

## Research Article

# Power Control in Distributed Wireless Sensor Networks Based on Noncooperative Game Theory

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A game theoretic method was proposed to adaptively maintain the energy efficiency in distributed wireless sensor networks. Based on a widely used transmission paradigm, the utility function was formulated under a proposed noncooperative framework and then the existence of Nash Equilibrium (NE) has been proved to guarantee system stability. To pursuit NE, an NPC algorithm was proposed to regulate heterogeneous nodes with various communication demands given the definition of urgency level. Results from both simulation and real testbed presented the robustness and rapid convergence of NPC algorithm. Furthermore, the network performance can remain in a promising state while the energy consumption is greatly decreased.

## 1. Introduction

Power control is one of the critical issues in wireless sensor networks (WSNs), especially when node is battery-powered. In wireless network, both throughput and bit error rate (BER) depend on the signal to interference and noise ratio (SINR) on receiver side, which will result in the transmission dilemma in wireless sensor networks. If transmitter raises its transmission power  $p_t$  to increase SINR, it will inevitably also act as noise to other nodes which are on the same channel. Therefore, power control in WSNs has been targeting to find certain appropriate strategies to alleviate the effect.

Most of solutions focus on regulating transmission power to increase the network capacity and prolong the battery life. To better manipulate transmitter power, Yates proposed an analytic method for power iteration, which is based on the satisfaction of signal to interference ratio (SIR) requirement [1]. A SIR balancing algorithm was developed by Zander that each and every terminal, by using this algorithm, would periodically adjust their power to converge to the corresponding SIR equilibrium [2].

As wireless sensor network has been evolving as the popular platform for large-scale applications, an alternative approach to the power control problem based on the

game theory has been discussed. For example, in military and emergency scenarios, wireless sensor nodes under the same authority tend to work with each other in a fully cooperative way. Wu et al. proposed a fill-fledged cross-layer optimization design, which operated in a bandwidth-limited regime and in an energy-limited regime. The significant performance could be achieved by making a tradeoff between throughput and energy efficiency [3]. Wu and Bertsekas pointed out that generally power levels are assigned from a discrete set, and each mobile node holds its own interest so that the acceptable signal quality would individually not be the same. Eventually, the optimal solution could be found in a finite number of iterations [4]. To effectively communicate in energy-constrained network, Zhou et al. investigated the minimum energy relay selection mechanism jointly with transmission power control [5].

Recently, the applications of wireless sensor networks tend to focus on civilian usage that lacks of authority for any single node. In this situation nodes can not fully cooperate with each other, therefore noncooperative frameworks for solving the power control problem have been proposed. Long et al. featured the network that each individual held its own independent decision for the power selection. Based on the theory of stochastic fictitious play, a pure Nash

Equilibrium was realized with QoS requirement [6]. Altman et al. taken SINR as objective function and characterized both cooperative scenario and noncooperative one, while in noncooperative scenario, the system is modeled in a Hawk-Dove game form and each individual can choose either conciliation or conflict fighting for shared subcarriers [7]. Considered both SINR and network capacity, Sun et al. presented a distributed noncooperative game algorithm for the system to reach the proved unique NE [8]. Shi et al. consider the problem of power control for two independent relay-assisted wireless systems that once both systems act noncooperatively to optimize their own rate, they can always reach a unique Nash equilibrium [9]. Tsiropoulou et al. studied the distributed power control problem via convex pricing of nodes' transmission power in the uplink of CDMA wireless networks and proved that their formulated MSUPC-CP game had a unique Pareto optimal Nash equilibrium. Finally a distributed iterative algorithm is proposed to compute the game's equilibrium [10]. Kesselheim analyzed the SINR capacity maximization problem, the proposed algorithm, under the SINR constraints, can maximize the number of simultaneous communications [11]. Lu et al. emphasized on noncooperative distributed power control in Gaussian interference channel and provide two types of power control schemes: gradient projection type and nonlinear type, both of which, however, were on the same propose of utility maximization. Convergence requirements were finally studied to supplement the utility function [12].

Those previous works, however, either did they not systematically analyze the convergence or did they not propose a reasonable solution to attain that convergence. For that matter, we have been fundamentally concerned about constructing a noncooperative game model for wireless sensor networks. Based on the importance levels of various messages, nodes in the game can define their own utility function individually. Because there is no central controller or infrastructure, the information of each node cannot be knowledgeable by others. Thereby, even if Nash Equilibrium (NE) exists, it may not be achieved directly through the Best Response (BR) choice. In this case a convergence algorithm is proposed so that nodes can be guided and quickly converge to the NE point with a stable network performance.

The remainder of the paper is organized as follows. Section 2 builds up system model and defines the utility function. Convergence analysis and detailed description of NPC algorithm are given in Section 3. Experiments from both the simulation and real testbed are evaluated in Section 4. Finally, Section 5 concludes the paper and discusses future work.

## 2. System Model and Utility Function

**2.1. Preliminaries.** In wireless communication, Energy is consumed by both receiver and transmitter denoted as  $p_{rx}$  and  $p_{tx}$ , respectively. During communication, the transmission power  $p_i$  also plays as noise to other nodes that share the same channel. Hence, the utility function can be defined as  $U_i(p_i, P_{-i})$ , where  $p_i$  denotes power usage on link  $i$  which is

comprised of both  $p_{tx}$  and  $p_{rx}$ , and  $P_{-i} = \sum_{j \neq i} p_j h_{ji}$  denotes the interference power from other transmission links, where  $p_{jt}$  is the link  $j$ 's transmission power at time  $t$  and  $h_{ji}$  represents the link gain from link  $j$ 's transmitter to link  $i$ 's receiver. To ensure power convergence of this noncooperative system, the existence of NE should first be guaranteed. The condition for the existence of NE points in noncooperative game was proposed in [13]. Let  $G = [N, \{P_i\}, \{U_i(*)\}]$  denote power control game for every  $i \in N$ . If the power strategy tuple  $P^* = (p_1^*, p_2^*, p_3^* \dots p_n^*)$  is NE of game  $G$ , the following condition should be satisfied for every  $i \in N$  and  $p'_i, p_i^* \in P_i$ :

$$U_i(p_i^*, P_{-i}^*) \geq U_i(p'_i, P_{-i}^*). \quad (1)$$

Nash Equilibrium is a fixed point of best response power strategy profile that everyone chooses its BR power based on the choices of others which builds up internal connection for everyone.

