game theory is explored to overcome the scalability issue due to a massive influx of new devices in future networks. In [9], a user-centric hierarchal game theory model for optimal resource allocation for users in a heterogeneous network is proposed. Similarly [10-12] propose optimal power allocation schemes for maximizing user utilities by using game theory approach for two-tier femtocell networks, ultra-dense networks, and NOMA networks. A distributed power control mechanism is proposed in [13] for device-to-device (D2D) links in an underlaying cellular network for interference coordination. Additional power is allocated to some D2D transmitters depending on experienced interference from other D2D and cellular links. A Nash equilibrium (NE) power control strategy is designed for each D2D link to ensure interference minimization. However, due to the large influx of users expected in the future generation networks, utility function modeling as well as acquiring a stable equilibrium state for all users with limited iterations becomes extensively difficult. Hence, advanced game theory models are necessary in which the convergence and equilibrium is independent of the player numbers (e.g. mean field game).

Mean field game (MFG) is an advanced concept as a potential alternative to conventional games, e.g., NE based non-cooperative games or evolutionary games. In MFG framework, the concept of mean field is defined which characterize the space-time dynamics of context, i.e. a player can make an optimal decision by only responding to the mean field, instead of strategies of all other players. MFG based decision making is intrinsically distributed thereby reducing signaling overhead associated with information acquisition and control in a centralized approach [14], [15]. MFG become more useful for a large set of players because mean field value approaches a real value with an increasing number of players [16], [17]. MFG can be thought of as a special form of the differential game suitable for a system with many players. This makes the application of mean field concept in the context of a massive MTC infrastructure a viable choice. In wireless networks, several efforts have focused on the application of MFG theory for the optimizing energy efficiency [18] as well as medium access control of devices [19].

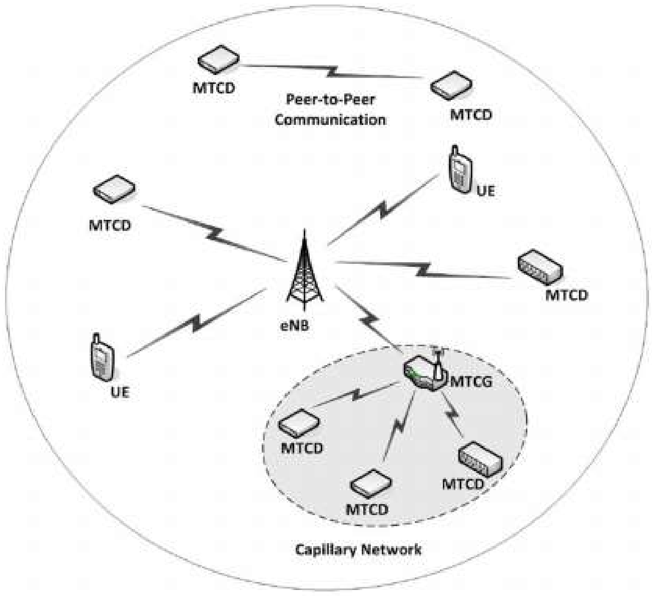

Fig. 1. An MTC/HTC hybrid scenario.

III. System Model

Consider a single cell, multi-user MTC/HTC coexistence scenario with a base station (BS) at its center and a massive number of MTCDs, which are randomly distributed according to a Poisson point process (PPP) as shown in Fig. 1. MTC devices are battery driven with primary design objective being the longevity of battery life with diverse application requirements as already discussed. Assume that a total of N users are present in the coverage area of BS. Consider J conventional HTC and K MTC devices are now present in the coverage area of the network. To ensure low latency and delay communication, uRLLC nodes are connected directly to a BS. A clustered approach is an energy efficient alternative in which mMTC devices are grouped to counter congestion and reduce the load on BS. An MTC gateway (MTCG) collects data from clustered mMTC devices and communicates with BS to provide access to all clustered nodes as depicted in Fig. 1.

Choice of a combined access protocol based on a typical time-frequency resource division is considered using the different demand requirements of HTC and MTC (mMTC or uRLLC) devices. As already discussed, mMTC devices will be served via an MTCG to avoid access network overload and resource depletion. Consider an m_{th} mMTC device has b_m data bits to be transmitted within a time period T_i. MTCG being a mMTC node also has a minimum rate requirement of b_h bits. Transmission times allocated to mMTC and MTCG are denoted respectively as t_m and t_h. MTCDs traffic is relayed using a decode-and-forward (DF) protocol in the proposed clustering design. uRLLC devices are served as stand-alone entities and allocation of uplink resource is done directly ensuring reliability condition and minimum delay.

