Noname manuscript No.
(will be inserted by the editor)

Cooperation and coalitional stability in decentralized wireless networks

Dávid Csercsik · Sándor Imre

Received: date / Accepted: date

Abstract In this paper we consider a wireless contextualization of the local routing protocol on scale-free networks embedded in a plane and analyze on the one hand how cooperation affects network efficiency, and on the other hand the stability of cooperation structures. Cooperation is interpreted on k-cliques as local exchange of topological information between cooperating agents. Cooperative activity of nodes in the proposed model changes the routing strategy at the level of the coalition group and consequently influences the entire routing process on the network. We show that the proposed cooperation model enhances the network performance in the sense of reduced passage time and jamming. Payoff of a certain node is defined based on its energy consumption during the routing process. We show that if the payoff of the nodes is the energy saving compared to the all-singleton case, basically coalitions are not stable, since increased activity within coalition increases costs. We introduce coalitional load balancing and net reward to enhance coalitional stability and thus the more efficient operation of the network. As in the proposed model cooperation strongly affects routing dynamics of the network, externalities will arise and the game is defined in a partition function form.

Keywords Cooperative game theory · Local routing · Wireless systems

Dávid Csercsik at Pázmány Péter Catholic University, Faculty of Information Technology and Bionics, P.O. Box 278, H-1444 Budapest
Tel.: +36-1 886 47 00
Fax: +36-1 886 47 24
E-mail: csercsik@itk.ppke.hu
Sándor Imre at Budapest University of Technology and Economics, Department of Networked Systems and Services, P.O. Box 91, H-1521 Budapest.
E-mail: imre@hit.bme.hu

1 Introduction

In the past years, game theoretic approaches in telecommunications (Douligeris and Mazumdar, 1992; Altman and Wynter, 2004; Altman et al, 2006; Cohen et al, 2013; Karamchandani et al, 2011) and wireless environment (Han et al, 2012; Al-Kanj et al, 2011) became more and more popular, including coalitional approaches as well (Saad et al, 2009a,b, 2008; Saad, 2010; Saad et al, 2009c; Pantisano et al, 2012; Karamchandani et al, 2011) - for a survey, see (Akkarajitsakul et al, 2011). Cooperation in these setups may have many different interpretations.

Considering the more traditional game theory literature, networks (Jackson, 2008) and routing have been among the popular topics of the field recently, however usually selfish (Feldmann et al, 2003; Roughgarden, 2005; Kontogiannis and Spirakis, 2005; Johari et al, 2006) or competitive (Orda et al, 1993; Cominetti et al, 2006) routing models are considered, while coalitional approaches and models including externalities (Csercsik and Sziklai, 2012; Csercsik and Imre, 2013) are less representative.

In this article we propose a model to describe cooperation and analyze coalitional stability in wireless local routing network models. Basic traffic models considering local routing assume that basically each node is aware of its list of neighbors, and the degree of these neighbors. The basic concept of local routing is as follows (Wang et al, 2006a). To navigate packets, nodes perform a local search. If the packet's destination is found among the neighbors, it is delivered directly to its target. Otherwise, it is forwarded to a random neighbor, with a preferential probability proportional to the actual neighbors degree.

Regarding practical applications, in several cases the assumption that a certain node is not aware of the topology of the whole system may be plausible. This may be especially true in wireless networks (Abolhasan et al, 2004; Hong et al, 2002; Garg et al, 2012; Mauve et al, 2001) where the network topology itself is often subject to change because of fading due to changing environmental effects and potential mobility of the nodes. In such cases it may be not possible or efficient to base the routing process on a complete map of connections. In these scenarios, alternatively the delivery of packages may be performed by local routing protocols (Wang et al, 2006a). Although results corresponding to cooperative approaches in wireless networks can be found in the literature (see e.g. (Khandani et al, 2005, 2007; Ibrahim et al, 2008)), these models usually do not consider Scale-free (SF) network type fixed communication structure and are not focusing on local routing methods.

Since the basic concept of local routing has been proposed, such protocols have been analyzed and improved in many papers (see eg. (Tadić et al, 2004; Tadić and Thurner, 2004; Tadić et al, 2007)). The paper by (Wang et al, 2006b) includes the queue length in the preference calculation formula of local routing resulting in a local dynamic routing algorithm. (Tadić and Rodgers, 2002) introduces a local routing method, which relaxes the assumption of local topological knowledge: In the concept proposed in this paper a router may directly deliver a packet to its destination, if it is found within 2 steps (next-to-nearest or next-to-neighbor routing). This approach may be regarded as a step from local towards global routing. The paper by (Yin et al, 2006) combines the local routing approach with the next-nearest neighbor strategy.

The results corresponding to local routing are basically related to SF networks in the literature. SF networks (Barabási and Albert, 1999; Barabási et al, 1999) are often used as a tool to describe the topology of communication networks (Albert et al, 1999).