**Lemma 1.** *An NE point exists in the game  $G$  if*

- (1) *Power strategy set  $P_i$  is a nonempty, convex, and compact subset of some Euclidean space  $R_n$ ;*
- (2)  *$U_i(*)$  is continuous in  $p$  and quasiconcave in  $p_i$ .*

In order to be compatible with the NE requirements, power strategy should first be quantified. The smallest unit is defined as  $(p_{i\max} - p_{i\min})/E_i$  where  $E_i$  denotes the degree of quantification which should not be infinite.

$p_i$  and  $P_{-i}$  are variables of Utility  $U_i$ . In order to achieve the maximum  $U_i$ , its partial derivative with respect to  $p_i$  should first be made, then let  $\partial U_i / \partial p_i = 0$  to calculate the extreme value strategies  $\{p_E\}$ . After that we bring those extreme values into the second-order partial derivative of  $U_i$  with respect to  $p_i$  and ground on the requirements of  $\partial^2 U_i / \partial^2 p_i |_{p_i=p_E} < 0$  to decide which one of them can make the max value for  $U_i$ . And, if the max value does exist, we denote this extreme value as  $p_{EM}$ . Because of possible irrational players and unexpected stimulus, power stability of the game model  $G$  should be taken into consideration.

**Theorem 2.** *Define  $F$  as the interference power, then game  $G$  will be power stabilized, if and only if  $\partial p_{iEM} / \partial F \leq 0$  and  $-1 < \sum_{j \neq i} (\partial p_{jEM} / \partial F) * h_{ji} \leq 0$ , for every  $i \in N$ .*

*Proof.* Consider a scenario that each transmitter has already reached to its balance point, and because of some unknown stimulus, there is an increment of  $\rho$  to the background noise of every node. If the system is power stabilized, there must be another balance point for each and every transmitter to assign its power strategy. Now let us define  $p_{jEMk}$  as link  $j$ 's extreme power value at time  $k$ , and each transmitter refreshes its  $p_{iEM}$  synchronously based on its interference power  $F$  that is composed by  $P_{-i}$  and background noise  $\Delta$ . Because of this, we take it as a Markov Process with memory only to the situation one step before.

Let  $K(F)$  denote  $\partial p_{iEM}/\partial F$ , then we can initiate  $p_{iEM}$ ,  $p_{-i}$  as

$$p_{iEM0} = \int_0^{P_{-i0} + \Delta} K(x) dx + p_{iEM} |_{p_{-i}, \Delta=0}, \quad (2)$$

$$p_{-i0} = \sum_{j \neq i} p_{jEM0} h_{ji}.$$

After  $\rho$  was added into the system, during the first iteration we have

$$p_{iEM1} = \int_0^{P_{-i0} + \Delta + \rho} K(x) dx + p_{iEM} |_{p_{-i}, \Delta=0}, \quad (3)$$

$$p_{-i1} = \sum_{j \neq i} p_{jEM1} h_{ji}.$$

Firstly,  $K(F) \leq 0$  should be the prerequisite of the following deduction. According to the Mean Value Theorem for Integrals,  $p_{iEM1}$  can be expressed as

$$p_{iEM1} = p_{iEM0} + \rho K(A_i), \quad (4)$$

where  $A_i \in (p_{-i0} + \Delta, p_{-i0} + \Delta + \rho)$ . If  $K(A_i) > 0$ ,  $p_{iEM1}$  will be larger than  $p_{iEM0}$  after first iteration. For the following iterations, because each link does the same process,  $p_{iEMk} |_{k \geq 2}$  would continue boosting up to its new balance level as shown in Figure 1. However, this new level may be beyond  $p_{i\max}$ ; therefore this power strategy will not be adopted for the energy saving matter. For the situation when  $K(F) \leq 0$ ,  $p_{iEM}$  is inversely proportional to the interference  $F$ . We need to make sure that the iterations sequence are convergent other than divergent, therefore, two more cases need to be considered. One is when  $p_{-i0} - \rho < p_{-i1} < p_{-i0}$  as shown in Figure 2, which means  $F_0 < F_1 < F_0 + \rho$ . Because of this, we have  $p_{iEM1} < p_{iEM2} < p_{iEM0}$ . For the rest of iteration, as a Markov Process,  $p_{iEMk} |_{k \geq 2}$  should be somewhere between  $p_{iEM0}$  and  $p_{iEM1}$ . As for another case when  $p_{-i1} < p_{-i0} - \rho$  as shown in Figure 3, which means  $F_1 < F_0$ . In order to be convergent,  $p_{-i2} < p_{-i0}$  should be guaranteed based on the Markov Process.  $p_{iEMk} |_{k \geq 2}$  would gradually be stabilized at the following iterations, otherwise the iteration sequence is divergent. Also because we have  $p_{-i2} = \sum_{j \neq i} p_{jEM2} h_{ji}$ , the condition  $p_{iEM2} < p_{iEM0}$  should first be satisfied, and then we have following deduction.