A. Hybrid Interference Model

A combined interaction model is considered to model the experienced interference by both HTC and MTC users in a hybrid environment. Inter-domain interference is considered between HTC and MTC nodes whereas intra-domain as the interference between MTC or HTC devices amongst each other. Inter-MTC is responsible for interference to HTC devices in a hybrid environment and vice versa. This inter-domain interference is modeled as an interaction between uRLLC nodes and HTC nodes as well as possible MTC nodes acting as MTCGs for relaying operations. This interference composiiton is described in (1) and (2) respectively

$$I_{k\to i}(t) = \sum_{i=1, i\neq k}^{K} P_k(t) G_{k,i}(t), \tag{1}$$

$$I_{k\to j}(t) = \sum_{j=1, j\neq k}^{J} P_k(t) G_{k,j}(t), \tag{2}$$

where $P_k(t)$ is the required transmit power for k_{th} MTCD , $k \in K$, $G_{k,i}(t)$ being the channel gain between k_{th} and i_{th} MTCDs, $i \in K$, and $G_{k,j}(t)$ is the channel gain between a k_{th} MTCD and a j_{th} HTC device respectively. Here, (1) represents the intra-domain interfering component and (2) the inter-domain component. Hence, signal-to-interference-plus-noise-ratio (SINR) for any k_{th} MTCD expereincing noise with variance σ^2 at any time instant t can be defined as

$$\gamma_k(t) = \frac{P_k(t) G_k(t)}{I_{k\to i}(t) + I_{k\to j}(t) + \sigma^2}. \tag{3}$$

B. Power Consumption and Battery Lifetime Model

Battery lifetime of MTC devices is an important performance constraint critical to maximize operation period. Lack of a recharging infrastructure for MTCDs also makes the maximization of battery life a primary consideration. Energy consumption levels may vary for a typical MTC node in different activity modes, including data collection, processing, synchronization, transmission, and sleeping. Denoting the remaining energy of the k_{th} MTC device at a time t^o as $E_k(t^o)$, transmission interval period as T_k and average packet size as D_k. Power consumption for transmission and sleeping modes is denoted as $(P_k + P_e)$ and P_s respectively. P_e is the power consumed by electronic components during data transmission mode and P_k is the transmit power required for reliable data transmission. Expected lifetime of MTCDs for each data transmission interval T_k for a node k can be defined as the product of data transmission interval period and the ratio between remaining energy and the average energy consumption, described as follows:

$$L_k(t^o) = \frac{E_k(t^o) T_k}{E_s + P_s\left[T_k - \frac{D_k}{R_k} - n_a^k T_a^k\right] + n_a^k T_a^k P_a + \frac{D_k}{R_k}[P_e + \eta P_k]}, \tag{4}$$

where R_k is the average expected data rate for node k, η is the inverse of power amplifier efficiency, and E_s is the average static energy consumption for each data transmission interval for synchronization, admission control, etc. For active modes, P_a is the power consumed for data collection in the active mode of operation with T_a^k being the duration of the active mode and n_a^k defined as the total number of active modes during the entire data transmission interval T_k. After denoting the energy consumption in transmitting and non-transmitting modes as $\acute{E}_s^k = E_s + P_s\left[T_k - \frac{D_k}{R_k} - n_a^k T_a^k\right] + n_a^k T_a^k P_a$ and $\acute{E}_d^k = \frac{D_k}{R_k}[P_e + \eta P_k]$ respectively, individual lifetime expression in (4) converts to:

$$L_k(t^o) = \frac{E_k(t^o) T_k}{\acute{E}_s^k + \acute{E}_d^k}, \tag{5}$$

C. Energy Efficiency and Battery Lifetime

Energy efficiency and battery lifetime of wireless devices are related to each other as shown by Miao [20]. Hence the energy efficiency of any node k during the transmission mode is represented as

$$U_k(R_k) = \frac{R_k}{P_e + \eta P_k(R_k)}. \tag{6}$$

It is shown that when $P_k(R_k)$ is strictly convex in R_k, $U_k(R_k)$ is strictly quasi-concave and an optimal R_k can be found which maximizes the energy efficiency. Consequently, battery lifetime expression from (5) can be rewritten as

$$L_k(t^o) = \frac{E_k(t^o) T_k}{D_k} \frac{R_k}{P_e + \eta\left[P_k + \acute{E}_s^k \frac{R_k}{D_k \eta}\right]}. \tag{7}$$

Now, define $P_k(R_k)$ as $P_k(R_k) + \acute{E}_s^k R_k / \eta D_k$ which will still be strictly convex in R_k as long as $P_k(R_k)$ remains strictly convex. Then, (7) can be modified in terms of energy efficiency as,

$$L_k(t^o) = \frac{E_k(t^o) T_k}{D_k} \frac{R_k}{P_e + \dot{P}_k} = \frac{E_k(t^o) T_k}{D_k} \acute{U}_k(R_k). \tag{8}$$

This expression shows the dependence of lifetime over energy efficiency $\acute{U}_k(R_k)$.

