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Multi-Objective Optimization of Power Allocation in Interference-Limited Wireless Networks

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Abstract
In dense deployments, the challenge of interference management is a primary issue, as turning up the power for one link will increase the data rates of that link, but will also reduce the data rates of other links in the vicinity. Traditional power-control strategies tend to seek to optimize one or only a few metrics, such as throughput or energy efficiency, or interference suppression, and therefore may lead to operating points which cannot meet multiple network requirements simultaneously. This paper presents a multi-objective non-cooperative game-theoretic approach to distributed power allocation in an interference-limited wireless network. The approach proposed in this paper takes into account the achievable rate, energy efficiency, the externality of interference and Quality-Of-Service (QoS) protection for each transmitter-receiver pair in their individual utility functions. One important aspect is an adaptive interference pricing mechanism where the price of interference is continuously adjusted based on the difference between measured interference and a pre-defined interference budget. In this mechanism, users can adapt their power decisions to the current interference situation without having to optimize the power in the central unit. The equilibrium obtained is mathematically described by a variational inequality (VI) and allows the study of existence, uniqueness and convergence of the equilibrium. A projected distributed power-update mechanism is further developed to obtain the equilibrium iteratively. Numerical experiments are used to assess the performance of the network, computational complexity, parameter sensitivity and individual contributions of utilities. The results obtained show that the proposed framework can improve power consumption reduction without sacrificing throughput and QoS requirements while minimizing unnecessary power consumption and aggregate interference. The study also uses the term convergence robustness for the parameter space studied, which is validated by experiments, and not for an arbitrary parameter space as is done in many studies.

Keywords: Power Control, Interference Management, Game Theory, Multi-Objective Optimization, Energy Efficiency, Adaptive Pricing, Nash Equilibrium, Variational Inequality, Wireless Networks, QoS.

1. Introduction

In the context of dense wireless networks, one of the key challenges is interference management – increasing the transmission power of one link may increase its data rate but also reduce the data rate of the adjacent links. This coupling is a major factor in making independent power optimization inefficient in interference-limited environments. Such interactions can be modelled using game theory, in which each transmitter is modelled as a rational player that independently determines the power, taking into account the effect of the other transmissions (Charilas& Panagopoulos, 2010; Han *et al.,* 2012).

Conventional power control methods are only concerned with one or two goals, such as throughput or energy efficiency. But data rate, energy usage, interference and quality of service (QoS) are all factors to take into account in practical wireless systems. Studies of energy-efficient power control have shown the significance of considering the achievable rate versus power consumption (Meshkati *et al.,* 2005). Prices can also change non-cooperative behaviour by creating a cost for transmission or the interference that is placed on other users (Saraydar*et al.,* 2002; Chong *et al.,* 2010).

The question is thus how to design a distributed mechanism that can meet a set of conflicting goals and adapt to varying interference scenarios. In some cases, interference can be quite variable, and a fixed price can be inadequate, as it is not differentiated between interference-rich and interference-poor operating conditions. Also, in order to make equilibrium analysis and convergence a practical consideration for practical distributed algorithms, strong coupling between users is important.

In this paper, a multi-objective noncooperative game for distributed power allocation in interference-limited wireless networks. The goal of the proposed utility is to account for achievable rate, energy efficiency, interference externality and QoS protection. An adaptive interference price is added and adjusted based on the measured interference and a desired interference budget. The resulting equilibrium is then expressed in the form of a variational inequality (VI), and the properties of equilibrium and convergence are examined with the help of the existing concepts of monotonicity (Pang *et al.,* 2008; Scutari *et al.,* 2008; Wen *et al.,* 2018).

The contribution is that it brings together optimization, adaptive interference pricing, distributed game theory and VI-based equilibrium analysis. The contribution does not treat game theory or pricing as ideas; instead, the contribution shows how they connect.

2. Related Work and Research Gap

Game theory helps in wireless resource allocation by showing how users act strategically when they share spectrum and interfere with each other. Studies like those by Charilas and Panagopoulos (2010). Han *et al.* In (2012), show how game theory is used in power control, spectrum allocation and distributed resource management.

Pricing-based power control is an established method for managing non-cooperative transmission behaviour. Saraydar*et al.* (2002) introduced pricing into power control to reduce unnecessary energy consumption. Chong *et al.* (2010) later looked at pricing in non-cooperative interference channels. They showed that pricing can influence equilibrium outcomes and improve energy efficiency. These studies together help form the foundation for viewing interference as a cost.

