Rethinking Power Control in Wireless Networks: The Perspective of Satisfaction Equilibrium

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***Abstract*—In this paper we propose a holistic framework that aims at a paradigm shift in the treatment of the uplink power control problem in wireless networks, under the perspective of games in satisfaction form. Novel satisfaction equilibrium points of special interest within the considered problem - such as the Minimum Efficient Satisfaction Equilibrium (MESE) and the Minimum Satisfaction Equilibrium (MSE) - are introduced, while their benefits, existence and uniqueness are investigated, considering a realistic and generic user utility function being quasiconcave with respect to its transmission power. It is proven that at the MESE and MSE points the system achieves the lowest possible cumulative cost, while each user individually is penalized with the minimum cost compared to the corresponding cost of any Efficient Satisfaction Equilibrium (ESE) and of any Satisfaction Equilibrium (SE), respectively. A decentralized low complexity algorithm, based on the Best Response Dynamics, is proposed that converges to the MSE equilibrium, while it can efficiently handle the dynamic behaviors of the users in the network. Numerical results are provided that validate and evaluate the benefits of the proposed novel power control framework, underlining the superiority of the MSE against other equilibrium points.**

***Index Terms*—Satisfaction equilibrium, energy efficiency, game theory, power control, resource management**

I. Introduction

THE emergence and evolution of 5G and Internet of Things (IoT), has pushed researchers and industries to be looking at the technological transformation to move towards an environment, where multiple devices will be able to connect, share information, interpret, and deliver a seamless experience for users. Despite the fact that significant advances have been realized through the use of enhanced network architectures and technologies, large amounts of spectrum – being a scarce resource - are still required to deliver massive increases in capacity and achieve high throughput. Unless a paradigm shift occurs in the resource allocation decision making process the problem of spectral efficiency will still remain a barrier towards the realization of 5G's full potential [1], [2].

Traditionally, towards devising intelligent resource allocation approaches in such resource constrained environments, the Expected Utility Theory (EUT) has been adopted targeting at the maximization of the users' benefits from allocating the available resources. Following the principles of EUT, each user aims at maximizing its personal utility in a selfish manner targeting at the highest possible performance [3], [4], [5]. Moreover, to enable the users' distributed intelligent decision making in a computationally efficient manner, while at the same time capturing the users' competitive behavioral patterns, Game Theory has arisen as a theoretical and practical powerful tool [6], [7]. The solution of the corresponding resource orchestration problems is the Nash Equilibrium (NE) point, where the users maximize their own utility, while they cannot achieve a better outcome by unilaterally changing their own strategies given the strategies of the rest of the users [8].

However, is the NE point really the best solution that it can be achieved by the users [9], in communications and computing systems where users' decision are interdependent? Even more, is the goal of maximizing each user's utility a reasonable and meaningful goal within such resource constrained systems? Those are the fundamental questions that this work aims to address, while introducing a novel efficient resource control framework based on the theory of Satisfaction Games.

A. Related Work & Motivation

Various resource management problems in wireless networks have been considered in the recent literature, based on the concept of EUT and non-cooperative Game Theory (e.g., [10]–[12]). However, the NE points stemming from users' selfish decision-making are generally inefficient. Towards guiding the selfish users to a more efficient operating point, various pricing mechanisms that penalize the users with respect to their resources' consumption, were introduced (e.g. [13]). These approaches constituted a first step towards treating the aforementioned inefficiency, without however offering a holistic treatment to the main disadvantage of the NE points. The latter is due to the fact that customized heuristic pricing mechanisms are required each time to treat different resource types and networking environments. Furthermore, even when pricing is considered, each user still aims at maximizing its own perceived Quality of Service (QoS).

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Towards treating the above issue in a formal and universal manner, a new concept of equilibrium is introduced, namely Satisfaction Equilibrium (SE), where the users aim to satisfy their minimum QoS prerequisites instead of targeting at QoS maximization [1], [14]. In particular, in [15] the definition of the SE and the general conditions for examining its existence have been discussed in detail. Furthermore, the concept of users' effort investment to achieve the SE has been introduced, leading to a refinement of the SE, namely the Efficient SE (ESE). At the ESE point, all the users conclude to a resource allocation strategy, which requires the lowest effort to satisfy their minimum QoS prerequisites. In [16] and [17], the concepts of SE and ESE are applied in a simplified uplink power control problem considering interference channels in a single-cell environment. In [18] machine learning has been adopted to determine the SEs and ESEs under different conditions and uncertainties, while in [19] a distributed learning algorithm that converges to specific correlated equilibria is provided. Nevertheless, many interesting properties that emerge when the holistic satisfaction equilibrium framework is applied have not been revealed yet [14], while several critical challenge remain unexploited.

B. Contributions and Outline

Our work aims at filling this gap, while focusing on the transformation and treatment of the uplink power control problem in next generation wireless networks under the perspective of satisfaction games, while proposing new concepts in the field of satisfaction games. A key differentiating aspect of our work, is the relaxation of the common assumption of using strictly increasing user utilities with respect to the user's uplink transmission power, when adopting the concept of satisfaction equilibrium in the current literature [15], [20]. Such assumption is quite restrictive, thus considerably limiting the exploitability and applicability of the corresponding approaches. Instead, in our work we consider generic enough and realistic users' utility functions, which are assumed to be quasiconcave with respect to the user's uplink transmission power. Two representative examples of such utility functions widely used in the literature regarding wireless networks, is the Shannon capacity and the energy efficiency function [21].

Accordingly, the novel concepts of Minimum Efficient Satisfaction Equilibrium (MESE) and Minimum Satisfaction Equilibrium (MSE) are introduced building on the existing concepts of SE and ESE, and their special interest and properties are underlined (Section II). Based on this new introduced framework, the corresponding uplink power control problem is formulated and studied as a game in its satisfaction form (Section III). In particular, assuming that each user is associated with a usage-based cost function that is increasing with respect to its transmission power, we prove that the MESE point is unique. The intuition behind and the physical notion of the MESE point is, that at this novel equilibrium point, the system achieves the lowest cumulative cost from every other ESE of the system, while at the same time each user is penalized with the minimum cost (i.e., transmission power) that could experience in every other ESE. Capitalizing on this observation subsequently we prove that the unique MESE point is also the unique MSE point of the game, which is the ultimate targeted and desired operation point. That is, in the considered uplink power control game, the MSE and the MESE points coincide, and from every other power allocation that satisfies the users' QoS prerequisites, this point allocates to each user the minimum possible transmission cost.

A decentralized algorithm based on the Best Response Dynamics is proposed, that enables the system to efficiently converge to its MESE/MSE point, or alternatively determine the non-existence of an SE (Section IV). Furthermore, capitalizing on the aforementioned theoretical foundations and algorithm, a holistic operationally efficient framework is offered to accommodate the users' dynamic behavior in the examined system (i.e. user decrease/increase of QoS demands, or user entrance/departure from the system), which typically occur in 5G networks (Section VI). A series of simulation experiments are performed that provide a proof of concept of the validity of the introduced theoretical framework, by: (i) comparing the MSE with other existing equilibria in the literature (SE, ESE, NE) while underlining its properties and superiority, and (ii) studying the behavior and the convergence of the proposed novel holistic framework based on games in satisfaction, under different scenarios (Section VI). Finally, Section VII concludes the paper.

II. Games in Satisfaction Form

In this section, we provide some definitions and the basic notation that will be used in the rest of the paper. A game in satisfaction form is defined as $\hat{G} = (K, \{A_k\}_{k\in K}, \{f_k\}_{k\in K})$, where $K = \{1, \ldots |K|\}$ represents the set of players, A_k is the strategy set of player $k \in K$, $u_k(a_k, \boldsymbol{a}_{-k})$ represents player's k payoff (i.e., utility function), and $f_k(\boldsymbol{a}_{-k}) = \{a_k \in A_k : u_k(a_k, \boldsymbol{a}_{-k}) \geq u_{thr}\}$ determines the set of actions of player k that allows its satisfaction, that is its payoff to be above a threshold value u_{thr}, given the actions $\boldsymbol{a}_{-k}$ played by all the other players [17]. A strategy profile is denoted by a vector $\boldsymbol{a} = (a_1, \ldots, a_{|K|}) \in A$, $A = A_1 \times \cdots \times A_k \times \cdots \times A_{|K|}$.

Definition 1: An action profile $\boldsymbol{a}^+$ is an *SE point* for the game $\hat{G} = (K, \{A_k\}_{k\in K}, \{f_k\}_{k\in K})$ if

$$a_k^+ \in f_k(\boldsymbol{a}_{-k}^+), \quad \forall k \in K \tag{1}$$

From this definition it is evident that at the SE point, each player satisfies its QoS prerequisites. It should be noted that there could exist multiple strategy vectors $\boldsymbol{a}^+ = (a_1^+, \ldots, a_{|K|}^+)$ satisfying player's minimum QoS prerequisites, some of which are of particular interest. A representative example is the *Efficient Satisfaction Equilibrium* (ESE) where each player of the system achieves its minimum QoS prerequisites via being simultaneously penalized with the minimum cost. To capture the notion of the players' penalty and effort associated with a given action choice, the concept of the cost function for each player is introduced. For all $k \in K$, the cost function $c_k : A_k \rightarrow [0, 1]$ satisfies the following condition: $c_k(a_k) < c_k(a_k^{'})$, $\forall (a_k, a_k^{'}) \in A_k^2$, if and only if, a_k requires a lower effort by player k than action $a_k^{'}$.