IV. Power Control As A Mean Field Game

A. Concept of Mean Field

The concept of mean field is the statistical distribution of state dynamics of the game and critical in the design of MFG. It can be defined for the proposed power control problem as,

$$m(t,S) = \lim_{K\to\infty} \frac{1}{K} \sum_{k=1}^{K} \mathbb{1}_{\{S_k(t)=S\}}, \quad (9)$$

where $\mathbb{1}$ is an indicator function having a value of one if given condition is true and zero elsewise. $S_k(t) = [\, E_k(t), \varphi_k(t)]$ is the state space of power control game. Mean field represents the probability distribution of the states in state space over the set of players.

MFG theory is a promising area in game theory suitable for studying the interactions and relationships between a large set of players. MFG models the individual's interaction with the effect of the collective behavior of the players, which is reflected in the mean field design. Individual player's interaction with the mean field is modeled by an HJB equation whereas the motion of the collective behavior according to the player actions is modeled by an FPK equation [6]. These coupled FPK and HJB equations known as backward and forward equations, respectively. The solution of an MFG is obtained by solving the FPK and HJB equations. MFG models the competition conditions amongst a large rational player base under certain symmetry conditions (i.e., the similarity of actions for all the players). Each individual player contributes a very small amount to the mass of all the other players as well as the MFG itself. A massive number of MTCD players lays the foundation of the continuity property of the mean field as defined in (9). All of the aforementioned properties make MFG appropriate for modeling the resource and power control problem for massive and reliable MTC design in a cellular environment. However, modeling the collective effect of the players (i.e., the effect of mass/mean field) has to be done in a realistic way. Accurate modeling of the effect of the mass is a major challenge when adopting MFGs to solve problems in wireless communications.

B. State Space Dynamics

The energy left at the MTC node and the interference, as well as the experienced channel gain between the MTCDs and BS, are considered for state space of the MFG. An MTCD must be able to transmit only for a finite amount of time, which in other words is considered the battery lifetime. Denote the energy left for node k at time t as $E_k(t)$, then there is a direct link to consumed power defined as

$$dE_k(t) = -P_k(t)dt, \quad (10)$$

which clearly indicates that remaining energy $E_k(t)$ decreases with time in relation to consumed power $P_k(t)$. Another dimension in state space is introduced by the impact of interference and channel gains on MTC and HTC nodes respectively. Intra-domain and inter-domain interference behavior are defined in (1) and (2) in the system model. From (3), total interference experienced by an MTC node can be stated as

$$\mu_k(t) = \sum_{i=1, i\neq k}^{K} P_k(t) G_{k,i}(t) + \sum_{j=1, j\neq k}^{J} P_k(t) G_{k,j}(t). \quad (11)$$

For simplicity, (11) can be represented in terms of a total channel gain $\omega_k(t)$ as

$$\mu_k(t) = P_k(t)\omega_k(t)$$

where,

$$\omega_k(t) = \sum_{i=1, i\neq k}^{K} G_{k,i}(t) + \sum_{j=1, j\neq k}^{J} G_{k,j}(t).$$

Now, the interference state of the MTCDs at any time t can be defined as,

$$d\varphi_k(t) = \omega_k(t) dP_k(t) + P_k(t)\partial_t \omega_k(t). \quad (12)$$

Consequently, state space for a generic player k composed of remaining energy and interference state can be defined as

$$S_k(t) = [\, E_k(t), \varphi_k(t)]. \quad (13)$$

C. Optimal Control Strategy and Utility Function

In the proposed design, each MTCD will select an optimal power control strategy $C_k{}^*(t)$ where t ∈ [T_i, T_f]. This cannot be achieved as long as the utility function is not minimized. Hence a general optimal control strategy and the value function can be defined as follows:

$$C_k{}^*(t) = \arg \min_{P_k(t)} \mathbb{E}\left[\int_{T_i}^{T_f} u_k(t)\, dt + u_k(T_f)\right], \quad (14)$$

$$V_k(t, S_k(t)) = \min_{P_k(t)} \mathbb{E}\left[\int_{T_i}^{T_f} u_k(t) dt + u_k(T_f, S_k(t))\right], \quad (15)$$

where $u_k(T_f)$ and $u_k(T_f, S_k(t))$ are the values at the time T_f.

A primary objective of utilizing MFG for an optimal power control design in the proposed model is the suitability for a massive number of MTC nodes. A single player's contribution to the mean field is very negligible due to the presence of a massive number of players in the formulated MFG. Interference terms from (1) can be estimated according to massive connectivity condition as

$$I_{k\to i}{}^m(t) = \sum_{i=1, i\neq k}^{K} P_k(t) G_{k,i}(t) \approx (K-1)\, P_k{}^m(t) G_{k,i}{}^m(t). \quad (16)$$

where $P_k{}^m(t)$ is the known transmit power level in the parameter estimation phase of the MFG used by all players. $G_{k,i}{}^m(t)$ is the mean field interference channel gain of the players due to the massive connectivity of devices. For a mean field transmit power $P_k{}^m(t)$, received power at the BS is defined as