In this paper we also use SF networks for the testing and demonstration of our results, since on the one hand results in the literature are corresponding to this topology, and this way comparison is possible, and on the other hand this structural class holds some properties, which may be beneficial considering wireless ad hoc routing networks. SF networks are easy to generate with the preferential attachment method (Barabási and Albert, 1999), and the shortest path between two randomly chosen nodes is relatively short comparing eg. to random graphs with the same number of nodes and edges.

Cooperation in the interpretation of the proposed model will mean that cooperating players exchange their local topological information (practically the list of their neighbors), which information is taken into account in the process of packet routing. For the aim of simplicity, we assume that only neighboring nodes may cooperate, which implies that coalitions have to form complete graphs in the network. In other words, the considered coalitions in this work assume a preexisting full graph (k-clique).

While singleton nodes use first order routing while forwarding the packets (they look for the packet's destination only among their own neighbors), nodes in a coalition may search the neighbor list of some of their neighbors (their coalitional partners), and forward the packet according to this if match with the packet destination is found.

Since such exchange and utilization of second degree local information will affect the routing dynamics (e.g. in general it is straightforward to assume that packets will spend less time in the network if the routing efficiency is increased this way), cooperation will affect the energy consumption of nodes not taking part in the coalition. Since node payoffs will be defined based on individual energy consumption, this implies that externalities will appear, thus the game will be described in partition function form (Thrall and Lucas, 1963).

Partition function form games represent a novel approach for telecommunication problems, and they have been recently successfully applied for OFDMA (Orthogonal Frequency Division Multiple Access) problems in femtocell networks (Pantisano et al, 2011b,a, 2012).

2 Materials and methods

First of all, we assume that the nodes of the graph correspond to players or in other words agents, who may determine their strategy, namely they may choose to cooperate with other nodes or act selfishly. As mentioned, we will interpret our model in a wireless context where it is assumed that the transmission cost a single packet is proportional (in this case for the aim of simplicity equal) to the square of the distance. This will mean that we assign geometric positions to the nodes of the graph, namely a coordinate pair in the unit square. Furthermore, during the generation of the communication graph we take spatial information into account as well.

For the generation of the network we use the geometry-modulated version of the Barabási-Albert algorithm (Barabási and Albert, 1999), as described in (Manna and Sen, 2002). A seed with n_{seed} nodes and m_{seed} link is used, and an iterative process is applied during which in each time step a new node with random position in the unit square is introduced and is randomly connected to m previous nodes. Any of these m links of the new node introduced at time t connects a previous node i with an attachment probability $\pi(t)$ which is linearly proportional to the degree $k_i(t)$ of the i-th node at time t and to l^β, where l denotes the Euclidean distance of the new node and node i, and β is a free parameter. $\beta < 0$ corresponds to the case when nodes are more likely to connect closer ones. Formally,

$$\pi_i(t) \sim k_i(t) l^\beta. \tag{1}$$

We call the resulting graph the *communication graph*. In the following we do only consider nodes connected to this graph. The basic traffic model based on (Wang et al, 2006a) is described as follows: at each time step, there are R packets generated in the system with randomly chosen sources and destinations. In general we assume that all the nodes are communicating with each other, and there are no traversing nodes. However, since sources and destinations are chosen randomly, theoretically (practically only in short simulations) it is possible that a node will not be chosen as source or destination. We assume that each packet in the network holds information about its destination node. The buffer (queue) size of the nodes is assumed to be infinite, but any node can forward at most C (finite) packets in each time step. To make the model independent of the update order of the nodes, we assume that one packet can hop only once during a certain time step. To navigate packets, singleton nodes perform a local search. If the packet's destination is found among the neighbors, it is delivered directly to its target. Otherwise, it is forwarded to a chosen neighbor via the local routing mechanism.

The proposed model of cooperation is similar to *dynamical clustering*, which topic has been studied on various networks regarding financial and other aspects (D'Hulst and Rodgers, 2000; Eguiluz and Zimmermann, 2000; Tadić and Rodgers, 2010).

In the current work we assume that the energy cost of cooperation (exchanging local topological information) can be neglected compared to the energy cost of packet forwarding. We assume that only those nodes may cooperate, who form a complete subgraph (clique) in the communication graph. This assumption implies a considerable restriction for the cooperating structures.

Nodes in a coalition perform first a local search, and if it is unsuccessful, they perform a second degree search among the neighbors of their coalitional partners as well. If a member of the actual coalition is found, which is adjacent to the packets destination, the packet will be forwarded to that node (since coalitions form complete graphs, this is always possible). In a coalition with three or more players it is possible that the packet destination is adjacent to multiple coalitional members. If we would perform the search according to the lexicographic ordering of the neighbors, the nodes with lesser index would be more loaded in such cases. To address this issue and equalize the load in such cases we always start the search from a random index among the coalitional neighbors. The next to nearest packet forwarding approach was already discussed by (Tadić and Rodgers, 2002) and (Tadić et al, 2004), however not in a cooperative game theoretic wireless context.