Definition 2: An action profile $\boldsymbol{a}^*$ is an *ESE point* for the game $\hat{G}$, with cost functions $\{c_k\}_{k\in K}$, if

$$a_k^* \in f_k(\boldsymbol{a}_{-k}^*), \quad \forall k \in K \tag{2a}$$

$$c_k(a_k) \geq c_k(a_k^*), \quad \forall k \in K, \forall a_k \in f_k(\boldsymbol{a}_{-k}^*) \tag{2b}$$

At the ESE point, each player satisfies its personal QoS prerequisites with its minimum possible personal cost. It is noted that an ESE point is also an SE point. Another equilibrium point of special interest is the *Minimum Efficient Satisfaction Equilibrium* (MESE). At the MESE point, all players satisfy their QoS prerequisites (Eq. 3a), with the minimum cost for themselves (Eq. 3b) and the minimum total cost from the system's perspective (Eq. 3c).

Definition 3: An action profile $\boldsymbol{a}^\dagger$ is a *Minimum Efficient Satisfaction Equilibrium (MESE)* for the game $\hat{G} = (K, \{A_k\}_{k\in K}, \{f_k\}_{k\in K})$, with cost functions $\{c_k\}_{k\in K}$, and set of action profiles that are ESEs $\{E\}$ if

$$a_k^\dagger \in f_k(\boldsymbol{a}_{-k}^\dagger), \quad \forall k \in K \tag{3a}$$

$$c_k(a_k) \geq c_k(a_k^\dagger), \quad \forall k \in K, \forall a_k \in f_k(\boldsymbol{a}_{-k}^\dagger) \tag{3b}$$

$$\sum_{k\in K} c_k(e_k) \geq \sum_{k\in K} c_k(a_k^\dagger), \quad \forall \boldsymbol{e} \in E \tag{3c}$$

From this definition it is implied that an MESE point is also an ESE point. Last, but not least, the concept of *Minimum Satisfaction Equilibrium* (MSE) is introduced, where all players satisfy their QoS prerequisites (Eq. 4a) and the system achieves its minimum possible cost (Eq. 4b).

Definition 4: An action profile $\boldsymbol{a^{opt}}$ is a *Minimum Satisfaction Equilibrium* (MSE) for the game $\hat{G} = (K, \{A_k\}_{k\in K}, \{f_k\}_{k\in K})$, with cost functions $\{c_k\}_{k\in K}$, and set of action profiles that are SEs $\{S\}$ if

$$a_k^{opt} \in f_k(\boldsymbol{a}_{-k}^{opt}), \quad \forall k \in K \tag{4a}$$

$$\sum_{k\in K} c_k(s_k) \geq \sum_{k\in K} c_k(a_k^{opt}), \quad \forall \boldsymbol{s} \in S \tag{4b}$$

III. Rethinking Uplink Power Control

A. System Model and Assumptions

Let us consider K transmitter/receiver pairs denoted by index $k \in K$. For all $k \in K$, transmitter k uses power level $p_k \in A_k$, with A_k generally defined as a compact sublattice. We denote p_k^{min} and p_k^{max} the minimum and maximum power levels in A_k, respectively, while g_{ij} is the channel gain coefficient between transmitter i and receiver j. We study uplink power control games in which each user has a utility function that is quasiconcave with respect to its own transmission power and decreasing with respect to the total summation over the powers of the rest of users, as the latter quantity acts as interference to the examined user's transmission. A general example of such utility function that satisfies this realistic assumption, is the commonly adopted in the literature energy efficiency function in typical interference limited communication environment, as presented in the seminal paper [21] and [17], and presented below :

$$u_k(p_k, \boldsymbol{p_{-k}}) = \frac{f(\gamma_k)}{p_k}, \gamma_k = \frac{W}{R} \frac{h_k p_k}{\sum_{j\neq k} h_j p_j + \sigma_k^2} \tag{5}$$

where σ_k^2 denotes the Additive White Gaussian Noise variance at receiver k, R is the requested user service data rate and W denotes the system bandwidth. $f(\gamma_k)$ is an efficiency function representing the probability of a successful packet transmission for user k and is an increasing and sigmoidal function with respect to p_k. An indicative form of this function that has been used in the existing literature, and is also adopted in this paper for evaluation purposes, is $f(\gamma_k) = (1-e^{-a\gamma_k})^M$, where parameters $a, M > 0$ control the shape of this function. [13], [21]. It has been shown that if every user adopts the utility function of Eq. 5, then the corresponding non-cooperative power control game possesses at least one NE [21].

In the following we consider discrete power levels, that is the user's strategy set is discrete, which in turn is translated to taking a sample from the energy efficiency function's possible values. This means that one interval of the possible energy efficiency values of each user is increasing with respect to power. This interval is from p_k^{min} to a power that maximizes $u_k()$, that is $[p_k^{min}, p_k^M]$. We refer to that interval as the left interval. Note that for a fixed value of $\boldsymbol{p_{-k}}$, $u_k(p_k^M, \boldsymbol{p_{-k}})$ is the maximum possible value of the sampled powers. That means that $p_k^M(\boldsymbol{p_{-k}})$ depends on the strategies of the others. In the other interval, i.e., the right interval, $(p_k^M, p_k^{max}]$, $u_k()$ is decreasing with respect to p_k. Note that the sampling we have over the utility function is following a quasiconcave function. Nevertheless, $u_k(p_k^M, \boldsymbol{p_{-k}})$ could be less or equal to the maximum value of the utility in the corresponding continuous interval of user's transmission power.

Definition 5: Given a strategy profile $\boldsymbol{p} \in A$, we define the set of users $R(\boldsymbol{p})$ as the users $k \in K : p_k > p_k^M(\boldsymbol{p_{-k}})$.

The following proposition states that for every possible SE of the game that there are users that transmit with power in the interval $(p_k^M, p_k^{max}]$, there exists another one that all of the users transmit in the interval $[p_k^{min}, p_k^M(\boldsymbol{p}_{-k})]$.

Proposition 1: Let an uplink power control game in the satisfaction form $\hat{G}$ with utility functions $\{u_k\}_{k\in K}$ (Eq. 5) and the set of all possible SEs $\{S\}$ of the game. Then $\forall \boldsymbol{p}^+ \in S : R(\boldsymbol{p}^+) \neq \emptyset$, $\exists \boldsymbol{e}^+ \in S : R(\boldsymbol{e}^+) = \emptyset$.

Proof: See Appendix I. ■

Proposition 1 shows that transmitting in $(p_k^M, p_k^{max}]$, given the strategies of the others, is inefficient as there would also be a lower p_k that could yield higher utility. For the rest of the paper, we assume increasing cost functions, $\{c_k\}_{k\in K}$, with respect to the users' transmission powers.

B. Best Response in Uplink Power Control

In the following we initially assume that each user always possesses a strategy that satisfies its QoS prerequisites. Nevertheless, as argued later in Section IV, this assumption is not restrictive and can be relaxed. Thus, we can easily conclude that given $\boldsymbol{p}_{-k}$, there is a $p_k \in [p_k^{min}, p_k^M(\boldsymbol{p}_{-k})]$ which satisfies the QoS prerequisites of the examined user k, and if a lower transmission power is used, this will leave the user unsatisfied. Contrary, if the user transmits with a greater power in that interval, then the user will remain satisfied. We will refer to that power as the Best Response $BR_k(\boldsymbol{p}_{-k}) = \{p_k \in A_k : p_k = \arg\min_{p_k \in f_k(\boldsymbol{p}_{-k})} c(p_k)\}$ of user k given $\boldsymbol{p}_{-k}$. With the following propositions we study users' best responses in the context described above.

Proposition 2: Given a strategy profile $\boldsymbol{p}_{-k}$, the user's k best response is in the user's left interval of transmission powers: $BR_k(\boldsymbol{p}_{-k}) \in [p_k^{min}, p_k^M]$.

Proof: See Appendix II. ∎

Based on proposition 2, if $\{E\}$ is the set of all possible ESEs of the game, it holds that $\forall \boldsymbol{p}^* \in \{E\}, R(\boldsymbol{p}^*) = \emptyset$. The proposition below states that if some users increase their transmitting powers, their best responses, if they exist, will also be increased or remain the same.

Proposition 3: Let a user $k \in K$, and two strategy profiles $\boldsymbol{p}^1, \boldsymbol{p}^2 \in A$. Then: $\boldsymbol{p}_{-k}^1 \preceq \boldsymbol{p}_{-k}^2 \Rightarrow BR_k(\boldsymbol{p}_{-k}^1) \leq BR_k(\boldsymbol{p}_{-k}^2)$.

Proof: See Appendix III. ∎

C. Existence of ESE and MESE

To prove the existence of at least one ESE point in the uplink power control game $\hat{G}$ in our setting we first mention the Tarski and Knaster's fixed point theorem [22].

Theorem 1 (Tarski and Knaster's fixed point theorem): Let $\mathcal{L}$ be a complete lattice and let $f : \mathcal{L} \to \mathcal{L}$ be an order-preserving function. Then, the set of fixed points of f in $\mathcal{L}$ is also a complete lattice.