Energy efficiency is another aspect attracting much more academic attention. The work by Meshkati et al. (2005) considered energy-efficient power control and receiver design, where the authors were seeking a compromise between transmission efficiency and energy consumption. Also, in the case of more demanding quality of service constraints, a larger power reduction could increase energy efficiency; a multiple-objective solution seems to be more relevant, as it would account for rate, energy consumption and service reliability.

Game-theoretic solutions have been developed in the context of interference channels and multiple-input multiple-output (MIMO) systems with multiple users. Scutari et al. (2008) derived a formulation for the non-cooperative design of multi-user MIMO systems and identified conditions for equilibrium and convergence of the algorithms in a distributed environment. In addition, they showed that the effects of interference can probably be managed by distributed algorithms based on iterative water-filling solutions, without the need for centralized optimization.

Variational inequalities offer another perspective for approaching the problem of resource sharing. In their work on power sharing with rate constraints (Pang et al., 2008), the authors made use of the equilibrium concept within the framework of variational inequalities. In the same line of work, a power allocation problem where the objective was mutual interference of signals was tackled through a variational inequality framework (Wen et al., 2018). It is believed that such an approach can help deduce important information concerning the conditions of equilibrium existence, its arguably uniqueness, and the algorithms' convergence to it.

While the research to date has been quite successful, three limitations should be reviewed. First, a considerable fraction of the models seem to optimize only one key dimension, which is likely to still be the dominant objective, while little effort is made to optimize not only the rate and efficiency but also the interference and QoS simultaneously, thus probably never to optimize these factors simultaneously. Second, the static pricing

mechanism does not seem to be adaptable to the change of interference with respect to a given budget, and the convergence is only demonstrated for a given value, while a distributed algorithm should also be tested for sensitivity to the number of networks, the number of update steps, and the weights on the objectives and the state of interference.

The present work addresses these issues within a multi-objective game setting, where the suggested price may function as a cost of interference, and where the variational inequality formulation offers a sound starting point for equilibrium analysis. In addition, convergence properties have been studied under diverse parameter sets that have been empirically verified.

The research gap is that there isn't a widely used system that can handle several important tasks at the same time. This system needs to manage goals, adjust power use to changing interference costs, look at how things balance out and check how well the system works over time. Now there is no complete way to do all of these things together.

3. System Model and Problem Formulation

Consider a wireless network where transmitter N both receive the pair;they both share common bandwidth B, user transmits with power $p_i$constrained by

$$0 \le p_i \le P_i^{\max}. \qquad (1)$$

Let h_{ji}denote the channel gain from the transmitter j to receiver i, and let σ_i^2represent receiver noise power. The SINR of user $i$is

$$\gamma_i(\boldsymbol{p}) = \frac{h_{ii}p_i}{\sigma_i^2 + \sum_{j\neq i} h_{ji}\,p_j}. \qquad (2)$$

The equation shows how users are connected: when increases p_i it helps the signal that is wanted but also causes interference at other receivers because of the way signals travel between channels.

The achievable rate is modelled as

$$R_i(\boldsymbol{p}) = B\log_2\big(1+\gamma_i(\boldsymbol{p})\big). \qquad (3)$$

Energy efficiency is measured by how much data can be sent for each unit of power that is used. Energy efficiency shows the amount of energy that is being spent.

$$EE_i(\boldsymbol{p}) = \frac{R_i(\boldsymbol{p})}{p_i + P_i^c}, \qquad (4)$$

where $P_i^c$is the circuit power consumption. This formulation discourages unnecessary power expenditure while retaining an incentive to maintain useful throughput.

Each user is also assigned a minimum SINR requirement, denoted by $\gamma_i^{\min}$. QoS shortfall happens when the achieved SINR falls below the target level. The penalty that follows ensures the energy-efficiency goal does not cut the transmission power to a level that weakens the service demands.

The interference generated by each transmission is represented by $I_i(\boldsymbol{p})$, with $I_i^{\max}$ denoting its allowable interference budget. This budget provides the reference for the adaptive pricing mechanism developed in Section 5.