For

$$p_{-i1} = \sum_{j \neq i} p_{jEM1} h_{ji} = p_{-i0} + \rho \sum_{j \neq i} K(A_j) h_{ji}, \quad (5)$$

we have

$$p_{iEM2} = \int_0^{P_{-i1} + \Delta + \rho} K(x) dx + p_{iEM} |_{p_{-i}, \Delta=0} \quad (6)$$

$$= p_{iEM0} + \rho \left( 1 + \sum_{j \neq i} K(A_j) h_{ji} \right) K(B_i).$$

Because  $p_{iEM2} < p_{iEM0}$ , we derive  $\rho(1 + \sum_{j \neq i} K(A_j) h_{ji}) K(B_i) < 0$  in which

$$B_i \in \left( p_{-i0} + \Delta, p_{-i0} + \Delta + \rho \left( 1 + \sum_{j \neq i} K(A_j) h_{ji} \right) \right). \quad (7)$$

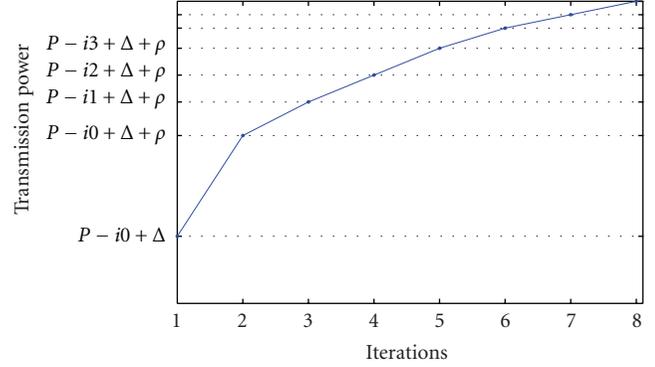


FIGURE 1: The escalation of interference.

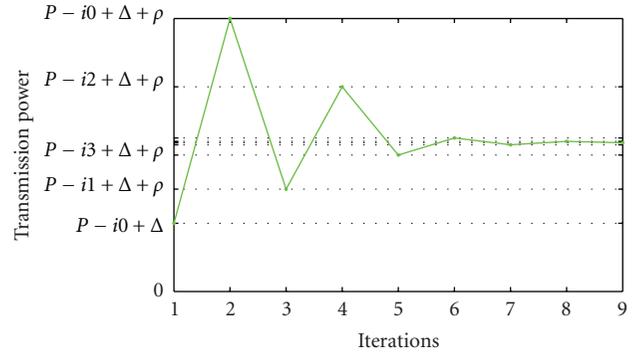


FIGURE 2: System converged with low magnitude of fluctuation.

Thus for  $K(B_i) \leq 0$ , we have

$$1 + \sum_{j \neq i} K(A_j) h_{ji} > 0 \implies \sum_{j \neq i} K(A_j) h_{ji} > -1. \quad (8)$$

This completes the proof of theorem.  $\square$

Based on the Theorem 2 one can verify whether the game model will be power stabilized.

**2.2. System Model.** In order to formulate a noncooperative framework, the utility function should first be made. According to the Shannon Theorem, channel capacity can be expressed as  $C = W \log_2(1+S/N)$ , which reasonably indicates the benefits that a link can achieve during communication. However, Shannon Capacity is more easily calculated than realized. In addition to different types of modulations, the maxima capacities approaching to the Shannon Capacity are numerically quite distinct. We choose the capacity model presented in [14] so that the achievable rate can be well approximated by  $F(\gamma) = W \log_2(1 + \gamma/\Gamma)$ , where  $\Gamma$  represents the gap to the Shannon capacity and  $\gamma$  denotes SINR.

During transmission, energy consumed by transmitter and receiver makes up the link consumption  $p_i$ . According to the data revealed in [15, 16], transmitting and receiving have so comparable power consumption that it is acceptable to assume  $p_{tx} = p_{rx}$  approximately.  $p_{tx}$  can simply be expressed as  $p_{tx} = \alpha p_t + \chi$ , where  $\alpha$  and  $\chi$  are constants depending on

process topology and architecture. Thereafter we have  $p_i = \eta p_t + \omega$ , where  $\eta, \omega$  are constants depending on hardware property.

**2.3. Utility Function.** Power consumption is taken as the cost for the game model, and the utility function is proposed as follows:

$$U_i(p_i, P_{-i}) = W \log_2 \left( 1 + \frac{\gamma(p_i, P_{-i})}{\Gamma} \right) - a_i p_i \gamma \geq \gamma_{\min}, \quad (9)$$

where  $a_i$  is urgency index which represents the urgency level of the transferred information,  $\gamma(p_i, P_{-i})$  is the SINR on link  $i$ 's receiver, and  $\gamma_{\min}$  is the minimum SINR that transmission can tolerate. In our system, we choose the path-loss model used in [17] with free space propagation model and Omnidirection antenna, the path-loss function can be described as  $p_r = p_t K [d_0/d]^\beta = p_t h_i$ , where  $d_0$  is the reference distance for the antenna,  $\beta$  denotes the path-loss exponent determined by the environments, and  $h_i$  is path gain from link  $i$ 's transmitter to receiver. When  $d > d_0$ ,  $K$  can empirically approximate as  $K dB = 20 \log_{10}(\lambda/4\pi d_0)$ , where  $\lambda$  is the signal wavelength.

Supposing that the background noise is AWGN with the same thermal noise power  $\sigma$  for every receiver, (9) could be rewritten as

$$\begin{aligned} U_i(p_i, P_{-i}) &= W \log_2 \left( 1 + \frac{p_i h_i}{(P_{-i} + \sigma)\Gamma} \right) - a_i (\eta p_i + \omega) \quad \gamma \geq \gamma_{\min}. \end{aligned} \quad (10)$$

In order to find out whether (10) is qualified for non-cooperative power control game; the existence of NE should firstly be proved [13]. Since we already quantified the power strategy set  $\{P_i\}$  and the given conditions shows that  $\{P_i\}$  is nonempty, convex, and compact set of some Euclidean space  $R_n$ , the first condition of Lemma 1 is satisfied. Additionally from (10) we can see that  $U_i$  is continuous in  $P$ , so it remains to show the quasiconcaveness of  $U_i$  in  $p_i$ . Firstly let us define the quasiconcaveness.

**Definition 3.** A function  $f : A \rightarrow \mathfrak{R}$  defined on a convex subset  $A$  of a real vector space is quasiconcave if it satisfies (11) where every  $x, y \in A$  and  $\mu \in [0, 1]$ :

$$f[\mu x + (1 - \mu)y] \geq \min[f(x), f(y)]. \quad (11)$$

According to [13] we can prove the quasiconcaveness of  $U_i$  by demonstrating that the local maximum of  $U_i$  is, at the same time, the global maximum.