If the destination is not found among the direct neighbors or among the neighbors of the coalitional partners of a node, the packet p is forwarded from node i to its neighbor j according to the preferential probability

$$\Pi_j = \frac{k_j^\alpha}{\sum_m k_m^\alpha}, \tag{2}$$

where k_p denotes the degree of node p, the sum runs over the neighbors, and α is a parameter describing the preference of high degree neighbours over low degree ones. The principle of local routing is that this 'random walk' will sooner or later get every package to its destination.

As shown in (Wang et al, 2006a), $\alpha = -1$ is optimal regarding network congestion. Similar to (Wang et al, 2006a), we assume that in a certain network none of the tokens may take the same edge again. There is a theoretical possibility that this assumption may lead to deadlock situations, but in practice the number of these scenarios is so low that they do not influence the results - Eg. in a network of 300 nodes with R=25 during a simulation of 1000 steps, from the 25000 package only about an average of 40 become deadlocked.

We will monitor the overall network efficiency with the total energy consumption E_T (which is simply the sum of the energy consumption of individual nodes) and the average packet arrival time $\bar{T}_{arr}$. Naturally, as the results will show as well, these two indicators correlate, since if the packets reach their destination earlier, in general less transmission steps are required. Before the exact definition of the game, we introduce some examples to show how cooperation affects network dynamics.

3 Results

3.1 Effect of cooperation on network efficiency

Regarding traffic dynamics, it is important to differentiate between congested and non congested cases. Following (Arenas et al, 2001) we define the congestion measure η as

$$\eta(R) = \lim_{t\to\infty} \frac{C}{R} \frac{\langle \Delta N_p \rangle}{\Delta t},$$

where $\Delta N_p = N(t+\Delta t) - N(t)$ with $\langle ... \rangle$ indicates average over time windows of length Δt and $N_p(t)$ represents the number of data packets present in the network at time t. If $\eta(R)$ is significantly greater than zero (we can say that approximately $\eta(R) > 0.25$), it indicates a congested state of the network (since the number of packets present in the network is steadily increasing). Although our aim in this article is not to determine the R_c values in various cases, we will use this indicator to describe non congested ($R < R_c$, $\eta \simeq 0$) and congested cases ($R > R_c$, $\eta > 0$).

Regarding the simulation results, first we show the basic aspects of the concept on a small 30 node network, where change implied by cooperation regarding single nodes can be efficiently demonstrated. Then we move on to a 300 node network to examine the phenomena in medium size networks, and study how increasing levels of cooperation affects efficiency. Last we examine a 3000 node network in order to analyze how the size of ratio between the size of coalitions and total node number is affecting the results.

3.1.1 Example I

When considering network size for the more detailed demonstration of the results, and corresponding phenomena, on the one hand we have to take into account that we need a minimum level of complexity for the routing not to be trivial, and on the other hand we have to keep computations tractable and we have to be able to visualize the results as well. The network of 30 nodes depicted in Fig. 1 was generated with parameters $m = 3$, $\beta = -2$ and a 10 node seed.

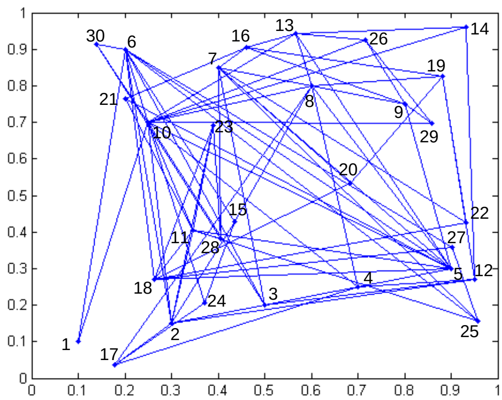

Fig. 1 Network 1.

In realistic environments, the transmission parameters are not homogenous in space. It is plausible to assume that during the generation of the communication graph, these heterogeneities are taken into account in addition to node-to-node distances. Transmission between close nodes (as eg. 1 and 17 in Fig 1) is not necessary efficient, assuming eg. a wall or other obstacle influencing the possible wireless channel.

If we simulate the traffic dynamics in a non-congested case with parameters $\alpha = -1$, $R = 5$ $C = 3$ Figure 2 depicts the energy usage results of nodes in 10 simulation.

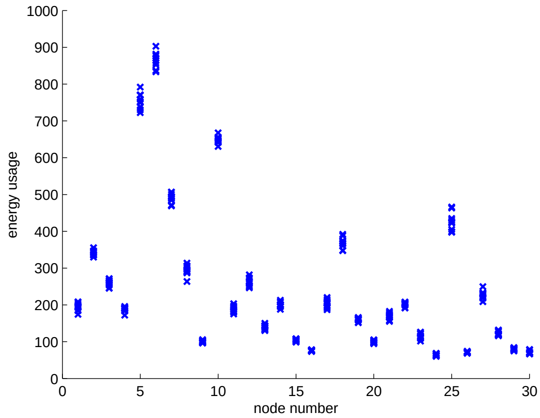

Fig. 2 Energy usage of the nodes in all-singleton configuration. Simulation length: 1000 steps. Results of 10 simulations.