Let A be the set of the strategy space of the game $\hat{G}$ as defined above. Let us also define the lattice $\mathcal{L} = \langle A, \preceq \rangle$, where $\preceq$ is the component-wise less or equal. Note that $\mathcal{L}$ is a complete lattice as all its subsets have both a supremum and an infimum. The next step is to construct an appropriate function $g : \mathcal{L} \to \mathcal{L}$. Thus we define $g : \mathcal{L} \to \mathcal{L}$ as follows:

$$g(\boldsymbol{p}) = (BR_1(\boldsymbol{p}_{-1}), \ldots, BR_{|K|}(\boldsymbol{p}_{-|K|})) \quad \forall \boldsymbol{p} \in A$$

Note that if $f_k(\cdot) \neq \emptyset$ for every user k, then $BR_k(\boldsymbol{p}_{-k}) \in A_k, \forall \boldsymbol{p}_{-k} \in A_{-k}, \forall k \in K$. Following those definitions we conclude to the following proposition.

Proposition 4: If an uplink power control game in satisfaction form $\hat{G}$ with cost function $\{c_k\}_{k\in K}$ and utility function $\{u_k\}_{k\in K}$ (Eq. 6), has $f_k(\cdot) \neq \emptyset, \forall k \in K$ for every input then it possesses at least one ESE.

Proof: See Appendix IV. ∎

Given the existence of at least on ESE, we can readily conclude to the existence of at least one MESE as well.

D. Uniqueness and Benefits of MESE

In the following, for simplicity in the discussion and without loss of generality, we assume that the f_k functions are non empty for every input and every user k, thus ensuring the possession of at least one ESE (Proposition 4). However, in Section IV it is argued that this assumption can be relaxed through the use of an additional auxiliary power stage.

Proposition 5: If there exists an action profile $\boldsymbol{p}^+$ that is SE of the game $\hat{G}$ there also exists one action profile $\boldsymbol{p}^*$ that is an ESE and it holds true that $c_k(p_k^+) \geq c_k(p_k^*), \forall k \in K$.

Proof: See Appendix V. ∎

Subsequently we prove the uniqueness of the MESE point.

Proposition 6: The MESE point $\boldsymbol{p}^\dagger$ of the game $\hat{G}$ is unique.

Proof: Let $\{E\}$ be the set of action profiles that are ESEs. Let us consider two MESEs $\boldsymbol{p}^{\dagger(1)}$ and $\boldsymbol{p}^{\dagger(2)}$ such that for one user k it holds that $c_k(p_k^{\dagger(1)}) \neq c_k(p_k^{\dagger(2)})$. In order for them to be MESEs, it should hold true that:

$$\forall \boldsymbol{p}^* \in E, \sum_{k\in K} c_k(p_k^*) \geq \sum_{k\in K} c_k(p_k^{\dagger(1)}) = \sum_{k\in K} c_k(p_k^{\dagger(2)}) \quad (6)$$

There is one user k that $c_k(p_k^{\dagger(1)}) \neq c_k(p_k^{\dagger(2)})$, thus, $p_k^{\dagger(1)} \neq p_k^{\dagger(2)}$. Without loss of generality, we assume $p_k^{\dagger(1)} < p_k^{\dagger(2)}$. Thus, the total summation over the costs of all users in $\boldsymbol{p}^{\dagger(1)}$ would be lower than the one of $\boldsymbol{p}^{\dagger(2)}$ if they do not differentiate in any other strategy. This means that there should be one other user $j \neq k$ that $c_j(p_j^{\dagger(1)}) > c_j(p_j^{\dagger(2)})$, so $p_j^{\dagger(1)} > p_j^{\dagger(2)}$.

Let $\boldsymbol{p}^+$ be an action profile with $p_k^+ = p_k^{\dagger(1)}$ and $p_j^+ = p_j^{\dagger(2)}$. Note that $\boldsymbol{p}^+$ has lower summation over the costs of users k, j from both $\boldsymbol{p}^{\dagger(1)}$ and $\boldsymbol{p}^{\dagger(2)}$. Continuing in that fashion, $\boldsymbol{p}^+$ strategy profile selects for every user k the lower power from $p_k^{\dagger(1)}$ and $p_k^{\dagger(2)}$ and thus the lower cost. Note that $\boldsymbol{p}^+$ is an SE as each user k was satisfied by playing p_k^+ either at $\boldsymbol{p}^{\dagger(1)}$ or at $\boldsymbol{p}^{\dagger(2)}$ while all the other users have played greater or equal transmission powers. So, at $\boldsymbol{p}^+$ it holds true that:

$$\sum_{k\in K} c_k(p_k^+) < \sum_{k\in K} c_k(p_k^{\dagger(1)}) = \sum_{k\in K} c_k(p_k^{\dagger(2)}) \quad (7)$$

Applying proposition 5 on $\boldsymbol{p}^+$ gives us an ESE $\boldsymbol{p}^\dagger$ with

$$\sum_{k\in K} c_k(p_k^+) \geq \sum_{k\in K} c_k(p_k^\dagger) \quad (8)$$

Combining Eq. 7 and Eq. 8, we conclude that:

$$\sum_{k\in K} c_k(p_k^\dagger) \leq \sum_{k\in K} c_k(p_k^+) < \sum_{k\in K} c_k(p_k^{\dagger(1)}) = \sum_{k\in K} c_k(p_k^{\dagger(2)})$$

which leads to contradiction with Eq. 6, as $\boldsymbol{p}^\dagger$ is an ESE. So, $c_k(p_k^{\dagger(1)}) = c_k(p_k^{\dagger(2)}), \forall k \in K$ and $p_k^{\dagger(1)} = p_k^{\dagger(2)}, \forall k \in K$. Thus, the MESE point $\boldsymbol{p}^\dagger$ is unique. ∎

The following proposition shows that each user achieves the minimum cost at a MESE point compared to the experienced cost at any other ESE point.

Proposition 7: In the considered uplink power control game, let $\boldsymbol{p}^\dagger$ be a MESE of the game and {E} the set of ESEs, it holds true that $c_k(p_k^\dagger) \leq c_k(p_k^*), \forall k \in K, \forall \boldsymbol{p}^* \in E$.

Proof: Let us study the strategy profile $\boldsymbol{p}$ that:

$$\forall k \in K, \quad \forall \boldsymbol{p}^* \in E, \quad p_k = \arg\min_{p_k^*} c_k(p_k^*) \quad (9)$$

Thus, the strategy profile $\boldsymbol{p}$ picks for each user the power that gives the lowest cost for the user over all its strategies that belong to the set of ESEs, i.e., $\forall k \in K, \forall \boldsymbol{p}^* \in E, p_k \leq p_k^*$. Let us focus on a random user k. Let $\boldsymbol{p}^*$ be one ESE such that $p_k = p_k^*$. So, from all the ESEs, $\boldsymbol{p}^*$ gives the lowest cost to user k, $c_k(p_k^*)$. As proved, $\forall i \in K, p_i \leq p_i^*$. Owing to the above, user k will certainly be satisfied in strategy profile $\boldsymbol{p}$ because it was satisfied at the ESE $\boldsymbol{p}^*$ in which the other users have played greater or equal transmission powers. The above analysis holds for every user k, thus every user in strategy profile $\boldsymbol{p}$ is satisfied, thus $\boldsymbol{p}$ is an SE. Now, we can apply Proposition 5 that gives us an ESE $\boldsymbol{p}^\dagger$ that:

$$\forall k \in K, \quad c_k(p_k) \geq c_k(p_k^\dagger) \quad (10a)$$

$$\sum_{k\in K} c_k(p_k) \geq \sum_{k\in K} c_k(p_k^\dagger) \quad (10b)$$

Taking into consideration Eq. 9, we can note that only the equality can hold in inequalities (12a), (12b) so: $\forall k \in K, c_k(p_k) = c_k(p_k^\dagger)$ and $\sum_{k\in K} c_k(p_k) = \sum_{k\in K} c_k(p_k^\dagger)$. Note that we cannot find an ESE that has lower total cost than $\boldsymbol{p}$. Thus, $\boldsymbol{p}^\dagger$ is the MESE. That means that every MESE allocates to each user the minimum cost that it could possibly have in an ESE, as exactly $\boldsymbol{p}$ does. ∎

Below we can harness the monotonicity of the assumed cost functions to prove that the MESE point is the best strategy profile that the system could possibly converge to, while when it does not exist, the system does not possess any SE at all.

Proposition 8: In the considered uplink power control game, the MESE point, $\boldsymbol{p}^{\dagger}$, is also the MSE point, $\boldsymbol{p}^{opt}$.

Proof: Let us apply proposition 5 in the MSE point, $\boldsymbol{p}^{opt}$ which gives an ESE point $\boldsymbol{p}^{*}$ that $c_k(p_k^{opt}) \geq c_k(p_k^{*}), \forall k \in K$. Let a user $k \in K$ have $p_k^{opt} \neq p_k^{*}$. That would imply that

$$\sum_{k \in K} c_k(p_k^{opt}) > \sum_{k \in K} c_k(p_k^{*}) \tag{11}$$

The above inequality leads to a contradiction because of the MSE's definition 4. Thereby, $\boldsymbol{p}^{*} = \boldsymbol{p}^{\dagger} = \boldsymbol{p}^{opt}$. ■

Following the above proposition and discussion it is noted that the MESE point is also an ESE point, and accordingly an SE point, as discussed in detail in Section II. Following the previous pattern, we can prove that the MSE is component-wise lower than any SE.

Proposition 9: In the considered uplink power control game, let $\boldsymbol{p}^{opt}$ be the MSE of the game and $\{S\}$ the set of SEs, it holds that $c_k(p_k^{opt}) \leq c_k(p_k^{+}), \forall k \in K, \forall \boldsymbol{p}^{+} \in S$.