The local maximum can be calculated from  $\partial U_i / \partial p_i = 0$ . Here we only modify  $p_i$  to be  $p_{it}$ , thus

$$\begin{aligned} \frac{\partial U_i}{\partial p_{it}} &= \frac{W h_i}{[(P_{-i} + \sigma)\Gamma + p_{it} h_i] \ln 2} - a_i \eta = 0 \\ \Rightarrow p_{iE} &= \frac{W}{a_i \eta \ln 2} - \frac{\Gamma(P_{-i} + \sigma)}{h_i}, \end{aligned} \quad (12)$$

where  $p_{iE}$  is the best response (BR) power strategy that is either global maximum or minimum. However,

$$\frac{\partial^2 U_i}{\partial p_{it}^2} = \frac{-W h_i^2}{[(P_{-i} + \sigma)\Gamma + p_{it} h_i]^2 \ln 2} < 0. \quad (13)$$

Therefore  $p_{iE}$  is global maximum, and Lemma 1 is satisfied. We conclude that NE exists in this noncooperative power control game  $G$ .

**Theorem 4.** NE in game  $G$  is unique.

*Proof.* Since  $P_{-i} = \sum_{j \neq i} p_{jt} h_{ji}$ , where  $h_{ji}$  denotes the path gain from link  $j$ 's transmitter to link  $i$ 's receiver, the power vector  $p = \langle p_{1E}, p_{2E}, p_{3E}, \dots, p_{nE} \rangle^T$  can be written in matrix notation that

$$p' = QM p + S. \quad (14)$$

In which  $p'$  is the BR power strategies of  $p$  of the next time step,  $Q$  equals to  $-\Gamma$ ,  $M$  is a  $N \times N$  matrix of path-gain expressed as follows:

$$M = \begin{pmatrix} 0 & \frac{h_{21}}{h_1} & \frac{h_{31}}{h_1} & \dots & \frac{h_{n1}}{h_1} \\ \frac{h_{12}}{h_2} & 0 & \frac{h_{32}}{h_2} & \dots & \frac{h_{n2}}{h_2} \\ \vdots & & \ddots & & \vdots \\ \vdots & & & \ddots & \vdots \\ \frac{h_{1n}}{h_n} & \frac{h_{2n}}{h_n} & \frac{h_{3n}}{h_n} & \dots & 0 \end{pmatrix}. \quad (15)$$

The above matrix makes up a seamless connection for each node within the network. And

$$S = (S_1, S_2, \dots, S_n)^T, \quad \text{where } S_i = \frac{W}{a_i \eta \ln 2} - \frac{\sigma \Gamma}{h_i}. \quad (16)$$

Since the existence of NE has been proved in game  $G$ , we have  $p = QM p + S$  at NE points. Thus, we derive (17) where  $E$  is an identity matrix of size  $N$ :

$$p = (E - QM)^{-1} S. \quad (17)$$

Since  $E, Q, M$ , and  $S$  are constants, the solution of (17) is unique, and NE is unique in game  $G$ .

Based on the two conditions in Theorem 2, the first condition  $\partial p_{iEM} / \partial F = -\Gamma / h_i < 0$  is satisfied and the second condition can be expressed as  $0 < \sum_{j \neq i} (h_{ji} / h_j) < 1/\Gamma$ , which, depending on the real situations, cannot be proved directly. However, it can act as a constraint for node density scale. If it is not satisfied, the transmitter will not finally be stabilized. Our experiment results in latter section show that if the link satisfies the condition of  $\gamma > \gamma_{\min}$ , system will eventually be stabilized.  $\square$

### 3. Convergence Analysis and NPC Algorithm

**3.1. Urgency Index.** Game model formulated in (10) can be applied individually. Generally the tradeoff making during the transmission is not merely about energy consumption and network capacity, but the urgency of information should also be taken into consideration. Here we define a parameter  $a_i$  to indicate the urgency level of data for different individuals.

According to (12)  $P_{-i}$  ranges from maximum  $\{P_{-i}\}$  to 0, thus, we have

$$\begin{aligned} \frac{W}{a_i \eta \ln 2} - \frac{\Gamma(\max\{P_{-i}\} + \sigma)}{h_i} &\leq p_{iEM} \\ &\leq \frac{W}{a_i \eta \ln 2} - \frac{\Gamma\sigma}{h_i} \quad \gamma \geq \gamma_{\min}, \end{aligned} \quad (18)$$

where  $\max\{P_{-i}\}$  is the maximum interference that link  $i$  can tolerate. It can be expressed as  $\max\{P_{-i}\} = (p_{i\max} h_i / \gamma_{\min}) - \sigma$ .

Since  $0 \leq p_{iEM} \leq p_{i\max}$ , we have (19)

$$\begin{aligned} 0 &\leq \frac{W}{a_i \eta \ln 2} - \frac{\Gamma(\max\{P_{-i}\} + \sigma)}{h_i} \leq p_{iEM} \\ &\leq \frac{W}{a_i \eta \ln 2} - \frac{\Gamma\sigma}{h_i} \leq p_{i\max}. \end{aligned} \quad (19)$$

For  $\gamma \geq \gamma_{\min}$  because

$$\frac{p_{iEM} h}{(P_{-i} + \sigma)} \geq \gamma_{\min}. \quad (20)$$

We also have (21)

$$p_{iEM} \geq \gamma_{\min} \frac{(P_{-i} + \sigma)}{h_i}. \quad (21)$$

Thus, from (12), (19), and (21) we get inequality set as follows:

$$\begin{aligned} 0 &\leq \frac{W}{a_i \eta \ln 2} - \frac{\Gamma(\max\{P_{-i}\} + \sigma)}{h_i}, \\ \frac{W}{a_i \eta \ln 2} - \frac{\Gamma(P_{-i} + \sigma)}{h_i} &\geq \gamma_{\min} \frac{(P_{-i} + \sigma)}{h_i}, \\ \frac{W}{a_i \eta \ln 2} - \frac{\Gamma\sigma}{h_i} &\leq p_{i\max}. \end{aligned} \quad (22)$$