On the one hand, it can bee seen in Fig. 2 that the energy usage values are quite stable, the variance of the values is relatively low (the mean variance is 8.72). This means that the average of several simulations can be regarded as a representative result. Furthermore it can be easily seen that, as expected, the energy consumption of the high degree nodes is high. The total energy used by the network is $E_T = 7491.5$ in this case, while $\bar{T}_{arr} = 4.54$.

Next we analyze how coalition formation affects energy consumption values and network efficiency. Let us pick one coalition, e.g. $\{5, 6, 18\}$. First, it can be checked that it is a valid coalition, since nodes 5,6 and 18 form a G_3 complete graph (a 3-clique) in the network. If we run the simulations according to the routing protocol defined in 2, we get the results depicted in Fig. 3.

Fig. 3 (see the averaged values in Table 1) shows that the energy consumption of the coalitional member nodes increased, while the energy consumption of all other nodes decreased.

As we will see, this is not surprising. Let us consider an i member of the coalition S, who is forwarding a package with destination d. Let us furthermore suppose that d is in the neighborhood of j, which is an element of S as well. If no cooperation is present, i will forward this package randomly (taking into account only node degrees) to one of its neighbors (k). This way the

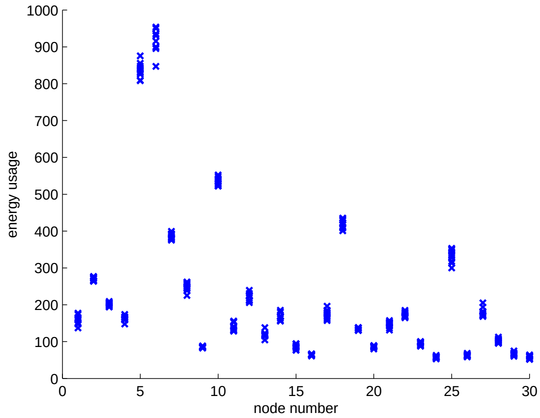

Fig. 3 Energy usage of the nodes in the case when coalition $\{5, 6, 18\}$ forms (all other players act as singletons). Simulation length: 1000 steps. Results of 10 simulations.

package will spend *at least* two more time steps in the network (if k is adjacent to d it may arrive in 2 steps), and in the future probably reach d via an undefined path, not necessary including j. In contrast, when the coalition S forms, the package will be forwarded to j. This means that coalitional members increase each others traffic load via applying the second order topological information. However as the values $E_T = 6651$ and $\bar{T}_{arr} = 3.76$ show in this case, network efficiency is greatly increased even by the formation of this single coalition. In other words, the coalition formation resulted in a significant positive externality regarding all the remaining nodes.

Table 1 shows the energy consumption of individual nodes, the total energy usage of the system and average packet arrival time, in the case when various coalitions form.

We can see that, the dominant trend is validating our intuition - the energy consumption of the nodes which take part in coalitions significantly increases. In some exceptional cases (see e.g. the coalition $\{2, 11, 23\}$), the benefits implied by more efficient routing may overcome the handicap of increased coalitional load. In other words, this means that if we define the payoff of players and coalitions purely as the energy saving compared to the all singleton case, coalitions will not be stable in most of the cases. Using terms of cooperative game theory, regarding energy saving as payoff, merging is subadditive in the proposed setup. On the other hand, considering the E_T and $\bar{T}_{arr}$ values, it can be clearly seen that coalition formation always enhances network performance, so from the point of view of network operation, it should be promoted.

If we repeat the simulations with $R = 7$, and depict the results in the same figure (Fig. 4), we can see the phenomena even more clearly. The energy usage of other nodes decrease, while for the nodes in the coalition, the value considering cooperation is greater or equal compared to the non-cooperative

	∅	{2, 3, 12}	{2, 6, 15}	{2, 11, 23}	{3, 5, 7}	{4, 8, 17}	{5, 6, 18}
1	195	179	169	174	176	189	160
2	341	364	404	333	285	328	269
3	260	236	235	243	258	260	207
4	188	174	171	178	168	189	164
5	755	699	676	691	783	742	826
6	866	797	914	782	726	845	898
7	491	453	433	450	579	479	378
8	294	282	259	274	264	330	255
9	100	96	91	93	85	96	83
10	649	594	584	610	580	641	541
11	188	172	165	185	159	179	139
12	263	303	242	242	224	250	222
13	140	128	128	129	119	134	117
14	201	188	184	188	179	193	174
15	105	98	116	97	90	101	91
16	76	71	71	71	67	74	64
17	203	193	185	195	179	225	175
18	368	344	337	345	318	362	414
19	160	149	147	149	139	155	132
20	100	95	93	97	89	98	83
21	169	154	153	160	152	163	147
22	201	185	193	195	180	200	169
23	116	106	105	116	106	114	93
24	64	64	57	64	59	66	58
25	427	394	387	385	374	414	332
26	71	71	68	67	65	70	61
27	227	211	213	214	196	215	171
28	122	116	112	108	110	122	99
29	80	74	73	76	71	78	69
30	71	69	66	66	61	71	58
E_T	7492	7060	7031	6977	6843	7382	6651
T_{arr}	4.54	4.22	4.14	4.23	3.98	4.42	3.76