$$P_k{}^{RX}(t) = P_k{}^m(t) G_k(t) + I_{k\to i}{}^m(t), \quad (17)$$

where $G_k(t)$ is the channel gain and $P_k{}^m(t)G_k(t)$ is the received power at the receiver. Also, $I_{k\to i}{}^m(t)$ is the received interference from all other players. Using (16) and (17) and after solving for $G_{k,i}{}^m(t)$, mean field SINR and utility functions are formulated respectively as

$$\gamma_k{}^m(t) = \frac{P_k(t) G_k(t)}{(K-1) P_k{}^m(t) G_{k,i}{}^m(t) + \sigma^2}, \quad (18)$$

$$\mu_k{}^m(t) = \left(\gamma_k{}^m(t) - \gamma_{th}(t)\right)^2 + \Omega P_k(t). \quad (19)$$

where γ_{th} is the SINR threshold value required for an effective communication link to be established and has an identical value for all k MTC nodes. Ω is included just to match the units of both transmit power and SINR difference.

D. MFG Formulation

Mean field models the collective behavior of all the players in an MFG whereas HJB and FPK equations model the interaction and nature of player behavior and interaction amongst players in an MFG design. Moreover, a combined system of HJB and FPK equations is sufficient to model the power control game. The HJB equation is formulated as [21],

$$-\partial_t V_k\big(t,S_k(t)\big) = \min_{P_k(t)}\big[u_k\big(t,S_k(t),P_k(t)\big) + \partial_t S_k(t)\,.\nabla\, u_k\big(t,S_k(t)\big)\ \big], \tag{20}$$

where Hamiltonian is defined as,

$$\boldsymbol{H}\Big(P_k(t),\ S_k(t), \nabla\, u_k\big(t,S_k(t)\big)\Big) = \min_{P_k(t)}\big[u_k\big(t,S_k(t),P_k(t)\big) + \partial_t S_k(t)\,.\nabla\, u_k\big(t,S_k(t)\big)\ \big].$$

Secondly, FPK or the backward equation is defined as [30],

$$\partial_t m(t,S) + \nabla\big(m(t,S).\partial_t S(t)\big) = 0. \tag{21}$$

It is clear that FPK equation is suitable for modeling the evolution of the mean field in terms of both time and space. Hence, an MFG design for power control for MTCDs can be accurately formulated using both HJB and FPK equations from (20) and (21) respectively.

E. MFG Solution using Finite Difference Method

Finite difference method [21] is utilized to achieve MFE by utilizing Lax-Freidrichs technique as it guarantees the positivity of mean field as well as offering the first-order accuracy in both time and space [22]. In the proposed design using the finite difference method, time [0, T_f] and state space [0, E_{max}] are discretized and mapped onto X and Y-axis respectively. In addition, interference state space [0, β_{max}] is mapped onto Z-axis. The goal is to find an optimal control policy and multiple control policies may exist, which are represented as unique paths from a maximum point in time to the origin as shown in Fig. 2. Grid iteration steps are defined in terms of time, energy and interference spaces shown as $\delta_t = T_f/X$, $\delta_E = E_{max}/Y$, and $\delta_\beta = \beta_{max}/Z$ respectively. It can be seen clearly that the evolution of the mean field takes place in three-dimensional space of time, energy and interference states. The backward nature of the HJB equation can be seen clearly from the direction of the control path during the course of the MFG.

1) Solution to HJB and FPK Equations

The FPK or the forward equation in (21) is solved by applying the Lax-Freidrichs technique and represented in (22). $M(i,j,k)$, $P(i,j,k)$, $\omega(i,j,k)$ represent the values of the mean field, power and interference at any time instant i with the energy level j and with interference state k within the formulated MFG finite difference framework. The value of mean field is depicted as

$$M(i+1,j,k) = \frac{1}{2}\begin{bmatrix} M(i,j-1,k) \\ +M(i,j+1,k) \\ +M(i,j,k-1) \\ +M(i,j,k+1) \end{bmatrix} + \frac{\delta_t}{2\delta_E}\begin{bmatrix} M(i,j+1,k)P(i,j+1,k) \\ -M(i,j-1,k)P(i,j-1,k) \end{bmatrix} + \frac{\delta_t}{2\delta_\beta}\begin{bmatrix} M(i,j,k+1)P(i,j,k+1)\omega(i,j,k+1) \\ -M(i,j,k-1)P(i,j,k-1)\omega(i,j,k-1) \end{bmatrix}. \tag{22}$$

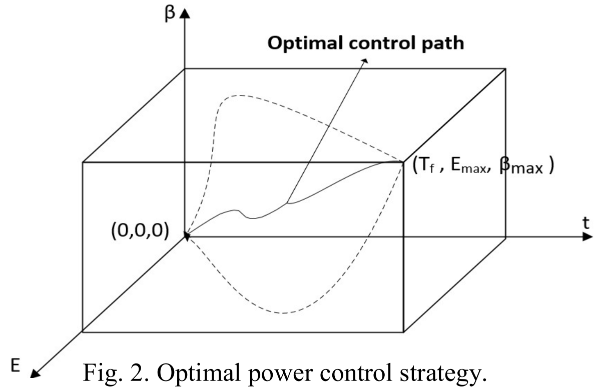

Fig. 2. Optimal power control strategy.