Proof: Because of proposition 8, the MSE is also the MESE point of the game. Because of that and based on proposition 7, we have that

$$c_k(p_k^{opt}) \leq c_k(p_k^{*}), \forall k \in K, \forall \boldsymbol{p}^{*} \in E \tag{12}$$

Let a random strategy profile that is an SE, $\boldsymbol{p}^{+}$. Applying proposition 5 in $\boldsymbol{p}^{+}$, we have an ESE $\boldsymbol{p}^{*}$ with

$$c_k(p_k^{*}) \leq c_k(p_k^{+}), \forall k \in K \tag{13}$$

Because of Eq. 12:

$$c_k(p_k^{opt}) \leq c_k(p_k^{*}), \forall k \in K \tag{14}$$

Thus, because of Eq. 13, 14 we have that:

$$c_k(p_k^{opt}) \leq c_k(p_k^{*}) \leq c_k(p_k^{+}), \forall k \in K \tag{15}$$

Because $\boldsymbol{p}^{+}$ was a random SE of the game it holds that: $c_k(p_k^{opt}) \leq c_k(p_k^{+}), \forall k \in K, \quad \forall \boldsymbol{p}^{+} \in S$ ■

IV. Algorithm & Convergence

In this section, we present a decentralized algorithm that converges at a Minimum Satisfaction Equilibrium (MSE) of the game $\hat{G} = (K, \{A_k\}_{k \in K}, \{f_k\}_{k \in K})$, based on the concept of Best Response Dynamics (BRD), properly applied in the context of a game in satisfaction form. In particular, Best Response Dynamics (BRD) is defined as the behavioral rule in which each user always chooses its strategy (i.e., its uplink transmission power) to be its best response (BR) to the strategies of the rest of the users. In the context of this paper, the dynamics should not be sequential but rather asynchronous. As it has been shown in [17], when all the users adopt utility functions given by the Shannon capacity and the BRD starts from an SE as an initial strategy profile, they converge monotonically to an ESE.

Algorithm: SDA Turn Phase

if $p_k \in f_k(\boldsymbol{p}_{-k})$ **then** {If user k is still satisfied with its previous power}
  play p_k; {transmit with the same power}
else
  $p_k^M(\boldsymbol{p}_{-k}) \leftarrow$ **ModifiedBinarySearch**($P_k[], 1, |A_k|, u_k(), \boldsymbol{p}_{-k}$); {Finds the power that maximizes k's utility in that turn}
  $BR_k(\boldsymbol{p}_{-k}) \leftarrow$ **BinarySearch**($P_k[], |A_k|, u_k(), \boldsymbol{p}_{-k}, p_k, p_k^M(\boldsymbol{p}_{-k})$); {Finds new BR (as the vector $\boldsymbol{p_{-k}}$ has changed) using binary search in $P_k[]$ from previous power (p_k) to p_k^M using the utility function of the user}
  play $BR_k(\boldsymbol{p}_{-k})$; {play the lowest power that satisfies}
end if

ModifiedBinarySearch($P_k[], low, high, u_k(), \boldsymbol{p}_{-k}$)

$mid \leftarrow (low + high)/2$;
if $low = high$ **then**
  return $P_k[low]$;
else if $u_k(P_k[mid], \boldsymbol{p}_{-k}) > u_k(P_k[mid+1], \boldsymbol{p}_{-k})$ **then**
  $result \leftarrow$ **ModifiedBinarySearch**($P_k[], low, mid, u_k(), \boldsymbol{p}_{-k}$);
else if $u_k(P_k[mid], \boldsymbol{p}_{-k}) < u_k(P_k[mid+1], \boldsymbol{p}_{-k})$ **then**
  $result \leftarrow$ **ModifiedBinarySearch**($P_k[], mid+1, high, u_k(), \boldsymbol{p}_{-k}$);
end if

A. Satisfaction Dynamics Algorithm (SDA)

Initially, each user transmits with its minimum power $P_k[0]$ having sorted its possible transmission powers in a vector $P_k[]$. This power could be considered as their best response in the initialization of the game. Note, that because of the monotonicity of the cost functions, by minimizing the power of a user we also minimize its cost in a turn. After the initial transmission, $\boldsymbol{p}_{start} = (P_1[0], \ldots, P_{|K|}[0])$ each user chooses the power that minimizes its cost function. That said, each user who is in turn to play executes the *Turn Phase* of the SDA algorithm (summarized in the pseudocode above) in order to find its BR and transmits with it. Note that each user k, first, has to find its p_k^M with a modified binary search, given the total interference, i.e., $\sum_{\forall j \in K} h_j p_j$. The total interference may be simply broadcasted by the base station to all the users, in order each user to determine its own sensed interference, i.e., $\sum_{\forall j \in K} h_j p_j - h_k p_k^M$. It is noted here that the base station does not make any decision with respect to the power control problem, a process that is fully executed at each user side. Then, because of Proposition 2, with a second binary search in the interval $[p_k^{min}, p_k^M(\boldsymbol{p}_{-k})]$ it can find its BR in that turn. Due to the the fact that each user either does not change or increases its transmission power at each turn (as we will prove in the section IV.B), user k should only do binary search from the BR of its previous turn to its new $p_k^M(\boldsymbol{p}_{-k})$ to find its new BR. The algorithm stops when no user has a new best response strategy to play.

B. Convergence & Complexity Analysis

In this section we initially prove that the SDA algorithm converges to an MESE, which is also the MSE point of the uplink power control game, under finite number of steps. Subsequently the complexity of the algorithm is analyzed.

Proposition 10: When an SE exists in a game, the SDA algorithm monotonically converges to a strategy profile $\boldsymbol{p}^{opt} \in A$ that is the MSE of the game.

Proof: See Appendix VI. ■

It is noted that in practice the convergence condition of the SDA algorithm is that the best responses of all the users within the examined network have not changed in two consecutive cycles of turns (i.e. iterations ite) of the algorithm, i.e., $|BR_k^{ite}(\boldsymbol{p}_{-k}) - BR_k^{ite-1}(\boldsymbol{p}_{-k})| = 0, \forall k \in K$. Note, that in line 1 of the SDA turn phase, each player, k, should check whether the previous BR coincides with the BR of the next turn, i.e., $|BR_k^{ite}(\boldsymbol{p}_{-k}) = BR_k^{ite-1}(\boldsymbol{p}_{-k})|$. In the case that the latter holds true, then $BR_k^{ite}(\boldsymbol{p}_{-k}) = BR_k^{ite-1}(\boldsymbol{p}_{-k}) = p_k$, which in turn means that the convergence criterion is met.

Furthermore, it should be clarified that so far we proved that SDA algorithm converges to the MSE point, under the assumption that $f_k(\cdot), \forall k \in K$ is not empty. In principle this assumption is not required and it can be easily relaxed by adding for each user k one auxiliary (virtually maximum) transmission power, p_k^V, in its strategy space such that $\forall \boldsymbol{p}_{-k} \in A_{-k}, \quad p_k^V \in f_k(\boldsymbol{p}_{-k})$ and $c_k(p_k^V) = +\infty$. If SDA converges to the strategy profile $\boldsymbol{p}^\dagger = (p_1^V, \dots, p_{|K|}^V)$ then the game does not possess any SE.

Below, the complexity of the algorithm is studied in the case of the users are playing sequentially in a given order. Let us concentrate on one user k in order to specify its CPU time complexity excluding the time that other users take in order to make their decisions as the proposed framework is implemented and executed in a decentralized manner. In every cycle of turns, someone should always increase its power, or else the algorithm converged to $\boldsymbol{p}^{opt}$. The worst case is bounded by the case where the game would have $\mathcal{C} = |A_1| + \dots + |A_{|K|}|$ cycles of turns. So, in $\mathcal{C} - |A_k|$ cycles, user k will find out, in constant time, that it is satisfied. On the other hand, in $|A_k|$ cycles of turns the user runs the modified binary search to find its current maximum, p_k^M, and then one binary search in $P_k[]$ in order to find out its next strategy. Therefore, for all of the cycles it will need $\mathcal{O}((\mathcal{C} - |A_k|) + 2 \cdot |A_k| \cdot log_2(|A_k|))$. Thus, the total time complexity is $\mathcal{O}((\mathcal{C} - |A_k|) + |A_k| \cdot log_2(|A_k|))$. Note, that if each user has the same cardinality in its strategy space, N, the total complexity will be $\mathcal{O}(|K| \cdot N + N \cdot log_2(N))$.

V. Dynamic System Changes - Enhancements

In this section, we discuss how the proposed framework can efficiently handle possible system changes that commonly arise in 5G networks, without having to re-initialize the SDA algorithm, in terms of: a) Increase/Decrease of the QoS thresholds, and b) Entrance/Departure of users from the system. We prove that we can harness the knowledge from the algorithm's previous run, to speed up the next run and accordingly find the MSE of the new game, in an evolutionary manner. Note, that to prove the following propositions we focus on the MESE points, however the same holds true for the MSE due to Proposition 9.

A. Study of MESE properties with system changes

In this section initially we study the properties (Proposition 11) of the MESE of the game, when the QoS requirements of all the users become stricter. Subsequently, Propositions 12 and 13, argue how the SDA framework can capitalize on these properties, in order to efficiently handle relevant changes in the system. Then we demonstrate how the obtained observations are used in order to treat different types of dynamic behaviors of the users (Sections V.B and V.C).