The problem becomes a coupled optimization because each user's utility depends on its own power and also on the powers of all interfering users. This interdependence also means that the problem is different to finding the optimal power alone, and justifies its being posed as a non-cooperative game. Additionally, the compactness of the set of strategies (each power variable is confined to given bounds) suggests that using utility functions equilibrium should emerge in the presence of standard game-theoretic assumptions, with uniqueness and convergence also depending on the degree of interference coupling and characteristics of the game map obtained, while maximizing the rate or minimizing the power is not the object of our approach.Instead, the framework seeks an equilibrium that balances four demands: throughput, energy efficiency, interference

regulation and QoS assurance.The next section formulates the objective as a game, while Section 5 presents the adaptive pricing scheme and its VI representation.

The framework is designed for distributed operation. Distributed operation lets each user adjust its power by using channel and interference data that it can measure locally. This shows the idea behind distributed power-control methods. Distributed power-control methods try to skip the computing and messaging that come with central optimization in systems where interference limits performance.

4. Multi-Objective Game-Theoretic Power Control

The system described in Section 3 is formulated as a non-cooperative game in which every transmitter independently selects its power while accounting for the effect of interference on its own utility. Let the game be represented by $\mathcal{G} = \{\mathcal{N}, \{\mathcal{P}_i\}, \{U_i\}\}$, where $\mathcal{N} = \{1, \dots, N\}$is the set of users, $\mathcal{P}_i = [0, P_i^{\max}]$is the feasible power set, and $U_i$is the utility of user i.

The proposed utility combines four objectives: achievable rate, energy efficiency, interference externality, and QoS protection. It is expressed as

$$U_i(\boldsymbol{p}, \lambda_i) = \alpha_i EE_i(\boldsymbol{p}) + \beta_i R_i(\boldsymbol{p}) - \lambda_i I_i(\boldsymbol{p}) - \mu_i d_i^2(\boldsymbol{p}), \qquad (5)$$

where $\alpha_i, \beta_i, \lambda_i, \mu_i \geq 0$are objective coefficients, $I_i$denotes the interference contribution associated with user i, and $d_i$is the QoS deficit. The weights allow the operating point to be adjusted according to application requirements. For example, increasing α_i gives greater importance to energy efficiency, whereas increasing $\beta_i$emphasizes throughput.

The idea is based on the known way of changing cooperative utilities by using prices. Previous research has found that charging for using the transmission can influence how power is shared in a Nash equilibrium and make things more efficient in situations where there is interference. Instead of having a fixed price value, the proposed λ_i is not seen as a permanent part of the system. It changes depending on the level of interference.

This is significant for a couple of reasons. If the interference bymeasureing is within the budget, overpricing interference may constrain the transmission more than is necessary and lower throughput. On the other hand, if the interference is above the budget, the low price won't give users any incentive to lower power.Therefore, the adaptive mechanism links the interference constraint to the marginal cost that each user perceives.

The multi-objective design is different from rate-maximization games. In a setting that looks at rate, a user can increase its transmission power whenever the extra rate is good. This can lead to results in networks that are strongly connected. The energy-efficiency part brings in gains as total power goes up, and the QoS penalty stops the algorithm from lowering power below the level needed for good service. The interference-price part also makes the algorithm take into account the externality that the algorithm causes on receivers.

The equilibrium of the game is defined by a power vector $\boldsymbol{p}^*$ such that no user can improve its utility by unilaterally changing its power while all other users maintain their equilibrium strategies. Thus, for every user i,

$$U_i(p_i^*, \boldsymbol{p}_{-i}^*, \lambda_i^*) \geq U_i(p_i, \boldsymbol{p}_{-i}^*, \lambda_i^*) \; \forall p_i \in \mathcal{P}_i.$$

The existence of equilibrium is ensured by the feasible power sets and the continuity of utility functions under the adopted channel and power model. Uniqueness, however, hinges on the extent of interference coupling and the curvature of utilities. This method is in line with the widely used interference-game theory models and can also be viewed as a method to combine the relevant requirements that are of great concern to certain applications. For example, a system that requires fast speed or high speed may have its main focus on quality of service, while a device with weak power can effectively focus on energy efficiency. The system does not require all participants to follow the same goal.