Due to the presence of Hamiltonian, the finite difference method cannot be applied directly to solve the optimal control problem. Hence, the newly formulated problem with FPK equation now acting as a constraint is defined as

$$\underbrace{\min}_{P_k(t)} \mathbb{E}\left[\int_o^{T_f} \mu_k(t)dt + \mu_k\big(T_f\big)\right]$$

subject to:

$$\partial_t m(t,S) + \nabla_E\, m(t,S)E(t) + \nabla_\beta\, m(t,S)\beta(t) = 0. \tag{23}$$

This modified problem is adapted by using Lagrange multipliers and a solution to the stated HJB equation is obtained. A Lagrangian $L(m(t,S),p(t,S),\lambda(t,S)$ is derived by setting $\mu_k\big(T_f\big) = 0$ and has been denoted in (24). At this point, a finite difference technique can be used to solve the newly modified equation from the proposed new problem (23). Another requirement of formulated three-dimensional state space is the discretization, which is achieved for the Lagrangian and represented as (25). Corresponding to (25), Γ, ζ, ϕ are defined as (26), (27) and (28) respectively as

$$L\big(m(t,S),p(t,S),\lambda(t,S)\big) = \int_{t=0}^{T_f}\int_{E=0}^{E_{max}}\int_{\beta=0}^{\beta_{max}} \Big[\mu_k(t,S)m(t,S) + \lambda(t,S)\Big(\partial_t m(t,S)\ \nabla_E\, m(t,S)E(t) + \nabla_\beta\, m(t,S)\beta(t)\Big)\Big]\,dtdEd\beta\,, \tag{24}$$

$$L_d = \delta_t\delta_E\delta_\beta \sum_{i=1}^{X+1}\sum_{j=1}^{Y+1}\sum_{k=1}^{Z+1}\begin{bmatrix} M(i,j,k)U(i,j,k) \\ +\lambda(i,j,k)(\Gamma+\phi+\zeta) \end{bmatrix}, \tag{25}$$

$$\Gamma = \frac{1}{\delta_t}\Big[M(i+1,j,k) - \frac{1}{2}M(i,j+1,k) + M(i,j-1,k) + M(i,j,k+1) + M(i,j,k-1)\Big], \tag{26}$$

$$\zeta = \frac{1}{2\delta_E}\begin{bmatrix} M(i,j+1,k)P(i,j+1,k) \\ -M(i,j-1,k)P(i,j-1,k) \end{bmatrix}, \tag{27}$$

$$\phi = \frac{1}{2\delta_\beta}\begin{bmatrix} M(i,j,k+1)P(i,j,k+1)\omega(i,j,k+1) \\ -M(i,j,k-1)P(i,j,k-1)\omega(i,j,k-1) \end{bmatrix}. \tag{28}$$

The optimal decision variables (P^*, M^*, λ^*) must also satisfy the Karush-Kuhn-Ticker (KKT) conditions. An optimal control policy for any point (i, j, k) for the discretized domain is derived by evaluating (29) to zero. Consequently, the Lagrangian multiplier is updated by solving $\delta L_d/\delta P(i,j,k) = 0$ and the formulation of $\lambda(i-1,j,k)$ is given in (30).

$$\frac{\delta L_d}{\delta P(i,j,k)} = \sum_{j=1}^{Y+1}\sum_{k=1}^{Z+1} M(i,j,k)\frac{\delta U(i,j,k)}{\delta P(i,j,k)} + \left[\frac{M(i,j,k)}{2\delta_E} + \frac{M(i,j,k)\omega(i,j,k)}{2\delta_\beta}\right]\begin{bmatrix}\lambda(i,j+1,k)\\ -\lambda(i,j-1,k)\end{bmatrix}, \quad (29)$$

$$\lambda(i-1,j,k) = \frac{1}{2}\begin{bmatrix}\lambda(i,j+1,k)\\ +\lambda(i,j-1,k)\end{bmatrix} + \frac{1}{2}\begin{bmatrix}\lambda(i,j,k+1)\\ +\lambda(i,j,k+1)\end{bmatrix} - \frac{1}{2}\delta_t P(i,j,k)\left[\frac{\omega(i,j,k)}{\delta_\beta} + \frac{1}{\delta_E}\right]\begin{bmatrix}\lambda(i,j+1,k)\\ -\lambda(i,j-1,k)\end{bmatrix} + \delta_t U(i,j,k). \quad (30)$$

2) *Power Control Scheme*

Each MTCD will optimize its power individually in a distributed manner with an aim to minimize the energy consumption during each transmission interval as described in Algorithm 1. Each MTCD will calculate the values for its mean field followed by the Lagrangian multiplier evaluation. This information is utilized to calculate the optimal power levels of the respective MTC node for achieving battery lifetime maximization.