Table 1 Energy consumption of individual nodes, total energy usage of the system, and average packet arrival time in the case of various coalition formations. ∅ means the all singleton coalition, in other cases only non-singleton coalitions are enumerated. Every result is an averaged value of 10 simulations. Typically, if a coalition is formed, the load of its members increase. See eg. node 2 in the coalitions which include it, or node 6.

scenario. The total energy consumption (averaged for the 10 simulations) drops from 1.03 10^4 to 9.14 10^3 while the energy need of coalition {5,6,18} raises from 2.745 10^3 to 2.773 10^3. The improvement in transmission time is very spectacular in this case. $\bar{T}_{arr}$ drops from 16.93 to 4.38 due to the cooperation of this single coalition.

3.1.2 Example II

In this example we use a network with 300 nodes to analyze how the efficiency-enhancing effect of coalition formation scales up, and how does it depend on the number of coalitions. The network used in this example was generated with a seed of 10 nodes, $m = 4$ and $\beta = -2$.

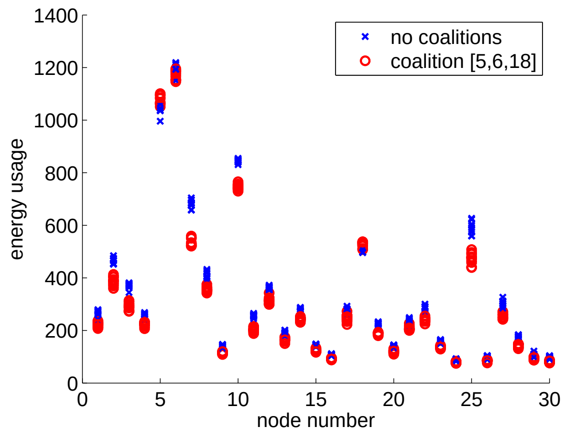

Fig. 4 How the formation of coalition $\{5, 6, 18\}$ affects the energy usage of single nodes. Simulation length: 1000 steps. Results of 10 simulations.

Non-congested case

First we analyze the network performance without congestion. We use the parameters $C = 7$ and $\alpha = -1$, $R = 10$. Results are summarized in Table 2.

Coalition structure	E_T	T_{arr}	η
$\emptyset$	51126	34.81	0.07
5x2	48579	33.28	-0.01
10x2	45307	30.90	-0.03
20x2	41078	28.05	-0.04
50x2	35078	23.88	0.03
100x2	31564	21.57	-0.02
1x5 2x4 7x3	38963	26.38	0.05
1x5 2x4 17x3	34705	23.07	0.01
1x5 2x4 27x3	33445	22.37	-0.08
1x5 2x4 31x3 16x2	31492	20.85	0
1x5 2x4 31x3 66x2	29209	19.13	0.02

Table 2 Network performance at various levels of cooperation and various coalitional structures in the case of the 300-node network, non-congested case. The column 'Coalition structures' indicates the number of different size coalitions (e.g. '1x5 2x4 31x3 66x2' indicates 1 coalition of size 5, 2 of size 4 etc.).

Table 2 shows that (as expected) as the level of cooperation increases, the network performance is enhanced. Simulation results show that this performance increase can be very significant. The presence of larger size coalitions implies further growth in network efficiency. The η values which are practically equal to 0 show that no congestion appears.

Congested case

Since the measure of congestion η is also a function of coalitional structure, we may analyze how increasing levels of cooperation affect congestion. Table 3 summarizes the corresponding results. We use the parameters $C = 7$ and $\alpha = 0$, $R = 25$

Coalition structure	E_T	T_{arr}	η
$\emptyset$	90421	103.29	1.86
5x2	89214	98.79	1.83
10x2	88279	91.79	1.54
20x2	84368	74.85	1.12
50x2	77642	45.26	0.5
100x2	73470	35.37	0.19
1x5 2x4 7x3	79237	71.52	1.07
1x5 2x4 17x3	75886	55.61	0.74
1x5 2x4 27x3	73792	47.62	0.52
1x5 2x4 31x3 16x2	71771	35.1	0.35
1x5 2x4 31x3 66x2	67934	29.65	0.27

Table 3 Network performance at various levels of cooperation and various coalitional structures in the case of the 300-node network, congested case. The column 'Coalition structures' indicates the number of different size coalitions.