Proposition 11: Let two games be $\hat{G}_1 = (K, \{A_k\}_{k\in K}, \{f_k^1\}_{k\in K})$ and $\hat{G}_2 = (K, \{A_k\}_{k\in K}, \{f_k^2\}_{k\in K})$ with $f_k^1(\boldsymbol{p}_{-k}) \supseteq f_k^2(\boldsymbol{p}_{-k}), \forall k \in K, \forall \boldsymbol{p}_{-k} \in A_{-k}$. Then, for the MESEs of $\hat{G}_1, \hat{G}_2$, $\boldsymbol{p}^{\dagger(1)}, \boldsymbol{p}^{\dagger(2)}$ it holds that $\boldsymbol{p}^{\dagger(1)} \preceq \boldsymbol{p}^{\dagger(2)}$.

Proof: First, note that it cannot be $\boldsymbol{p}^{\dagger(1)} \succ \boldsymbol{p}^{\dagger(2)}$ as in this situation $\boldsymbol{p}^{\dagger(1)}$ would not be the MESE of $\hat{G}_1$. Let now a set of users $J \in K, J \neq \emptyset : \forall j \in J, p_j^{\dagger(1)} > p_j^{\dagger(2)}$. Let also $\boldsymbol{p}$ be a strategy profile that for each user k, it picks the lower transmission power among $p_k^{\dagger(1)}$ and $p_j^{\dagger(2)}$. Specifically $p_k = p_k^{\dagger(1)} \forall k \in K \setminus J$ and $p_j = p_j^{\dagger(2)} \forall j \in J$. Summarizing the above discussion we have:

$$\boldsymbol{p} \prec \boldsymbol{p}^{\dagger(1)} \quad and \quad \boldsymbol{p} \preceq \boldsymbol{p}^{\dagger(2)}. \tag{16}$$

Let us now focus on the strategy profile $\boldsymbol{p}$ in game $\hat{G}_1$:

-$\forall k \in K \setminus J, p_k \in f_k^1(\boldsymbol{p}_{-k})$ as they were satisfied while the others, i.e., $j \in J$, had played $p_j^{\dagger(1)} > p_j^{\dagger(2)} = p_j$ in $\boldsymbol{p}^{\dagger(1)}$. So, the interference was decreased for them.

- $\forall j \in J, p_j = p_j^{\dagger(2)} \in f_j^2(\boldsymbol{p}_{-j}^{\dagger(2)})$ so from our assumptions $\forall j \in J, p_j = p_j^{\dagger(2)} \in f_j^1(\boldsymbol{p}_{-j}^{\dagger(2)})$ and because of Eq. 16, it holds true that $\forall j \in J, p_j = p_j^{\dagger(2)} \in f_j^1(\boldsymbol{p}_{-j})$.

Thus, we have: $\forall k \in K, p_k \in f_k^1(\boldsymbol{p}_{-k})$ which means that $\boldsymbol{p}$ is an SE for the game $\hat{G}_1$. Thus, from proposition 5, we have an ESE $\boldsymbol{p}^* : \forall k \in K, p_k^* \leq p_k$. The aforementioned fact combined with Eq.16 gives: $\sum_{k\in K} p_k^* \leq \sum_{k\in K} p_k < \sum_{k\in K} p_k^{\dagger(1)}$, which gives: $\sum_{k\in K} c_k(p_k^*) \leq \sum_{k\in K} c_k(p_k) < \sum_{k\in K} c_k(p_k^{\dagger(1)})$, which is a contradiction, so $J = \emptyset$. ■

Proposition 12: Let the MESE of the game be $\boldsymbol{p}\dagger$ and a strategy profile $\boldsymbol{p} : p_k \leq p_k^\dagger, \forall k \in K$. If SDA algorithm is initiated with $\boldsymbol{p}$, it will also converge to $\boldsymbol{p}^\dagger$.

Proof: If each user $k \in K$ excludes the powers $p_k^d : p_k^d < p_k$ and executes the SDA algorithm, it will converge to the MESE $\boldsymbol{p}^\dagger$. ■

Proposition 13: Let the MESE of the game be $\boldsymbol{p}\dagger$ and a strategy profile $\boldsymbol{p} : p_k \geq p_k^\dagger \forall k \in K$. If each user initiates the SDA algorithm with $p_k^{max} = p_k$, it will also converge to $\boldsymbol{p}^\dagger$.

Proof: Once again, if each user $k \in K$ excludes the powers $p_k^d : p_k^d > p_k$ and executes the SDA algorithm it will converge to the MESE $\boldsymbol{p}^\dagger$. ■

In both cases, although the functions $\{f_k\}_{k\in K}$ may change, we can exploit the information of the previous convergence point of the SDA algorithm to make the next run more efficient. In the first case, i.e. stricter QoS prerequisites, we run the SDA algorithm from the point that it stopped, while in the latter we exclude the powers that are greater from the previous convergence point.

B. Change in the utility thresholds

Proposition 14: In an uplink power control game $\hat{G} = (K, \{A_k\}_{k\in K}, \{f_k\}_{k\in K})$ in case a user $j \in K$ increases its threshold u_j^{trh} to $u_j^{trh(2)}$, the system can be modeled by a game $\hat{G}_2 = (K, \{A_k\}_{k\in K}, \{f_k^2\}_{k\in K})$ with $f_k(\boldsymbol{p}_{-k}) \supseteq f_k^2(\boldsymbol{p}_{-k}) \forall \boldsymbol{p}_{-k} \in A_{-k}$.

Proof: For the users $k \in K : k \neq j, f_k(\boldsymbol{p}_{-k}) = f_k^2(\boldsymbol{p}_{-k})$ as their QoS requirements remained the same. For user j, $f_j(\boldsymbol{p}_{-j}) \supseteq f_j^2(\boldsymbol{p}_{-j}) \forall \boldsymbol{p}_{-j} \in A_{-j}$. That holds true as $\forall p_j \in A_j, \forall \boldsymbol{p}_{-j} \in A_{-j}$, we have: $u_j(p_j, \boldsymbol{p}_{-j}) \geq u_j^{thr(2)} \Rightarrow u_j(p_j, \boldsymbol{p}_{-j}) \geq u_j^{thr}$ and $u_j(p_j, \boldsymbol{p}_{-j}) < u_j^{thr} \Rightarrow u_j(p_j, \boldsymbol{p}_{-j}) < u_j^{thr(2)}$. Thus: $f_k(\boldsymbol{p}_{-k}) \supseteq f_k^2(\boldsymbol{p}_{-k}) \forall \boldsymbol{p}_{-k} \in A_{-k}$. ■

Inversely and with similar arguments if a user $j \in K$ decreases its threshold u_j^{trh} to $u_j^{trh(2)}$, the system can be modeled by an uplink power control game $\hat{G}_2 = (K, \{A_k\}_{k\in K}, \{f_k^2\}_{k\in K})$, $f_k(\boldsymbol{p}_{-k}) \subseteq f_k^2(\boldsymbol{p}_{-k}) \forall \boldsymbol{p}_{-k} \in A_{-k}$.

C. Entrance and departure of users

In this section, we treat a possible change in the set K of the users in the system (i.e. entrance or departure).

Proposition 15: Let an uplink power control game $\hat{G}_1 = (K, \{A_k\}_{k\in K}, \{f_k\}_{k\in K})$ with MESE $\boldsymbol{p}^{\dagger(1)}$. Let also the same game with an extra user j: $\hat{G}_2 = (K + \{j\}, \{A_k\}_{k\in K} + \{A_j\}, \{f_k\}_{k\in K} + \{f_j\})$ with MESE $\boldsymbol{p}^{\dagger(2)}$. Then $(\boldsymbol{p}^{\dagger(1)}, p_j^{min}) \preceq \boldsymbol{p}^{\dagger(2)}$.

Proof: Let us consider the game $\hat{G}^{'} = (K + \{j\}, \{A_k\}_{k\in K} + \{A_j^{'}\}, \{f_k\}_{k\in K} + \{f_j^{'}\})$ with MESE $\boldsymbol{p}^{\dagger(')}$. Let also $A_j^{'} = A_j + \{\emptyset\}$ and $f_j^{'}(\boldsymbol{p}_{-j}) = f_j(\boldsymbol{p}_{-j}) + \{\emptyset\}$, $\forall \boldsymbol{p}_{-j} \in A_{-j}$. Note that we added a virtual power to user's j strategy space that corresponds to zero transmission and we allowed user j to be satisfied by not transmitting at all. Let us also consider the game $\hat{G}^{''} = (K + \{j\}, \{A_k\}_{k\in K} + \{A_j^{'}\}, \{f_k\}_{k\in K} + \{f_j\})$ with MESE $\boldsymbol{p}^{\dagger('')}$. Note that this game has the same strategy space for user j but it is not satisfied by not transmitting at all. By definition, $f_j^{'}(\boldsymbol{p}_{-j}) \supseteq f_j(\boldsymbol{p}_{-j}), \forall \boldsymbol{p}_{-j} \in A_{-j}$. Thus, because of proposition 11 we have that $\boldsymbol{p}^{\dagger(')} \preceq \boldsymbol{p}^{\dagger('')}$. Given that in $\hat{G}^{''}$, the $\{\emptyset\}$ power will be useless to user j in every satisfaction equilibrium it also means that: $\boldsymbol{p}^{\dagger(2)} = \boldsymbol{p}^{\dagger('')}$ Therefore we conclude that:

$$\boldsymbol{p}^{\dagger(2)} = \boldsymbol{p}^{\dagger('')} \succeq \boldsymbol{p}^{\dagger(')} \tag{17}$$

On the other hand, in game $\hat{G}^{'}$, we know for sure that at the MESE $\boldsymbol{p}^{\dagger(')}$, user j will transmit with $\{\emptyset\}$ power thus adding zero interference to the other users. That would mean that:

$$p_k^{\dagger(1)} = p_k^{\dagger(')}, \forall k \in K, k \neq j \tag{18}$$

Finally because of Eq. 17 and Eq. 18 we get that: $\forall k \in K, k \neq j, p_k^{\dagger(2)} \geq p_k^{\dagger(1)}$ and $p_j^{\dagger(2)} \geq p_j^{min}$. ■

From proposition 12, we can conclude that when a user enters the system, we could execute SDA algorithm starting from the previous MESE for the existing users and from the minimum power for the entering user. Similarly, for the case of a user departure the following proposition holds true (the proof follows similar steps with the case of a user entering the system and is omitted due to space limitation).