And then, we have (23)

$$\begin{aligned} \frac{W h_i}{(p_{i\max} h_i + \Gamma\sigma) \eta \ln 2} &\leq a_i \\ &\leq \text{Min} \left\{ \frac{W \gamma_{\min}}{\Gamma p_{i\max} \eta \ln 2}, \frac{W h_i}{(\gamma_{\min} + \Gamma)(P_{-i} + \sigma) \eta \ln 2} \right\}. \end{aligned} \quad (23)$$

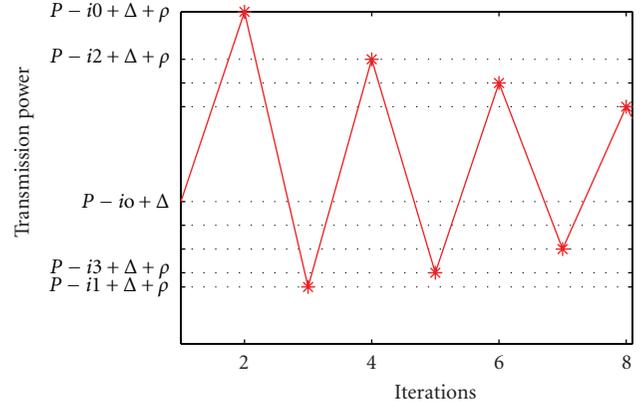


FIGURE 3: System converged with high magnitude of fluctuation.

From (19) we notice that in any circumstances (24) is satisfied, thus (25) is always satisfied:

$$0 \leq \frac{W}{a_i \eta \ln 2} - \frac{\Gamma(\max\{P_{-i}\} + \sigma)}{h_i}, \quad (24)$$

$$\frac{W}{a_i \eta \ln 2} - \frac{\Gamma\sigma}{h_i} \leq p_{i\max},$$

$$\frac{W h_i}{(p_{i\max} h_i + \Gamma\sigma) \eta \ln 2} \leq a_i \leq \frac{W \gamma_{\min}}{\Gamma p_{i\max} \eta \ln 2}. \quad (25)$$

Therefore in (23) the communication can be well established if

$$(p_{i\max} h_i + \Gamma\sigma) > (\gamma_{\min} + \Gamma)(P_{-i} + \sigma). \quad (26)$$

Otherwise the communication will shut down.

So players, based on their needs, could adjust the value of  $a_i$  under the restriction of (23).

**3.2. NPC Algorithm.** Assuming that each transmitter knows its SINR before making their self-fulfilling choice based on the feedback of the receiver. Let  $p_n$  denote power strategy on step  $n$  and  $p_n^*$  denote BR power strategy of step  $n$  based on (12). Because we took it as Markov process, the power strategy selection is given in (27) to avoid highly fluctuation of the system during iterations, where  $\psi$  is a preset parameter that guarantees the smoothness of variation during power updating. In order to be eligible,  $\psi$  should be at least in the same order of magnitude of  $P_{\max}$ :

$$\begin{aligned} p_{n+1} &= p_n \frac{|p_n - p_n^*| + n + \psi}{p_{\max} + n + \psi} + p_n^* \frac{p_{\max} - |p_n - p_n^*|}{p_{\max} + n + \psi}, \\ &n \geq 0. \end{aligned} \quad (27)$$

Figure 4 presents the whole process of NPC algorithm in details.

Each time step transmitter update its power strategy based on (27).  $C_{TH}$  is a threshold that is defined individually. Transmission power is stable when Counter =  $C_{TH}$  is