3) *Complexity and Equilibrium Analysis*

The complexity of proposed power control MFG is proportional to the number of states or the maximum battery capacity. Convergence of proposed mean field based power control framework does not depend on the number of players engaged in the MFG. It is directly dependent on the method, which is used to solve the HJB and FPK partial differential equations (PDEs). In this paper, the finite difference method [29] is used to solve the proposed MFG. Mean field equilibrium (MFE) is the converged and stable combination of the optimal control policy $v^*(t, S)$ and the mean field $m^*(t, S)$. This can be achieved by solving the coupled MFG equations (20) and (21). The value function v (t, S) is the solution of HJB equation (20) and it is solved backward in time whereas m(t,S) is the solution to FPK equation (21) and it is solved forward in time.

The proposed algorithm guarantees the MFE for the given MFG based power control design. As proven in [14], the Hessian w.r.t $\mathrm{M(i,j,k)}$, $\mathrm{P(i,j,k)}$, and $\mathrm{I(i,j,k)}$ of the HJB equation (23) is positive for any discrete point (i,j,k). This existence of the Hessian makes (23) a convex optimization objective function in the converted optimization problem. An optimal solution for the convex optimization problem is ensured if the KKT conditions are met. This also confirms that convergence of the problem (23) is actually the MFE of the MFG defined by the coupled set of equations (21) and (23). The algorithm treats the MFE to have been attained if the difference between consecutive mean field values to be greater than or equal to 10^{-5}.

Algorithm 1: Finite difference scheme for MFG solution

Initialization: Initialize game parameters
M(0, 0, 0), P(X+1, 0, 0), λ(X+1, 0, 0)

<u>**Step 1: Evaluating the Mean Field**</u>

```
for all i = 1: 1: X, do
   for all j = 1: 1: Y do
      for all k = 1: 1: K do
         Calculate mean field M(i+1, j, k) using Eq. (22)
            if P(i, j+1, k) = 0
                M(i+1, j+1, k+1) = M(i, j, k)
            else M(i+1, j+1, k+1) = 0
            end
      end
   end
end
```

<u>**Step 2: Evaluating the Lagrangian**</u>

```
for all i = X+1: -1: 1 do
   for all j = 1: 1: Y+1 do
      for all k = 1: 1: K do
         Calculate λ(i-1,j,k) using Eq. (29)
      end
   end
end
```

<u>**Step 3: Finding the Transmit Power**</u>

```
for all i = 1: 1: X+1 do
   for all j = 1: 1: Y+1 do
      for all k = 1: 1: K do
         Calculate P(i-1,j,k) using Eq. (30)
      end
   end
end
```

V. Performance Evaluation And Results

This section presents a performance analysis of the proposed MFG based power control scheme along with simulations performed in MATLAB environment.

A. Simulation Setup

A coexisting cellular network scenario is designed consisting of both HTC and MTC devices generated independently of each other. For the simulation design, a total number of MTC nodes will vary between 100 to 500 and the HTC nodes 10 to 100 in a single cell of the coexisting network with a total system bandwidth of 20 MHz. The path loss model used for simulations is $128.1 + 37.6 \log_{10} d$ where d is the distance in km and the standard deviation of shadow fading is 3 dB. The background noise power is 2 x 10^{-9} W with power spectral density as -170dBm/Hz and receiver sensitivity threshold is set as 0.1 mW. An LTE-A framework is adopted with a frame structure having a single frame duration of 10ms and a total number of frames as 500 amounting to a time interval of T = 5s. A battery capacity of 200 μJ and a max transmit power for the MTC devices is defined to be 50 mW. A mean field is defined for modeling the state dynamics of the MTC dynamics of the game. The state space is divided into a 50x50x50 grid with respective player states analyzed at different time instances throughout the duration of the MFG with maximum values of energy level E_{max} and tolerable interference level β_{max} are defined as 0.5J and 6 x 10^{-6} W respectively.

B. Simulation Results

The primary objective of the proposed power control scheme is to optimize the transmit power allocation to MTCDs thereby leading to an improved energy efficiency and a prolonged network and battery lifetimes. The power control problem for the MTC nodes is rather complex and more susceptible to externalities due to the limitations in available energy at the nodes as well as the lack of availability of an alternate energy source. The MTC power control problem is formulated as an MFG and an optimal control policy is required to achieve the mentioned objectives. This is achieved by obtaining a mean field which best describes the collective behavior of all MTC nodes playing the MFG. The mean field is described using a 3D discretized grid and a finite difference method is utilized for solving the power control MFG.