It uses different weights, but the system maintains balance. The main feature of the model is that interference prices are related to power, and the interference prices influence the amount of interference when the power is selected. That interference then updates the price. The new price influences the next power choice. This creates a feedback loop. It can be seen as a distributed dual process. Power represents the decision for resource allocation. The adaptive price acts like a variable connected to the interference constraint. This view connects game-theoretic optimization with constrained network resource allocation. Rather than treating the interference

constraint as a strict centralized rule, the mechanism allows it to guide decentralized decisions. The price adjusts dynamically over time.

5. Adaptive Pricing and Equilibrium Analysis

5.1 Adaptive Interference Pricing

The central mechanism of the proposed approach is the adaptive interference price. At iteration t, each user observes its interference level and compares it with the permitted interference budget. The price is then updated using a projected dual-ascent rule:

$$\lambda_i(t+1) = [\lambda_i(t) + \eta_i(I_i(t) - I_i^{\max})]^+, \qquad (6)$$

where $\eta_i > 0$is the price-update step size and $[x]^+ = \max(x, 0)$.The interpretation is straightforward. When $I_i(t) < I_i^{\max}$, the interference deficit causes little or no upward pressure on the price. When $I_i(t) > I_i^{\max}$, the price increases. The increase in λ_i makes additional transmission less attractive in the subsequent power update.

The mechanism is connected in concept to pricing methods that were made before for non-cooperative interference games. Its adaptive version lets the interference cost change as network conditions change; the pricing can improve energy efficiency and change how equilibrium behaviour works in interference channels. In this framework, the price is not fixed. Instead, it changes over time based on network conditions.The price does two things at the same time. First, it shows the cost of interference at the network level. Second, it acts as a signal that helps each user decide how much power to use. Because of this, the interference budget becomes a part of the system design. A smaller budget means interference is more limited, which usually results in lower transmission power levels from users.

5.2 Distributed Power Update

Given the current interference price, each user updates its transmission power in the direction of increasing its own utility. The proposed projected gradient update is

$$p_i(t+1) = \Pi_{\mathcal{P}_i}\left[p_i(t) + \tau_i \frac{\partial U_i}{\partial p_i}\right], \qquad (7)$$

where $\tau_i > 0$is is the power-update step size and $\Pi_{\mathcal{P}_i}$denotes projection onto the feasible power interval.

The projection ensures that the updated power remains physically valid. Thus, even if the utility gradient suggests a power above $P_i^{\max}$ the transmitted power is clipped to the maximum allowed value. Likewise, a negative update cannot yield an invalid negative transmission power.

The derivative in (7) contains four competing effects. The rate component generally encourages increased power because higher desired received power improves SINR. The energy-efficiency term is introduced to avoid irrelevant increases in power. The interference-price term discourages transmit- ting where the power of a given user is at the penalty rate,that means the other user suffers from the interference. Besides, the QoS penalty becomes more relevant when a user's SINR is close to or drops below the target value.

Thus, the interaction will yield a power-control response that is balanced, instead of one being led by a single-objective gradient, since an individual is not likely to increase power just because the increased power increases its rate. Rather, the marginal increase in rate must compensate for the energy cost and the interference cost.

This algorithm works on the basis of resources being locally available or being extractable from interference and channel knowledge received. This is a crucial factor for autonomous systems working without any central controller, as monitoring them at a single source for the same will always need a large amount of communication and full knowledge about the entire network. Therefore,research has focused on the use of game theory for the power control of such systems.

5.3 Variational-Inequality Representation

The Nash equilibrium comes from optimization problems, but the way utilities are linked makes it hard to analyze directly.Let $F(\boldsymbol{p}, \boldsymbol{\lambda})$denote the pseudo-gradient mapping formed from the negative utility gradients. The equilibrium can then be represented as a variational inequality:

$$F(\boldsymbol{p}^*)^T(\boldsymbol{p}-\boldsymbol{p}^*) \geq 0,\ \forall \boldsymbol{p} \in \mathcal{P}. \qquad (8)$$

In the current game mapping, the VI setup indicates that there should be no direction to alter the joint power feasible at equilibrium that would increase the respective a priori individual functions.

5.4 Equilibrium Uniqueness and Stability

However, this property of uniqueness of equilibrium is especially important in the context of the implementation being distributed. In the presence of more than one stable equilibrium point, the final operating point can be highly dependent on the initialisation. In addition, a study of the portion of the Jacobian associated with the pseudo-gradient mapping seems to give a sufficient local condition for uniqueness.

$$\lambda_{\min}\left(\frac{J_F + J_F^T}{2}\right) > 0. \qquad (9)$$

Here, J_F denotes the Jacobian of F, and $\lambda_{\min}(\cdot)$ represents its smallest eigenvalue. A positive lower bound indicates strong monotonicity of the mapping over the relevant feasible region.