Regarding the performance indicators, the results are similar to the non-congested case, except that the benefits of cooperation in the congested case are even more prominent. On the other hand, if we analyze the η values in Table 3 we can see that increasing level of nodal cooperation alleviates network congestion as well. Very high levels of cooperation almost eliminate network congestion.

Heterogenous traffic, non-congested case, spatially random senders

As described in section 2, basically the simulations deal with random source-destination pairs. We may also consider a traffic-asymmetric scenario, where we apply the Pareto-rule (Reh, 2005): we assume that the 80% of the traffic is generated by 20% of the nodes (dominant senders). Since in the generation of the network the nodes with lower index were connected first, they usually have larger degrees. If high degree nodes were the main source of traffic, this would enhance network efficiency (thanks to large degrees of sources in the first steps packets have more chance to find the destination). Furthermore at this simulation, the positions of dominant senders may be anywhere. To avoid this unwanted correlation we choose dominant sender nodes randomly. As we see in table 4, increasing levels of cooperation, enhance the network performance in a similar manner compared to table 2.

Heterogenous traffic, non-congested case, unilateral traffic

In this scenario we consider homogenous traffic flow regarding the first coordinate. We define the 50 nodes closest to the $x = 0$ coordinate as senders and the 50 nodes closest to the $x = 1$ as receivers.

Coalition structure	E_T	T_{arr}	η
∅	51015	34.79	-0.01
5x2	49013	33.48	0.01
10x2	46449	31.65	0.00
20x2	40402	27.46	0.01
50x2	33973	23.10	0.03
100x2	31108	21.05	-0.01
1x5 2x4 7x3	39188	26.43	-0.01
1x5 2x4 17x3	35643	23.87	0.02
1x5 2x4 27x3	33109	22.06	0.01
1x5 2x4 31x3 16x2	31021	20.55	0.00
1x5 2x4 31x3 66x2	29584	19.42	0.01

Table 4 Network performance at various levels of cooperation and various coalitional structures in the case of the 300-node network, non-congested case, heterogenous traffic. The column 'Coalition structures' indicates the number of different size coalitions.

Coalition structure	E_T	T_{arr}	η
∅	50119	34.15	0.00
5x2	48797	33.18	0.02
10x2	45678	30.99	0.00
20x2	40590	27.423	0.01
50x2	33890	22.92	0.00
100x2	30651	20.64	0.00
1x5 2x4 7x3	38895	26.08	0.03
1x5 2x4 17x3	36623	24.30	0.01
1x5 2x4 27x3	33798	22.40	0.02
1x5 2x4 31x3 16x2	30501	20.05	0.00
1x5 2x4 31x3 66x2	28974	18.81	0.00

Table 5 Network performance at various levels of cooperation and various coalitional structures in the case of the 300-node network, non-congested case, unilateral. The column 'Coalition structures' indicates the number of different size coalitions.

As we see in table 5, the results are very similar to the previous non-congested cases - the improvement implied by cooperation is also significant in this case.

3.1.3 Example III

If we would like to move on to a network with several thousands of nodes to compare coalitions of different size, we have to take the following problem into account. As already discussed, the cooperation method proposed in this article assumes a preexisting full graph (k-clique). As we generated the 300-node network, the biggest clique was of the size of 5 nodes. This maximal node size dose not significantly grow as we increase the number of points in the network. This means that if we would like to compare the effect of different size coalitions on routing efficiency, we have to overcome this problem.

In this subsection we use clusterized nonrandom structure to demonstrate the results corresponding to cluster size efficiency. The graph used in this subsection was obtained as follows. First, we used the geometry modulated preferential attachment method (Manna and Sen, 2002) to generate a 3000 node network. The cluster maximal size in this network is still about 5-10 nodes. Second we did choose some random nodes, and generated artificial clusters relying only on euclidian distance. The resulting network holds five of each such artificial clusters of the following sizes: 5, 10, 25, 50, 75, 100.

As we can see the μ values in the table summarizing the results of this example (Table 6), the parameters used previously in the non-congested case ($C = 7$ and $\alpha = -1$, $R = 10$) already resulted in congestion. The reason for this is that in the 3000-node network, the average time a packet spends in the network is much higher (as shown in Table 6). This can be explained by the fact that the average distance between a randomly chosen source-node pair is higher: 2.893 in the case of the 300-node network and 3.797 in the case of the 3000-node network.

Regrading the required computational capacity, in the case of this example, the simulation performed in MATLAB took 1 week on a standard desktop PC (4 GB ram, 3.3GHz CPU, 64 bit OS).