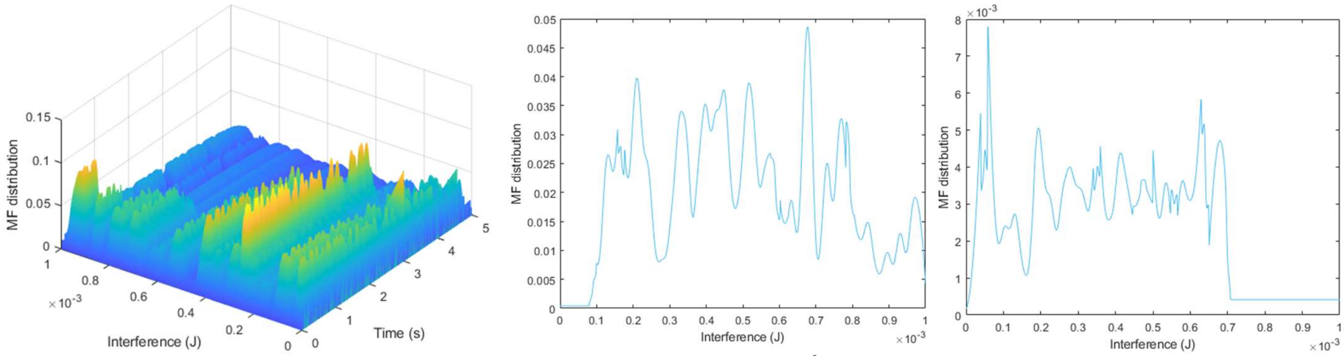

Fig. 3. Mean field distribution for $\beta_{max} = 6 \times 10^{-6}$ W at T = 2s and 5s.

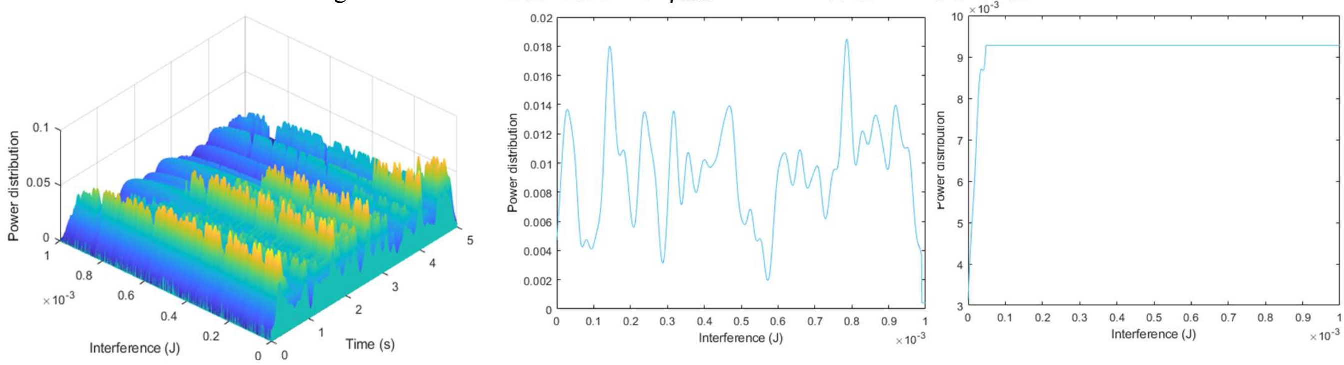

Fig. 4. Power distribution for $\beta_{max} = 6 \times 10^{-6}$ W at T = 2s and 5s.

The mean field distribution for the massive MTC nodes is depicted in terms of interference and energy state dynamics of the MTC devices. The effect of state dynamics on the allocated power levels to MTCDs in a hybrid environment is depicted in the mean field and power distribution grid as shown in Fig. 3 and 4 respectively. By fixing the value of available energy at the MTC batteries to 0.5J, simulations are performed to analyze the behavior of power and mean field of the MTC nodes. The randomness in the distribution patterns for both mean field and power for MTCDs can be attributed to the inclusion of interference term in the utility function. The cross-section of the mean field and power distributions at T = 2 and 5s are depicted in Fig. 3 and 4 to study the impact of interference on the mean field and the power allocations to MFG players. It can be seen that at equilibrium, a stable and converged optimal power control policy can be achieved by the proposed power control scheme despite different levels of interference suffered by MTCDs. This convergence of power and mean field for final states of energy and interference with respect to time makes the proposed mean field design a suitable design to achieve the optimal power control policy for the formulated MFG.