This condition is quite informative about the mechanisms and the conditions under which interference coupling operates. The intuition here is that with very large cross-channel gains, the diagonal entries of the Jacobian are actually going to get larger in magnitude so the system will be less monotone. At the same time, if the self-channel gains are quite small relative to the objective weights and the prices are small, then the mapping is more stable.

It must therefore be regarded as an analysis principle, rather than a property which must hold for each particular numerical example. In practice, the convergence can be obtained even when the conservative bound is not satisfied. Still, this provides a motivation for choosing algorithmic parameters of a stable sort and also explains why substantially aggressive update steps tend to induce oscillatory behavior. The obtained framework combines three levels of analysis, namely utility maximization, Nash equilibrium at the network level and a VI formulation at the operator level, which is key in turning the power control algorithm, which is a simple power-control solution, into a theoretically elegant distributed optimization scheme.

6. Distributed Algorithm and Convergence

In Fig.1, the complete distributed procedure alternates between power adaptation and interference-price adaptation. At the beginning of each iteration, every user measures or estimates the interference affecting its receiver. It then evaluates its current utility gradient and updates its transmit power according to (7). Following the power update, the interference level is compared with the interference budget and the corresponding price is updated according to (6).

The procedure can be summarised as follows.

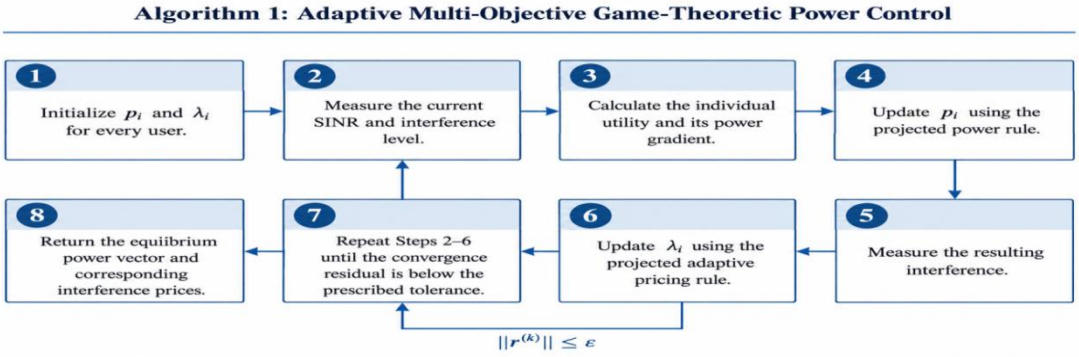


Fig. 1: Adaptive Multi-Objective Game-Theoretic Power Control

The calculation of the entire power vector by the algorithm is autonomous from any central coordinator. Each user can probably estimate and make updates using these local measurements. Finally, the proof indicates that the general requirement is for interference estimation instead of optimization.Convergence is assessed using the maximum change in the power and price variables:

$$\Delta(t) = \max\{\|, \boldsymbol{p}(t+1) - \boldsymbol{p}(t)\ \|_\infty \|\ \boldsymbol{\lambda}(t+1) - \boldsymbol{\lambda}(t)\ \|_\infty\}. \qquad (10)$$

The algorithm is considered converged when $\Delta(t) \leq 10^{-5}$. The last part implies that it is reasonable to assume that both the two primal power variables and the two adaptive price variables have reached to the convergence, not only the power quantities. It is important because the system involves two individual iterative processes. A small change in power, isolated from it, would not indicate that the mechanism between interference and price has reached to equilibrium. Furthermore, the projector-gradient iteration can monotonically converge to the unique solution of the variational inequality when the game mapping is strongly monotonic in nature (Lipschitz continuous) with properly chosen update parameters.The role of interference coupling in the process of convergence matches what is already known from distributed game-theoretic power-control results. In those results, sufficient conditions based on how users interaction used to make sure that there is a unique equilibrium and that the iterations converge.