Proposition 16: Let an uplink power control game $\hat{G}_1 = (K, \{A_k\}_{k\in K}, \{f_k\}_{k\in K})$ with MESE $\boldsymbol{p}^{\dagger(1)}$. Let also the same game without the user j be $\hat{G}_2 = (K \setminus \{j\}, \{A_k\}_{k\in K} \setminus \{A_j\}, \{f_k\}_{k\in K} \setminus \{f_j\})$ with MESE $\boldsymbol{p}^{\dagger(2)}$. Then $(p_1^{\dagger(1)}, \ldots, p_{j-1}^{\dagger(1)}, p_{j+1}^{\dagger(1)}, \ldots, p_{|K|}^{\dagger(1)}) \succeq \boldsymbol{p}^{\dagger(2)}$.

In a nutshell, Fig. 1 below provides a flow diagram of the operations of the aforementioned holistic framework. Specifically, based on Proposition 14-16 the required arguments for the efficient operation of the SDA algorithm at a given instance - that is the starting points and corresponding users' maximum powers - are defined. Note also that the evolutionary operation of the framework enables the users to harness the resources of the network as much as possible, ensuring on one hand the satisfaction of the QoS requirements of the existing users, while on the other hand allowing the dynamic increase in the system capacity in terms of satisfied users, if this is feasible.

D. Discussion and application in 5G systems

The proposed holistic framework offers and supports the realization of user-centric operating models, as the ones emerging in 5G wireless systems. Such approach, owing to its decentralized nature, is a promising alternative to network-centric solutions that are more complex while also bearing significantly higher overhead and signaling for implementation purposes. The adoption and realization of our proposed satisfaction equilibrium-oriented game theoretic power control framework, supports the proliferation of 5G networks, due to its flexibility, dynamicity and adaptability.

There exist several key characteristics of the emerging wireless communication environment that call for the use of approaches like the ones proposed in our framework based on the adoption of satisfaction equilibrium (increasing the system capacity in terms of satisfied users) and game theory for decentralized operation. Indicatively, we outline the following: (i) the densification of the wireless communication systems with heterogeneous types of cells [23], (ii) the increasing number of nodes in 5G networks along with the variety of the communication types [24], (iii) the heterogeneity of the available communication and multiple access techniques in 5G networks [25], [26], and (iv) the need of supporting a large number of devices with diverse and dynamically changing QoS requirements and behavior [23]. Indeed, Game Theory is largely considered as a building block of the artificial intelligent solutions envisioned in next generation communications and computing systems [27].

The observations drawn form the analysis and discussion in previous sections, supports the claim that an approach adopting the principles introduced in our framework, arises as a powerful tool providing intelligence to the end-user to make optimal decisions about itself, considering the available feedback from the heterogeneous communications environment. The latter is well aligned with the new advances in the intelligence and processing capability of the next generation end-user smart devices. Additionally, the security and privacy concerns can be explicitly and/or implicitly mitigated, given that control information is not exchanged among the end-users

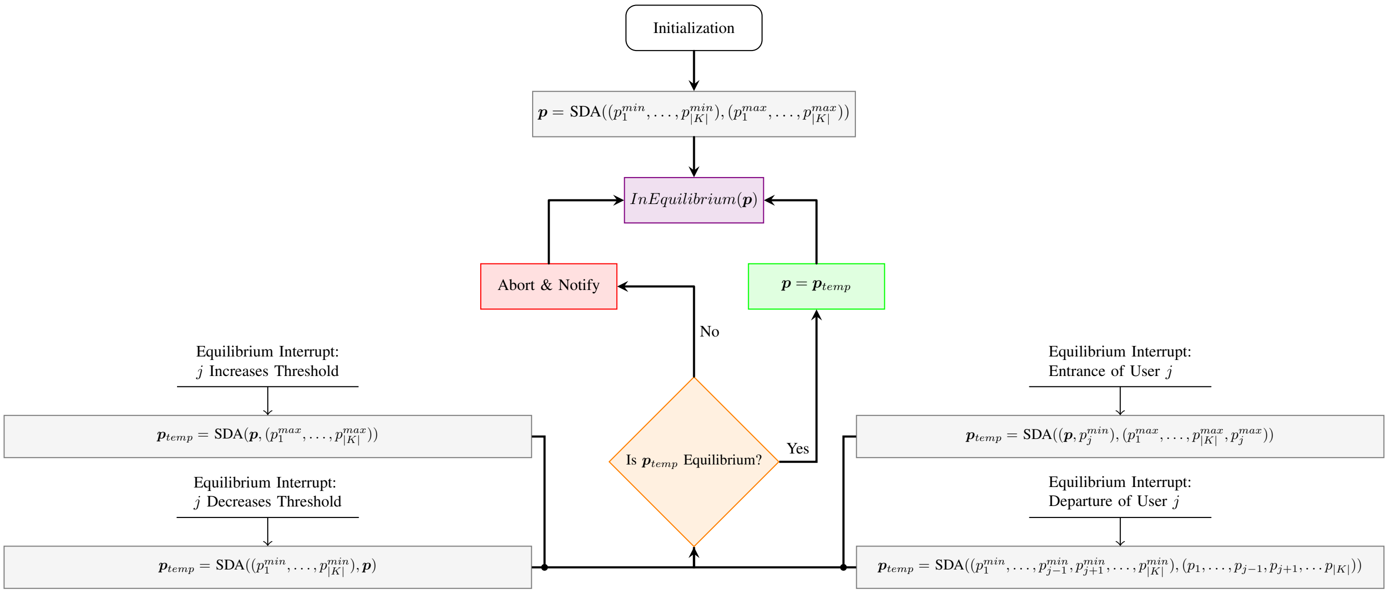


Figure 1 *A flow diagram of the holistic framework*

and a central entity in the case of the game-theoretic power control, making the users less susceptible to intrusions. Last, but not least, it has been concluded that the proposed approach can effectively embed, as needed, the opportunistic behavior and rationale to the end-users, while it can efficiently handle dynamic system and user requirement changes, events that often occur in next generation wireless networks. The latter, in our framework is realized in an incremental and evolutionary manner thus facilitating the real time processing required in 5G systems. Along these lines, indicative numerical results presented later in Section VI, show that the proposed SDA algorithm converges very fast (in approximately 10msec) to the MSE point for the overall examined system, which is well aligned with the requirements in 5G systems [28].

VI. Numerical Results

In this section, we provide indicative numerical results to evaluate the performance of the SDA algorithm and illustrate the key benefits of the MSE point as well as the operation of the framework as a whole. In particular, the focus is placed on the evaluation of the validity and superiority of the introduced theoretical framework by comparing the MSE with other existing equilibria (SE, ESE, NE) (Sections VI.A and VI.B), and on the study of the behavior and convergence of the proposed novel holistic framework, under different scenarios (Section VI.C). Finally, in Section VI.D a comparative study demonstrating its benefits against approaches targeting directly utility maximization outcomes is provided. The user distance $d_k, \forall k \in K$ from the base station is randomly and uniformly distributed within the range of 20 to 150 m. The gain g_k of each user k is inversely proportional to the square of its distance d_k, i.e., $g_k = \frac{1}{d_k^2}$. Each user is assumed to have 150 discrete achievable power levels, randomly chosen within the interval of $[0.1, 1.7]$ Watts. The utility function of each user, unless otherwise explicitly stated, follows the form of Eq. 5. Finally, for demonstration only purposes and without loss of generality, we have assumed $R = 64Kbps$ and $W = 10^6 Hz$.

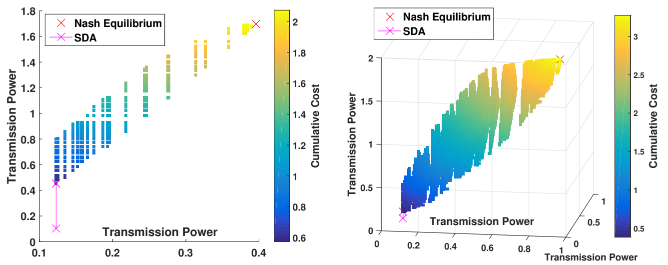
A. Satisfaction Equilibria and Convergence of SDA

Fig. 2 presents the set of all possible Satisfaction Equilibria as well as the convergence of the SDA algorithm and the unique NE of a 2-user (Fig. 2a) or a 3-user game (Fig. 2b). Specifically, the colored region represents all the strategy profiles that are SEs and each point's color depends on the cumulative transmission power of the users, where the light and dark color represent high and low summation, respectively. It is noted that the SDA algorithm monotonically converges to the unique MSE, which is also the SE that charges each user with the lowest power.