The state dynamics of the formulated power control MFG include the states of energy as well as the experienced interference at each individual MTCD. Simulations are performed for variable battery levels with a different number of MTC nodes to depict the change in transmit power allocation according to changing levels of interferences. Fig. 6 shows the varying transmit power according to different available energy states of MTC nodes. The analysis is performed for varying user densities with the following scenarios defined accordingly. Case-I: low MTC node density (150 nodes), and Case-II: high MTC node density (500 nodes). In the first case, as shown in Fig. 5(a), a relatively lower number of MTC devices are present in the cell coverage area. In the proposed power control game, the convergence condition is defined as the point where MTC nodes satisfy the reliability condition. The devices with higher initial energy in their batteries will start with a higher transmit power allocated during the MFG. The allocated transmit power will gradually be reduced to a value depending on the selected reliability condition determined by the SINR threshold. For devices with lower energy levels at the start of the MFG, have no choice but to allocate lower transmit powers initially and increasing with the progression of the game until the SINR threshold is achieved. In the second case as shown in Fig. 5(b), the number of MTC devices are increased leading to a more complex interference state and need of higher allocated powers to reach SINR threshold. A similar trend is observed for users with higher initial energy levels with more power being allocated at the start and declining as MFG progresses over time. The MTC devices with lower levels of energy in their batteries must still meet the SINR threshold for satisfying reliability condition. Hence their allocated powers increase up to a point when they meet the mentioned criterion and then the power levels are maintained for the duration of the game or until the energy level drops significantly in their batteries.

The energy efficiency of the proposed algorithm can be proven by comparing allocated transmit power levels to different MTC nodes over the duration of the game. The average SINR of different types of MTC devices in each cell is analyzed according to changing node densities in light of the proposed MFG based power control policy. For MFG based power control model, the average SINR increases as the number of MTC devices in a cell are increased owing to the increased interference from HTC users. As seen from previous results, the MTC devices will have no choice but to increase device transmit powers in order to compensate for increased interferences from HTC users in the cell. After a certain point, the MTC device density increases such that mutual interference of MTC nodes dominates the total interference effect on devices. Hence, a drop in allocated power eventually will

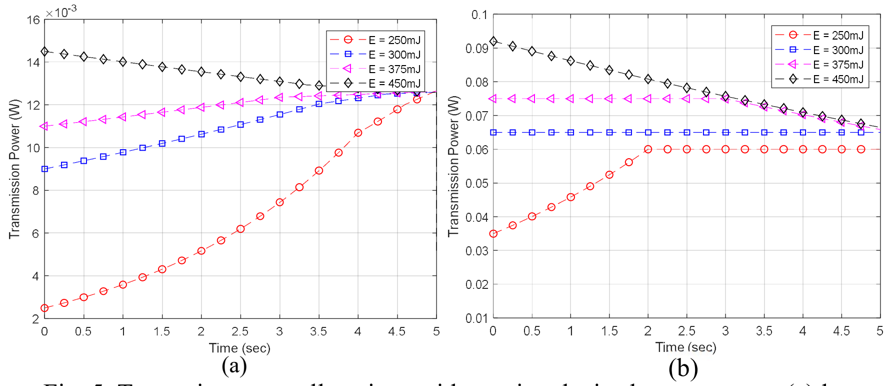

Fig. 5. Transmit powers allocations with varying device battery energy (a) low user density, (b) high user density.

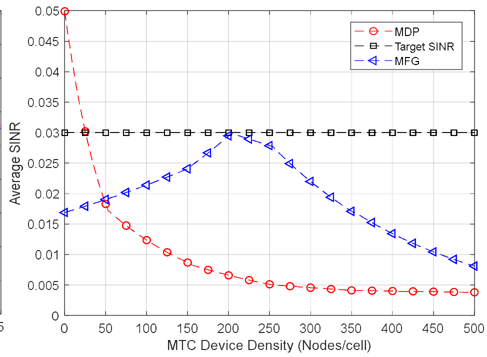

Fig. 6. SINR and device density analysis.

degrade the average SINR values for MTC devices beyond this point. The significance of this behavior for MFG based approach is the guarantee of the highest possible average SINR value for the MTC devices, which happens to be closest to the target SINR as compared to other approaches like Markov decision process (MDP). The MDP approach is a simple stochastic game in which each player has its own optimal control strategy, which it tries to achieve. A comparison has been performed between the proposed MFG model and MDP model from [23] as depicted in Fig. 6 along with the chosen target SINR value. In contrast to the proposed MFG approach, the MDP model clearly fails to cope with the increasing user density of MTC devices and therefore the average SINR value experiences a steady decline due to increased interferences. The complexity is also a concern for the MDP model due to the dependence on choices of other players.

VI. Conclusion

In this paper, a futuristic wireless network environment is proposed in which coexistence of conventional user devices known as HTC type nodes along with MTC type nodes is discussed and analyzed. The aim of this paper is to maximize the energy efficiency of the MTC devices with the constrained energy source and maximize their battery lifetimes in the process. This problem is indirectly solved by using the dependence of effective transmit power control on the energy efficiency of these devices. The devised MFG is described as a set of partial differential equations (HJB & FPK) of value and utility functions obtained by application of mean field approximation theory. Simulation results confirm the energy efficient nature of the proposed power control scheme.

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