Coalition structure	E_T	T_{arr}	η
$\emptyset$	67396	176.32	1.84
5x5	67238	175.8	1.84
5x10	66280	175.15	1.94
5x25	63374	166.08	1.71
5x50	59444	149.65	1.59
5x75	56873	139.85	1.37
5x100	56740	136.22	1.47

Table 6 Network performance at various levels of coalitional size in the case of the 3000-node network. $C = 7$ and $\alpha = -1$, $R = 10$

Observing the results of Example III, summarized in Table 6, we make the following points.

- If we compare Table 6 to Table 3, we can see that in the case when no coalitions are present, the total energy usage is lower in the case of the 3000 network. There are two factors affecting this value: On the one hand the packets naturally travel more in the case of the 3000-node network until they reach their destination (compare $\bar{T}_{arr}$), but on the other hand, the nodes are much more dense on the same area, and one hop takes significantly less energy (consequence of the square-of-distance rule).
- As the size of the coalitions increase, the improvement in E_T and $\bar{T}_{arr}$ is clear also in this case, and there is a (not strictly monotonic but clearly improving) trend in decongestion as well.
- In we would like to compare the most cooperative cases in Tables 3 and 6, we have to take also in account that in the case of the 300-node network and the coalition structure $\{1x5,\ 2x4,\ 31x3,\ 66x2\}$ the 79% of the total nodes were covered by coalitions, and here this ratio is only 16%.

If we cover the 50% of the 3000-node network (this can be done eg. by the following disjoint coalitions: 4x100, 2x75, 2x50, 4x25, 4x10, 3x5, 346x2) we get the values $E_T = 43485$, $\bar{T}_{arr} = 114.73$ and $\mu = 0.74$. This result points to the conclusion that the ratio between the number of nodes covered by coalitions and the number of total nodes affects the transport efficiency significantly more than the size of the coalitions present.

3.2 Stability of cooperating structures

According to the results observed in section 3.1, namely that cooperation increases the activity of cooperating agents and thus is basically disadvantageous for rational nodes if the payoff would be the energy saving. Based on this observation we introduce two modelling assumptions, and define the payoffs of nodes. Once the payoffs are defined, the tools of cooperative game theory are possible to use. As a coalition forms, the traffic of the network is affected and the payoffs of the nodes change - even the payoffs for nodes outside the coalition. In game theoretic terms this phenomenon is called an externality, and implies the class of partition function form (PFF) games).

In the case of partition function form games there are multiple concepts of stability analysis. The α-core (Aumann and Peleg, 1960) assumes that a coalition deviates only if it gets a higher payoff irrespective of the induced partition. Core stability (Shenoy, 1979) is more permissive: a coalition deviates if any of the induced partitions gives a higher payoff. In the γ-core (Chander and Tulkens, 1997) the coalition faces individually best responses. Here we use the concept of the *recursive core* (Kóczy, 2007a), that allows the remaining, residual players to freely react and form a core-stable partition before the payoff of the deviating coalition is evaluated. The recursive core is less sensitive to the optimism or pessimism of the players and reflects the profit-seeking behaviour of the agents even after a new balancing group formed. The detailed definition of the recursive core may be found in Appendix A.

Since the calculations regarding the stability analysis of the introduced game are computationally demanding (especially the calculation of recursive core (Kóczy, 2007a)), we restrict our stability analysis for the network 1., depicted in Fig. 1.

3.2.1 Key assumptions and definition of the game

- First, we modify the routing protocol as follows. We introduce *coalitional load balancing* (CLB), which means that a parameter σ_1 is defined to account for load relief of the coalitions. CLB works in the following way. If a member of a coalition is forwarding a packet, the destination of which can not be found neither among his own neighbors, nor the neighbors of among coalitional members, he will take into account the parameter sigma during the routing procedure. Namely the probability describing he will forward the package to his neighbor j will be

$$\Pi_j = \frac{k_j^\alpha}{\sum_m k_m^\alpha}\sigma, \tag{3}$$

where $\sigma = \sigma_1$ if j is in the coalition of i and $\sigma = 1 - \sigma_1$ otherwise. This, in the case of $\sigma_1 < 0.5$ will ensure that packets, who do not have their destination in the neighborhood of the coalition, will be probably turned away from it (in exchange for packets who have, will be drawn into it). We have to note that the inequality $0 < \sigma_1$ shall be strict, because $\sigma_1 = 0$ may lead to blocking situations as depicted in Fig. 5.

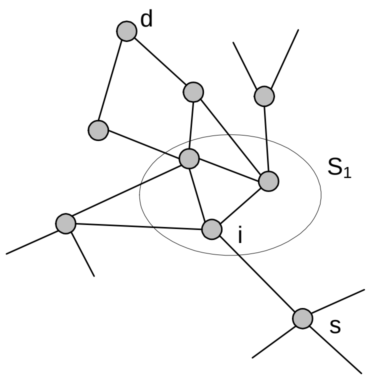

Fig. 5 Coincidence of deadlock and blocking in the case of $\sigma = 0$ and a packet with destination d arriving from s to i.