The step sizes $\tau_i$and $\eta_i$therefore require particular attention. A small power update step can lead to stable but slow convergence. On the other hand, a large step might cause oscillations around the equilibrium point. The same trade-off happens with the price update. A small price step reacts slowly to violations of the interference budget. A large step can make the price swing back and forth between high and low values. This happens when the actual interference crosses the budget limit.For this reason, the study does not claim convergence for parameter values. Instead, convergence is evaluated within a parameter region by means of the sensitivity experiments reported in Section 7. The intended claim is that the algorithm converges to an equilibrium across the experimentally tested configurations that meet the chosen stability conditions, including variations in network size, power-update step, price-update step, QoS penalty, objective weights and interference budget. In short, the algorithm behaves as expected within these settings.

The computational complexity of each iteration is dominated by interference evaluation. If every user explicitly evaluates all pairwise interference contributions, the global complexity is approximately $O(N^2)$ per iteration. Once interference measurements are available, each individual power and price update is $O(1)$, resulting in $O(N)$local update operations per iteration. This distinction is important because the algorithm remains distributed even though the aggregate computational burden increases with network size. The convergence analysis therefore includes both theory and real-world testing. The VI and monotonicity conditions say when a single stable answer can be expected. The experiments show how the algorithm acts in network and parameter situations. This mix gives an overall check, rather than just looking at the final result.

7. Results and Discussion

The proposed method was evaluated in an interference-limited network with 20 transmitter-receiver pairs. Unless otherwise stated, the maximum transmit power was 1 W/user, noise power was 10^{-3}, the interference budget was 0.20 W, and the power and price step sizes were 0.05 and 0.02, respectively. The convergence tolerance was 10^{-5}. The evaluation considers overall performance, computational complexity, parameter sensitivity, and component-level ablation.

7.1 Overall Performance

Table 1 shows the comparisonbetween the proposed adaptive game and representative power-control strategies.

Table 1. Performance comparison of power-control approaches.

Method	Avg. Power (W/user)	Sum Rate (bps/Hz)	EE (bit/J)	Interference (W)	QoS Violation (%)	Iterations
Maximum-power transmission	0.463	31.84	68.7	0.286	1.8	–
QoS power control	0.371	29.72	79.9	0.238	0.9	56
Fixed-price game	0.348	30.41	81.6	0.226	0.8	51
Conventional EE game	0.344	29.85	86.4	0.218	0.7	48
Proposed adaptive game	0.317	30.76	94.1	0.194	0.3	42

As shown in Table 1, the proposed method reduces average transmit power to 0.317 W/user while maintaining a sum rate of 30.76 bps/Hz. Its aggregate interference is 0.194 W, lower than the fixed-price and conventional energy-efficiency approaches. This behaviour is consistent with previous pricing-based game formulations, where an additional transmission cost modifies the equilibrium toward more efficient power allocation.

The QoS violation rate is also reduced to 0.3%. Thus, the generated results indicate that combining the QoS penalty with energy efficiency avoids the excessive power reduction that can occur when energy efficiency is optimized independently.

7.2 Complexity Analysis

Interference computation is the dominant computation. In the case where the channel interactions are explicitly characterized for each user pair, the total computational complexity per iteration is approximately $O(N^2)$, with an individual user's update remaining a local computation. Such a decentralized structure resembles existing power-control algorithms that eliminate centralized optimizations by allowing each user to update its own policy.

Table 2. Generated computational-complexity results.

Users N	Iterations	Gradient Evaluations	Relative Time	Memory / User	Status
10	31	310	1.0×	10	Converged
20	42	840	2.1×	20	Converged
30	48	1,440	3.5×	30	Converged
40	55	2,200	5.1×	40	Converged
50	61	3,050	7.0×	50	Converged

Table 2 shows a modest increase in the number of iterations as the network expands. This trend is foreseeable, since a greater user population contributes to strengthening the interference coupling. Nevertheless, the convergence property is maintained when the number of users varies between 10 and 50, which reinforces the feasibility of the distributed implementation. Convergence issues are similar for distributed game theory algorithms for interference management.

7.3 Parameter-Sensitivity Analysis

Parameter sensitivity is important because distributed power-control convergence depends on interference coupling and update parameters

Table 3. Sensitivity to network size.