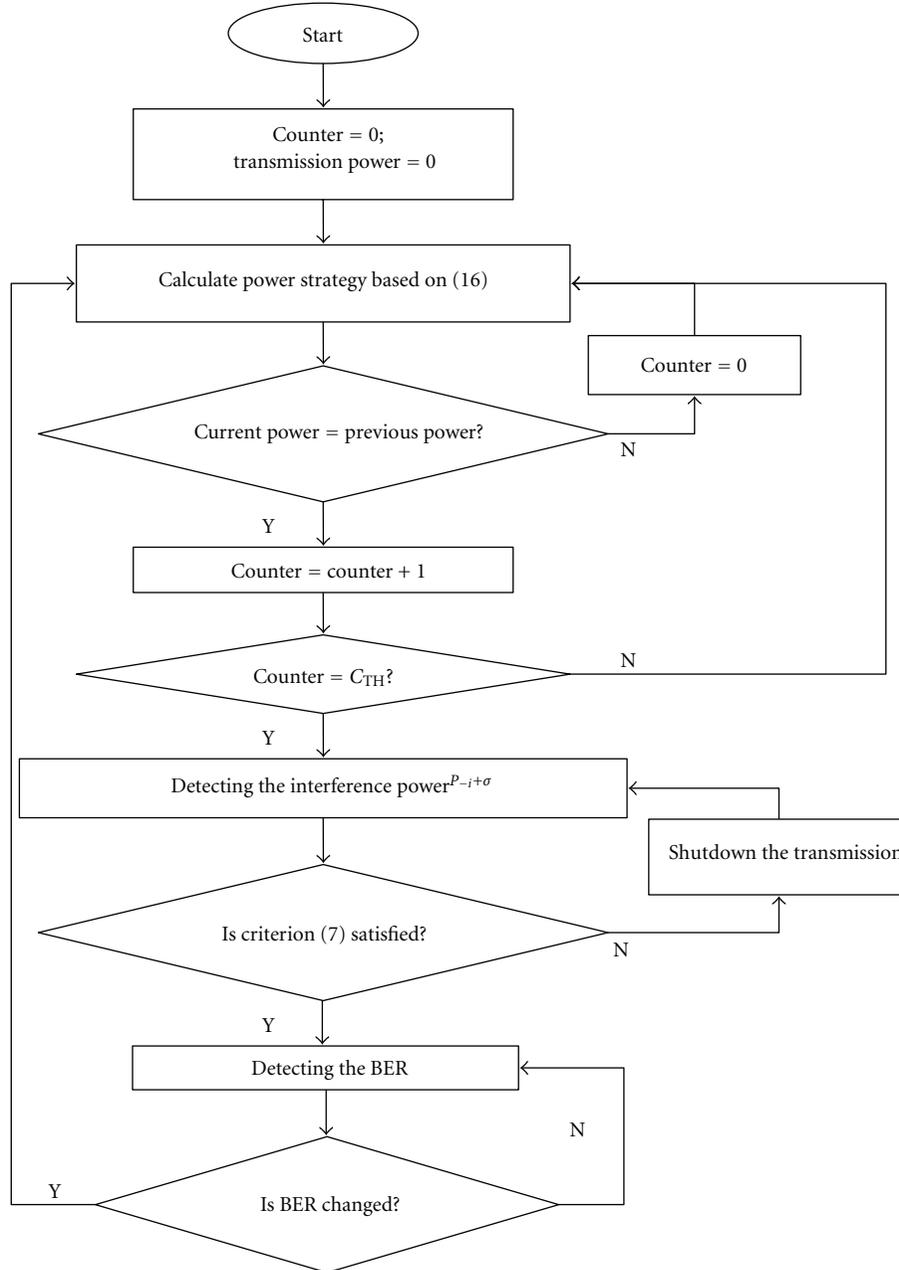


FIGURE 4: The process of NPC algorithm.

satisfied.  $n$  is the time step that has the same order of quantity as the smallest unit of transmission power. When power is stable, node will check if the criterion (26) is satisfied. If not, node will turn off transmission immediately, because in this case it is too much costly for node to communicate with high BER. After that node will wait until the above criterion is satisfied and starts the transmission again.

## 4. Experimental Results

**4.1. Theoretic Simulation.** We simulated a network on the MATLAB platform in a  $500 \times 500$  square meters area with 100

nodes randomly placed on it. Two nodes can communicate normally if their SINR level is higher than  $\gamma_{\min}$ . Without loss of generality, the utility function is parameterized conservatively as follows to model the typical environment outside.

The bandwidth  $W = 2 \times 10^7$  Hz, the AWGN power  $\sigma = 10^{-10}$  w, SINR boundary  $\gamma_{\min} = 50$ , and  $\Gamma = 1.5$ . For  $p_r = p_t K [d_0/d]^\beta$ ,  $K$ ,  $d_0$ , and  $\beta$  were given by  $K = 10^{-4}$ ,  $d_0 = 10$  m, and  $\beta = 4$ , respectively. Transmission power  $p_t$  was quantitatively ranged from 0 mw to 200 mw, and urgency index  $a_i$  was given with the boundary of (23). Finally the parameter  $\psi$  and  $\eta$  were defined as 400 and 5.

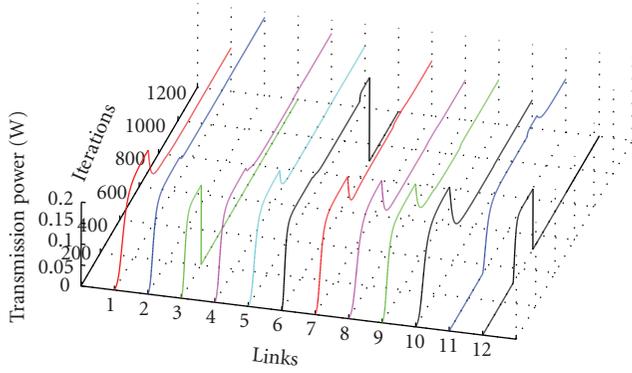


FIGURE 5: Transmission power of each link during iterations.

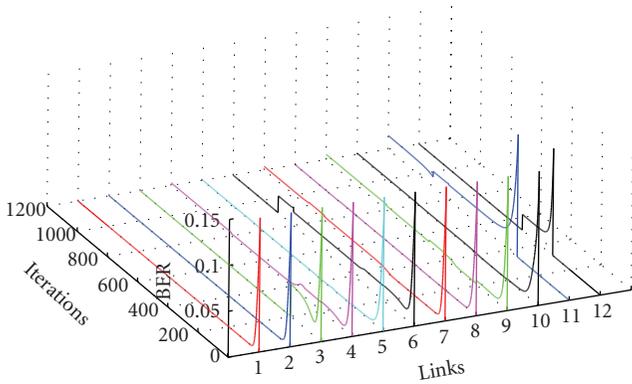


FIGURE 6: BER of each link during iterations.

We randomly chose  $N$  links in the above scenario, and each link with its own utility function working successfully if  $\text{SINR} \geq \gamma_{\min}$ . The results were evaluated by stability of the system as well as network performance.

We chose 12 different links. On the first stage 10 links started working at the same time under the highest data urgency level. After that each link defined its own unique urgency index asynchronously while link 11 and 12 joined the network. Finally the background noise was raised to examine robustness of the system.

Figure 5 shows that on the first stage (0–300), for approximately 200 iterations, nodes could be power stabilized with smooth changes. However, for link 3 it was so unsustainable to its current BER that the communication will be shut down. The second stage (300–800) reveals that no matter new links access joined or the existing links changed their data urgency level, the system can still reach to the balance, and it is the same truth that those cannot afford the high BER will do the same as link 3 did. Finally on the last stage (800–1200), we raised the background noise and the result shows that the system was sustainable for the sudden changes. The respective BER for each node during the whole process is shown in Figure 6. When system is stable, the BER of each node which remains in the system is in a relatively low level.

The links showed in Tables 1 and 2 are typical to represent the quality status of all the experimental links. From Table 1

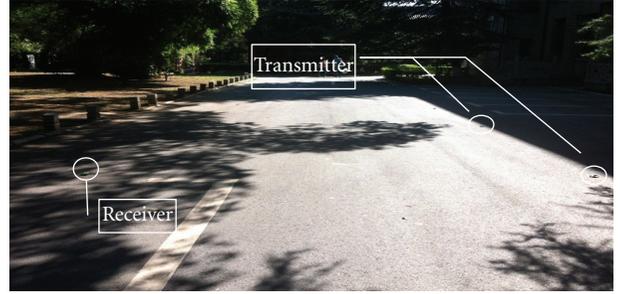


FIGURE 7: Network topology of the experiment.

TABLE 1: Power strategies of certain links during the iterations.