In this experiment, the value of u_k^{thr} for user k is set to be the utility it scores if all of the users are transmitting with the powers that the NE point indicates. Thereby, all the strategy profiles in the colored region represent points where the users enjoy the same or greater energy efficiency compared to the unique NE point. That said, at any middle point, whereas users are transmitting with lower power than in the NE, they also enjoy greater or equal energy efficiency. Thus, the framework of satisfaction games and specifically the MSE point along with the SDA algorithm propose more power efficient strategy profiles. It is also observed that the unique NE - commonly adopted in literature - leads to ultimately arbitrary solutions. Although there are seemingly plenty of strategy profiles with the same or greater energy efficiency, which are basically a combination of transmission power and the achieved channel capacity, the NE is utterly arbitrary and depends merely on the configuration of the network, thus, ignoring the user needs.

B. Comparison of the NE with the MSE

The previous result arises the question of whether there are strategy profiles that the system can converge to, where all the users achieve strictly greater energy efficiency score than the one of the NE. Indeed, Fig. 3 presents what happens if all of the users gradually increase their QoS prerequisites from the NE outcome. Surprisingly, in the 3-user game (Fig.

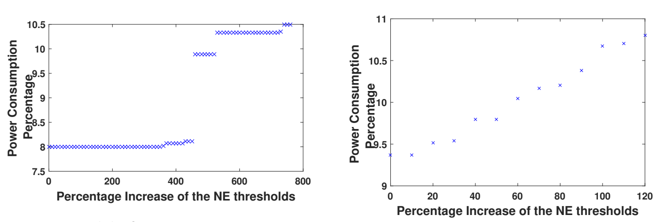


(a) 2-user game (b) 3-user game

***Figure 2** Satisfaction Equilibria and Convergence of the SDA algorithm in a 2 and 3-user power control game*

3a) the three users can augment their QoS prerequisites and simultaneously achieve, when in the MSE, 860% of their achieved energy efficiency score of the NE with just 10.5% of the cumulative transmission power for the system. Similarly, when considering 20 users (Fig. 3b), it was rather possible to achieve 220% of the energy efficiency score of the NE with just 10.8% of the cumulative power.

Thus, directly maximizing the energy efficiency utility turns to be not a good incentive for a user, as by stating its prerequisites, strategy profiles with greater energy efficiency score can be obtained. With the framework of satisfaction games, we could alternatively conclude to energy beneficial solutions for the system, by simply targeting channel capacity instead of energy efficiency. For instance, assuming that the users' utility is the Shannon capacity, then the users can achieve their quality prerequisites, but with the minimum power consumption. That is, if the system converges to the MSE of the game, there would not exist any other strategy profile where everyone meets his threshold, while someone transmits with lower power.



(a) 3-user game (b) 20-user game

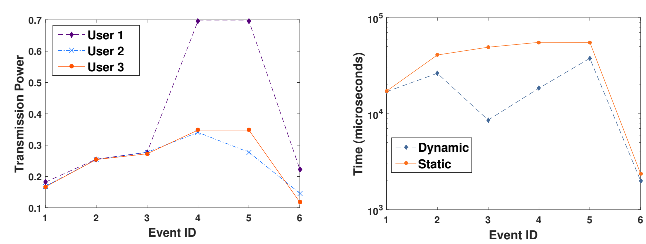
***Figure 3** Satisfaction Equilibria that lead to strictly greater energy efficiency score with lower power consumption*

C. Holistic framework dynamic operation

Following the above argument and in order to show the holistic nature of our framework, below we adopt the Shannon capacity as the considered user utility function. To demonstrate the efficient dynamic operation of the proposed framework, we assume six different events (system stages) taking place sequentially, as follows: a) The system starts with 200 users; b) 10 users enter; c) 1 user enters; d) 3 users double their QoS prerequisites; e) 3 users set their thresholds to 0.8 times the previous one; and f) 21 users depart.

Fig. 4a represents the transmission powers of $three$ different users in the MSEs of the system after each of the six different events took place. In particular, the user with id 1 doubled its threshold (event 4), the one with id 2 decreased its threshold (event 5), while the user with id 3 has stayed in the system after the event 6 without changing its threshold. As it is expected, after the entrance of the 10 users (event 2), the users had to increase their transmission power to achieve the same QoS levels. After the 3 users increased their thresholds (event 4), we observe that all users had to increase their powers as well, in the new MSE. While the user with id 1 was one of the users that had to achieve greater QoS prerequisites, the others had to also increase their powers to achieve their previous thresholds due to the increased interference in the system. Similarly, when the 3 users decreased their thresholds (event 5), they decreased their transmission powers to be in the MSE. Finally, when the network was left with 190 users (event 6), they all were able to decrease their transmission powers to meet their prerequisites.

Fig. 4b presents the time required for convergence during the occurrence of those events (horizontal axis), under the scenario (static) where the users had to completely re-run the SDA algorithm (orange line) and the scenario (dynamic) where the dynamic proposed holistic framework (blue line) was applied. It is noted that using the dynamic framework significant execution time savings are obtained, particularly for minor changes in the system. From the obtained results we notice that the convergence time of our proposed framework is approximately in the range of 10 msecs, which is within the requirements of 5G for real time communications. Furthermore, it should be noted that in a realistic 5G network, the channel gain conditions do not change that fast and often, i.e., in the order of magnitude of msec, thus in a realistic implementation the outcome of the proposed algorithm can be used for a consecutive number of time slots, reducing further the corresponding overhead.



(a) Transmission powers of 3 users at the MSE point. (b) Convergence to MSE under static and dynamic operation

***Figure 4** SDA Static & Dynamic Operation*

D. Comparative Results of Different Strategy Profiles

In this section, we compare the MSE point with the corresponding NE points achieved when either Energy Efficiency Maximization or Shannon Maximization is targeted. The latter is selected for comparison and benchmarking purposes, as the Shannon capacity has been commonly and widely used in the relevant literature to capture the users' achievable data rate [17], [21]. In this scenario, six users are considered that are located at decreasing distances from the base station, with users with lower ID having the highest distances from the base station, thus worse channel conditions. In particular, Fig. 5a suggests that for the first 3 users (the 3 users that are the farthest from the base station) the energy efficiency maximization approach, achieves as expected higher scores in the energy efficiency metric. It is noted here that the presented energy

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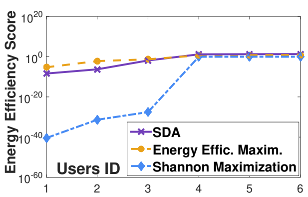
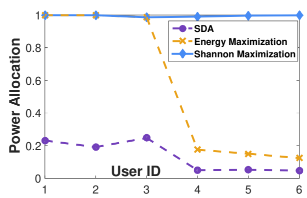
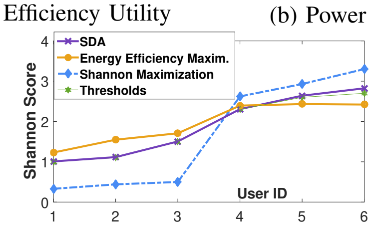
efficiency is measured in [bits/Joule], and it is calculated per one unit of available bandwidth measured in [Hz]. However, as shown in Fig. 5b this happens at the cost that each of the three users transmits with a very high transmission power compared to the MSE, hence gaining higher bit rate than required from their QoS prerequisites (Fig. 5c) while, dramatically increasing the interference in the system. The latter wasteful energy consumption and corresponding negative impact, is observed by the power allocations of the last 2 users, where although they transmit with higher powers under the energy efficiency maximization strategy profile - than the respective ones in the MSE - they ultimately are assigned lower Shannon capacity scores than their requirements (QoS thresholds). On the other hand, the MSE strategy profile converges to quite low transmission powers, while assigning to each user transmission rate close to its threshold (green line in Fig. 5c), therefore satisfying each user's requirement.



(a) Energy Efficiency Utility



(b) Power Allocation



(c) Shannon Capacity

Figure 5 *Comparison of strategies for SDA, Energy-Efficiency Maximization & Shannon Maximization*

VII. Conclusion

In this paper we adopted the concept of games in satisfaction form in order to treat the uplink power control problem in wireless networks. First, we defined different types of equilibrium points (SE, ESE, MESE, MSE) that are of special interest within this framework, while highlighting the benefits, existence and uniqueness of the MSE equilibrium point. In particular, we proved that in this strategy profile the users of the network meet their QoS prerequisites, while being penalized with the lowest possible cost/power. Underlining the need of the system to transmit in this specific point, we proposed a decentralized and low complexity algorithm (SDA) that is shown to converge to this point. Capitalizing on the key properties of the MSE operation point and the SDA algorithm, a holistic framework was proposed to efficiently deal with the dynamic behavior of the users in the network. Finally, detailed numerical results were presented to reveal the properties and superiority of the MSE equilibrium, especially compared to other equilibrium points that have been proposed in the literature with respect to the resource allocation problems in wireless networks.