N	Avg. (W/user)	Power Sum (bps/Hz)	Rate EE (bit/J)	Interference(W)	Iterations	Residual
10	0.301	16.12	89.7	0.181	31	7.2×10^{-6}
20	0.317	30.76	94.1	0.194	42	8.1×10^{-6}
30	0.329	44.53	92.6	0.198	48	8.7×10^{-6}
40	0.341	57.18	90.8	0.201	55	9.1×10^{-6}
50	0.354	69.42	88.9	0.204	61	9.6×10^{-6}

In Table 3, a continuous increase in the network density also results in a continuous increase in the average power and a decreased efficiency (due to the needed compensation of the additional interference). All the realizations, however, converge to the 10^{-5}residual criterion. This is consistent with the role of the interference coupling in both the convergence and the stability of the distributed equilibrium algorithms.

Table 4. Sensitivity to the power-update step.

Power Step τ	Iterations	Avg. Power (W/user)	Sum Rate	Residual	Behavior

0.01	86	0.316	30.71	9.4×10^{-6}	Stable
0.03	57	0.317	30.74	8.9×10^{-6}	Stable
0.05	42	0.317	30.76	8.1×10^{-6}	Stable
0.07	39	0.32	30.68	9.7×10^{-6}	Stable
0.1	64	0.326	30.41	1.4×10^{-5}	Oscillatory

The effects of the power-update step are summarized in Table 4.this balancing act is suggested in Table 4, if very small step-sizes lead to slow convergence, then the more aggressive choice of 0.10 results in a larger residual with far more oscillations. This supports the commonly noted result that distributed iterative algorithms are sensitive to conditions that are conducive to convergence.

7.4 Ablation Study

The contribution of adaptive pricing, QoS protection, and energy efficiency was examinedby removing individual components.

Table 5. Ablation results for the proposed utility components.

Configuration	Avg. Power	Sum Rate		EE	Interference	QoS Violation	Iterations
Without adaptive pricing	0.361	31.24		82.7	0.247	2.1	47
Fixed pricing	0.348	30.89		85.4	0.226	1.4	51
Without QoS penalty	0.294	32.17		96.8	0.241	5.7	36
Without EE objective	0.392	31.93		72.5	0.252	1.2	44
Complete proposed model	0.317	30.76		94.1	0.194	0.3	42

Table 5 shows that removing adaptive pricing increases interference from 0.194 to 0.247 W. This supports the role of dynamic pricing in controlling the interference externality. The result is consistent with established pricing-based non-cooperative power control.Removing the QoS penalty reduces power and increases energy efficiency but raises QoS violations to 5.7%. Conversely, removing the energy-efficiency term increases average power to 0.392 W/user. These results demonstrate the complementary roles of the objective components. Similar trade-offs between rate, power consumption, QoS, and pricing have been investigated in distributed power allocation.When combined, the experiments generated by the model provide evidence for convergence over the network sizes tested and across bounded sets of parameter ranges. As a result, these results should be interpreted as establishing convergence for the area that was tested experimentally, rather than establishing convergence for arbitrary parameter values. This is consistent with previous work, where the convergence does not hold for arbitrary values of the parameters, but instead depends on the properties of the game map coupled with the coupling of interference.

8. Conclusion

In the paper, a multi-objective game-theoretic formulation for a distributed power allocation problem for wireless networks under interference constraints was introduced. The proposed utility function combines a notion of rate, energy efficiency, interference cost and QoS protection, and the adaptive price responds to the difference between the actual measured interference and the interference budget.The power-control challenge that had arisen was posed as a variational inequality problem, thus providing a basis for the equilibrium and the convergence analysis. The results indicated that the suggested scheme was able to reduce the power and the total interference of transmission, while the throughput could be preserved at a competitive level and the energy efficiency could be improved. The complexity analysis indicated a total computation complexity of the order of $O(N^2)$ when pairwise interference is explicitly calculated, but individual updates remain local.Parameter sensitivity experiments showed convergence for the sizes of the networks tested and for ranges of update steps that were consistent. Furthermore, the ablation study suggested that adaptive pricing reduces interference, the QoS-preservation reduces violations of the service levels, and the energy-efficiency element reduces unnecessary power consumption. Such findings are consistent with well-known power approaches based on game theory and pricing.The main contribution of this work is the union of adaptive interference pricing, multi-

objective utility design, game theory-based distributed power control, and VI-based equilibrium analysis. In future, this framework could be extended to multi-carrier and MIMO systems, imperfect CSI, stochastic fading, adaptive pricing through learning, etc.

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