Iterations	Link			
	1	5	6	11
100	0.1251	0.1607	0.1916	0.0000
300	0.1976	0.1985	0.1945	0.0000
400	0.1196	0.1475	0.1834	0.1034
600	0.1051	0.1462	0.1825	0.1463
800	0.1035	0.1460	0.1824	0.1469
900	0.1041	0.1477	0.2000*	0.1574
1200	0.1041	0.1471	—	0.1276

TABLE 2: BER of certain links during the iteration.

Iterations	Link			
	1	5	6	11
10	$8.77e-2$	$8.92e-2$	$8.91e-2$	—
30	$1.18e-2$	$2.51e-2$	$2.32e-2$	—
100	$9.83e-7$	$1.51e-3$	$1.42e-2$	—
300	$8.95e-9$	$4.59e-4$	$1.64e-2$	—
350	$1.22e-7$	$8.21e-4$	$1.51e-2$	$1.13e-1$
400	$1.24e-5$	$5.11e-4$	$1.44e-2$	$2.73e-2$
600	$9.74e-8$	$4.59e-4$	$1.45e-2$	$1.62e-2$
800	$1.19e-8$	$4.47e-4$	$1.45e-2$	$1.61e-2$
900	$5.98e-7$	$7.57e-4$	$1.83e-2^*$	$1.66e-2$
1200	$5.54e-7$	$6.21e-4$	—	$1.48e-2$

we can see that link 1's quality was good because its BER was constantly at a low level, which means link 1 was rarely affected by the neighbors. However, for link 6, it was always with a high transmission power. Finally when the power stabilized BER was unaffordably high as marked with asterisk token, the transmitter of link 6 chose to shutdown transmission immediately. For link 5 it did not perform as good as link 1 did, because its noise was much higher. Link 11 accessed into the network after 300 iterations, despite the fact that the (26) is satisfied, its BER was constantly high. The reason for this is that link 11 was under a relatively low urgency level, so it was unnecessary for link 11 to raise its transmission power.

4.2. *Real Testbed.* To analyze the feasibility of our approaches, a SOC solution, CC2530, tailored for IEEE

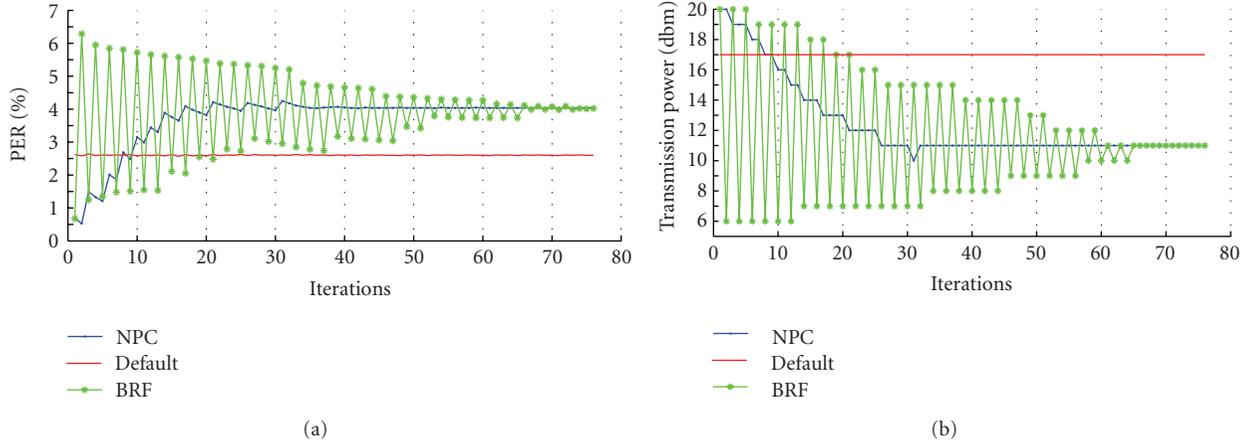


FIGURE 8: PER and Transmission Power of the best performed node.

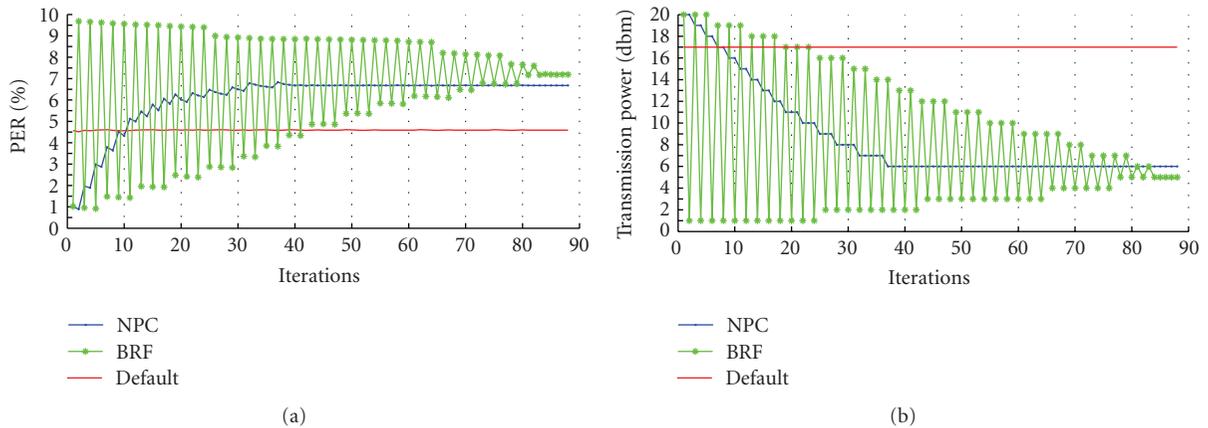


FIGURE 9: PER and Transmission Power of the worst performed node.

802.15.4/Zigbee applications, was used in our implementation for real testbed. The transmission power cannot be quantized into as many as the theoretic analysis did, but by connecting with the RF front-end, CC2591, there were 20 available levels of transmission power to operate.