Appendix I
Proof of Proposition 1

Let $\boldsymbol{p}^+ \in S : R(\boldsymbol{p}^+) \neq \emptyset$ and a user $k \in R(\boldsymbol{p}^+)$. Then, the strategy profile $\boldsymbol{p} = (p_1^+, p_2^+, \ldots, p_k^M(\boldsymbol{p}_{-k}^+), \ldots, p_{|K|}^+)$ will be an SE of the game as user k received greater utility than in $\boldsymbol{p}^+$ while it lowered its power, something that proves that the others will still be satisfied. Repeating this process for every user in $R(\boldsymbol{p})$ will eliminate this set (each user in $R(\boldsymbol{p}^+)$ decreases its power) and conclude to the strategy profile $\boldsymbol{e}^+$.

Appendix II
Proof of Proposition 2

Let us assume that for a user k, $BR_k(\boldsymbol{p}_{-k}) = p$, $p \in (p_k^M, p_k^{max}]$, when the others have played $\boldsymbol{p_{-k}}$. Due to the fact that p is a best response it should hold true that $u_k(p, \boldsymbol{p_{-k}}) \geq u_k^{thr}$ and $u_k(p_k^M, \boldsymbol{p_{-k}}) < u_k^{thr}$. However this cannot hold true as by definition $u_k(p_k^M)$ is the maximum possible value for a fixed $\boldsymbol{p_{-k}}$.

Appendix III
Proof of Proposition 3

Let $\boldsymbol{p^1}$ be a random strategy profile, and $p = BR_k(\boldsymbol{p^1_{-k}})$ be user k's best response. Let $\boldsymbol{p^2_{-k}}$ be a strategy profile that is acquired when a set of users in $K - \{k\}$ increase their powers from $\boldsymbol{p^1_{-k}}$. That is $\boldsymbol{p^2_{-k}} > \boldsymbol{p^1_{-k}}$, thus, $\sum_{j\neq k} h_j p_j^2 \geq \sum_{j\neq k} h_j p_j^1$. Given that the user's k utility function is decreasing with respect to the interference for a fixed transmitting power of k, we have that: $u_k(p, \boldsymbol{p}^1_{-k}) > u_k(p, \boldsymbol{p}^2_{-k})$. Given that p is the $BR(\boldsymbol{p^1_{-k}})$, then based on proposition 2, we have that $p \in [p_k^{min}, p_k^M]$, when the others are playing $\boldsymbol{p^1_{-k}}$. We can distinguish the following two cases.

I) $u_k(p, \boldsymbol{p}^1_{-k}) > u_k(p, \boldsymbol{p}^2_{-k}) \geq u_k^{thr}$: In that case, $p \in f_k(\boldsymbol{p^2_{-k}})$ as $u_k(p, \boldsymbol{p^2_{-k}}) \geq u_k^{thr}$. Moreover, $p = BR(\boldsymbol{p^2_{-k}})$ as it was the best response in $\boldsymbol{p^1_{-k}}$ where the others had lower or equal transmission powers. Thus, $BR_k(\boldsymbol{p^1_{-k}}) = BR_k(\boldsymbol{p^2_{-k}})$. Again, because of proposition 2, $p \in [p_k^{min}, p_k^M]$ when the others have played $\boldsymbol{p^2_{-k}}$.

II) $u_k(p, \boldsymbol{p}^1_{-k}) \geq u_k^{trh} > u_k(p, \boldsymbol{p}^2_{-k})$: Because of the fact that $p \in [p_k^{min}, p_k^M]$ when the others are playing $\boldsymbol{p^1_{-k}}$ and is equal to $BR_k(\boldsymbol{p^1_{-k}})$ there cannot be any satisfying power that is less than p. That will also hold true when the others change strategies to $\boldsymbol{p^2_{-k}}$ because for sure the corresponding utilities will be further decreased. If $p \in (p_k^M, p_k^{max}]$ when the others have played $\boldsymbol{p^2_{-k}}$, then user k does not have a best response nor a satisfying power when the others have played $\boldsymbol{p^2_{-k}}$ or a strategy profile that is component wise greater. In the other case, where $p \in [p_k^{min}, p_k^M]$, when the others have played $\boldsymbol{p^2_{-k}}$, again if there is no satisfying power there will also not exist any satisfying power for strategy profiles that are component wise greater than $\boldsymbol{p^2_{-k}}$. Nevertheless, if there exists a satisfying power that is also the best response we have proven that it will be in the interval $[p_k^{min}, p_k^M]$ and consequently it will be greater than p. Because the above cases represent the only two possible orderings of those quantities, we have proven that $p = BR_k(\boldsymbol{p}^1_{-k}) \leq BR_k(\boldsymbol{p}^2_{-k})$.

APPENDIX IV
PROOF OF PROPOSITION 4

The proof comes from the Theorem 1. As mentioned, $\mathcal{L}$ is a complete lattice. Thus, $\forall \boldsymbol{p}, \boldsymbol{p}^{'} \in A : \boldsymbol{p} \preceq \boldsymbol{p}^{'}$ it holds true that: $(BR_1(\boldsymbol{p}_{-1}), \ldots, BR_{|K|}(\boldsymbol{p}_{-|K|})) \preceq (BR_1(\boldsymbol{p}^{'}_{-1}), \ldots, BR_{|K|}(\boldsymbol{p}^{'}_{-|K|}))$, or equivalently $g(\boldsymbol{p}) \preceq g(\boldsymbol{p}^{'})$, based on proposition 3. Therefore, we also proved that g is an order-preserving function. Following the previous analysis, Tarski-Kraskel's theorem ensures the existence of a fixed point of function g. That is, $\exists \boldsymbol{p} \in A : \boldsymbol{p} = g(\boldsymbol{p}) \Leftrightarrow (p_1, \ldots, p_{|K|}) = (BR_1(\boldsymbol{p}_{-1}), \ldots, BR_{|K|}(\boldsymbol{p}_{-|K|})$. That would mean that for the strategy profile $\boldsymbol{p}$, every user has played its best response strategy given the strategies of the rest of the users. So, $\boldsymbol{p}$ is an ESE for the game $\hat{G}$.

APPENDIX V
PROOF OF PROPOSITION 5

For the proof, we exclude the powers $p_d : p_d > p_k^+, \forall k \in K$, as they do not conclude to an ESE. Thus, the modified strategy space is denoted by $A_k^{'}$, and the corresponding game is $\hat{G}^{'}$. In the game $\hat{G}^{'}$, we know that the strategy p_k^+ will satisfy the user k, $\forall k \in K$, regardless the strategies of the rest of the users as the interference can only be decreased. By applying the proposition 4, we prove the existence of an action profile $\boldsymbol{p}^*$ that is an ESE for $\hat{G}'$, i.e., $\forall k \in K, \forall p_k \in A_k' : p_k \in f_k(\boldsymbol{p}^*_{-k}), \quad c_k(p_k) \geq c_k(p_k^*)$. Because by default p_k^+ is the maximum transmission power of the set A_k' of the k^{th} user in $\hat{G}'$, it means that $p_k^+ \geq p_k^*$ and consequently $c_k(p_k^+) \geq c_k(p_k^*)$. So, because the excluded powers (i.e., $p_d > p_k^+$) were greater than p_k^+, we can conclude to the following statement regarding the initial game $\hat{G}$:

$$\forall k \in K, \quad \forall p \in A_k : p \in f_k(\boldsymbol{p}^*_{-k}), \quad c_k(p) \geq c_k(p_k^*)$$

Due to the above statement and given that $\boldsymbol{p}^*$ is an SE in $\hat{G}$, we conclude that $\boldsymbol{p}^*$ is also an ESE in $\hat{G}$. Thus we have also proven that $\sum_{k \in K} c_k(p_k^+) \geq \sum_{k \in K} c_k(p_k^*)$.

APPENDIX VI
PROOF OF PROPOSITION 10

From proposition 5, because of the existence of an SE we also have the existence of at least one ESE. Therefore, the MESE $\boldsymbol{p}^{\dagger}$ also exists. Because of the fact that there exists a strategy profile that is ESE (and the MESE in that case), in every strategy profile that is component wise less than $\boldsymbol{p}^{\dagger}$, each user will have a satisfying power. The starting strategy profile of SDA is the $\boldsymbol{p_{start}} = (p_1^{min}, \ldots p_{|K|}^{min})$. As proved above, if each user k does not exceed $p_k^{\dagger}$ (and no one else does also), it will always possess a BR_k that is increasing with respect to the powers of the others (Proposition 3). Thereby, in each turn a user either keeps its transmission power (if satisfied) or increases it by playing its new BR. Let us assume that user j was the first one that exceeded its $p_j^{\dagger}$ during one of its turns. Let us also denote the strategy profile of the SDA before j exceeded its $p_j^{\dagger}$ as $\boldsymbol{p}$. That would mean that for every user $k \in K$, $p_k \leq p_k^{\dagger}$, thus, $\boldsymbol{p}_{-j} \preceq \boldsymbol{p}^{\dagger}_{-j}$. Therefore, from proposition 3 we have that $BR_j(\boldsymbol{p}_{-j}) \leq BR_j(\boldsymbol{p}^{\dagger}_{-j}) = p_j^{\dagger}$. Given that in every turn each user responds with its BR, we note that as long as each user k is below its $p_k^{\dagger}$, user j will not exceed its $p_j^{\dagger}$ (contradiction). Because of that, no one will exceed its $p_k^{\dagger}$ when the dynamics start from $\boldsymbol{p_{start}}$. Given that everyone increases its power by playing their BR when they are not satisfied and they do not exceed $p_j^{\dagger}$, SDA will converge at the MESE $\boldsymbol{p}^{\dagger}$ which is also the MSE $\boldsymbol{p}^{opt}$.

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