The network was made up of 5 pairs of nodes with each pair consisting of one transmitter and receiver. Nodes were placed in a mesh form as shown in Figure 7. The distance from transmitter to receiver of each pair was 5 m. And any adjacent pair was 6 m away from each other. Each node was working in the same channel, and message was delivered with only one hop.

The receivers at each end got the best quality of signal for the reception, while the receivers at middle got the signal with most interference. The transmitter can adjust its transmission power according to the feedback of its SINR, which was detected by its own pair of receiver.

The parameters of the node and algorithm were defined as follows.

The maximum transmission power was 20 dbm and the minimum interval of the transmission power was 1 dbm, the

bandwidth was  $5 \times 10^6$  Hz, and we defined  $\psi$  as 40 dbm. Since path-loss exponent cannot be detected directly, we used SINR as an alternative way to calculate the extreme value of transmission power in (12). The rest parameters were same as that in simulations.

To evaluate performance of NPC, 5 transmitters were initialized with the maximum transmission power which was 20 dbm. Two other counterpart methods were applied as comparison. The Default is a default setting of transmission power recommended by Manufacture Company. BRF is a strategy selection method directly based on the best response function (12) that is applied by [8].

We compared the performance of two pairs of links which had the highest interference and lowest interference, respectively.

Figure 8 shows that in less than 50 iterations the transmission power was stabilized by NPC algorithm, and the transmission power of the least interfered link pair ended up to be 11 dbm with packet error rate (PER) of 4%. While on default setting, the power level was 17 dbm, and placed on the same position, the PER was 2.7%. BRF ended up with the

same power as NPC did. However on default setting the PER was not much lower than NPC but the power consumption was exaggeratedly higher. While on BRF, the fluctuation of the transmission power would greatly jeopardize the stability of the network. Our network scale was not big enough; otherwise the transmission power would risk to be evolved divergently.

Figure 9 shows the comparison of PER and Transmission power of each methods on link pair with the heaviest interference. The whole process is the same like Figure 8 illustrated. As we can see, because of the high interference, the transmitter had a great cutback in its power, and compared with the default setting, PER was only less than 2%, but the amount of power diminished was 17 dbm–6 dbm, which on a great extent, conserved the energy for the node. To the BRF, the Transmission power ended up to be 1 level lower than on the NPC algorithm, the result may due to the variation of the environment.

To analyze the energy efficiency of NPC algorithm, we evaluated the performance of each pair under the three different methods with PER/Consumption as measurement of energy efficiency and stabilization time as convergence speed.

During the experiment, consumption was measured as total consumption of link pair. Figure 10 shows that NPC and BRF were with almost the same energy efficiency which was much better than default setting, however according to Figure 11 BRF iterated with twice more time than NPC and as interference increased convergence speed will become smaller. Thus, energy efficiency has been remarkably enhanced by NPC algorithm, while the convergence speed was a little less than default setting and was much faster than BRF offered. Therefore, the superiority of the NPC algorithm is that without accessing into the profile of others, the power selection strategy can optimize the energy usage of each node with guaranteed smooth changes without which the sudden burst of interference is inevitable.

## 5. Conclusions

In wireless sensor network, nodes prefer to form and organize the system in a distributed way. Without central node, it is quite recommendable to take Noncooperative behavior into consideration. The conditions of formulating a NPC game were firstly proved in the paper. After that we presented a utility function based on the dilemma of power usage and proved the existence of unique NE in this specific game model. The notion of urgency index was given for node to define its utility with the consideration of data urgency level. For system convergence, NPC algorithm was presented and compared with other methods. The experiments showed that, without inquiring the profile of each node, NPC algorithm can quickly lead the system to stabilize with relatively smooth changes as well as good network performance. For those qualities, NPC algorithm can be applied to the scenarios where nodes do not share information together while the system design requires energy efficiency. Currently the design, however, mainly concentrates on the physical

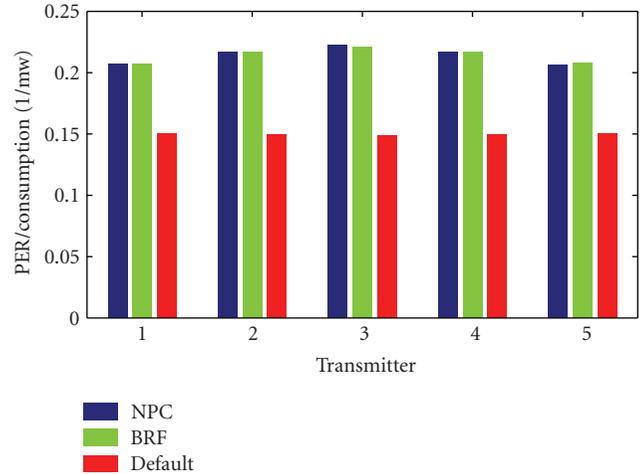


FIGURE 10: Energy Efficiency of 5 nodes under different methods.

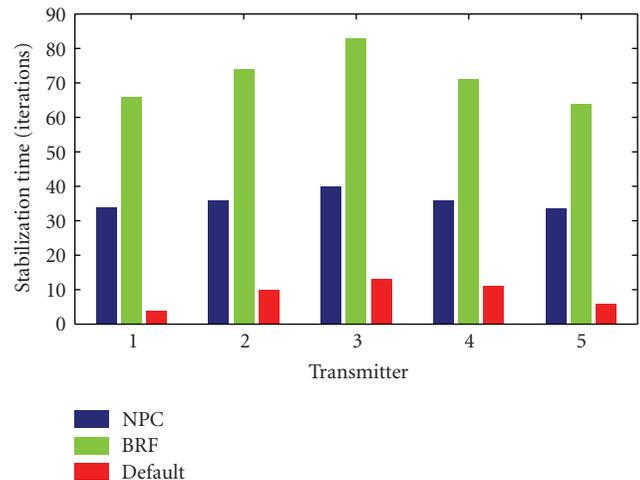


FIGURE 11: Convergence Speed of 5 nodes under different methods.

layer for transmitter to choose its transmission power based on the SINR that makes the network performance not quite good at the beginning. For this reason the next step of our research will focus on the cross-layer power control design with noncooperative game approaches.

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