Consider a packet with destination d arriving from s to i. As node i can not find d neither among his neighbors, nor among the neighbors of his coalition partners, in the case of $\sigma_1 = 0$ it is theoretically forbidden to route it towards any coalitional partner. In the case of the given topology it can be seen that node d is reachable from s only via coalition S_1, which means that the actual packet will never reach its destination.

– Second, we assume an independent network operator, who is interested in efficient operation of the system. It is assumed that this network operator is able to reward, or in other words somehow compensate cooperating players for their increased traffic. Formally we will assume that some reward equivalent to the $0 < p_{re} < 1$ part of the total energy saving of the system, compared to the all-singleton reference case, will be redistributed among the nodes, proportional to their actual traffic. This way the nodes who choose to cooperate and thus increase their traffic and enhance network performance, will gain more reward from the network operator. We will call this compensation *net reward*.

Since wireless devices are mostly neither able to transmit energy to each other, nor receive energy from the system operator, it is straightforward to ask what is the nature of this compensation. If we suppose that nodes represent commercial mobile devices the most straightforward interpretation of this transaction is if we assume that this compensation can be included in the service fee. However, other means of compensation interpretation are also imaginable (e.g. the packets of cooperating nodes get priority in the routing process etc). The assumption of energy-money convertibility on the the other hand is also a critical issue regarding the transferable utility assumption, which is a primary element of our model.

According to these considerations, during the routing protocol we apply CLB, and the payoff of single node i ($v(i)$) is determined as his energy saving compared to the all singleton case plus the net reward. If according to these assumptions we repeat the simulations with $\sigma_1 = 0.05$ for coalitions detailed in Table 1, and calculate nodal payoffs with $p_{re} = 0.7$, we get the results summarized in Table 7.

The first thing we can see in Table 7 is that all payoffs in the case of coalition formations are positive. This means that now (at least dominantly) superadditivity holds (the total payoff of mergers does not decrease), which points toward the direction of cooperation and coalitional stability. Second, the significant positive externalities still hold in all cases. Third, the application of CLB does not decrease network efficiency, in contrast the E_T and $\bar{T}_{arr}$ values are slightly enhanced.

3.2.2 Coalitional stability

To get an impression about the stability of coalitions and about scenarios where multiple coalitions coexist let us analyze the stability of coalitions $\{2, 6, 15\}$, $\{3, 5, 7\}$ and $\{4, 8, 17\}$. To keep computations feasible, we restrict our calculations, and assume that potential deviators may not form coalitions with external nodes. Furthermore, for the same reason, we assume that only one coalition may break up in the same time. According to this, the node relevant payoffs, from which the values of the partition functions can be calculated by summing over the coalitions, are summarized in Table 8.

Let us consider coalition $\{2, 6, 15\}$ first. In this case, if we restrict ourselves to this residual game, the partition function will be as summarized in Table 9

If we stick to the previously discussed transferable utility assumption (which may be realistic e.g. in the case of mobile commercial devices where the players may be compensated for higher energy consumption via lower service fees), and calculate the (pessimistic) recursive core (Kóczy, 2007a) for the partition function presented in Table 9, we find that the partition $\{2, 6\}, \{15\}$ is stable, with the payoff configuration

$$x(2) + x(6) = 416 \quad x(15) = 39 \quad 116 < x(2) < 161. \tag{4}$$

If we take a closer look on the E_T and $\bar{T}_{arr}$ values in Table 8, we can see that (assuming that the members of the other coalitions do not deviate) this partition of $\{2, 6, 15\}$ results in the most efficient operation of the network.

	∅	{2, 3, 12}	{2, 6, 15}	{2, 11, 23}	{3, 5, 7}	{4, 8, 17}	{5, 6, 18}
1	0	30	45	33	43	8	59
2	0	46	30	56	93	13	101
3	0	66	57	40	62	7	83
4	0	23	32	28	40	59	51
5	0	117	143	123	112	38	101
6	0	138	112	146	225	31	145
7	0	73	97	77	37	27	160
8	0	36	52	44	63	63	73
9	0	13	17	15	26	6	28
10	0	103	127	98	149	35	186
11	0	29	44	28	50	13	66
12	0	21	48	34	69	18	67
13	0	21	22	16	33	13	37
14	0	24	33	27	49	12	51
15	0	15	22	15	22	5	30
16	0	9	11	9	17	4	21
17	0	25	38	29	41	97	51
18	0	45	70	50	82	12	42
19	0	17	26	23	38	11	43
20	0	12	15	11	19	5	25
21	0	19	31	24	32	7	43
22	0	27	32	28	37	8	53
23	0	15	23	31	23	3	33
24	0	7	10	8	12	2	14
25	0	67	91	73	102	24	141
26	0	10	11	10	17	2	20
27	0	29	40	29	47	7	66
28	0	15	24	15	24	9	35
29	0	10	17	11	18	3	21
30	0	9	15	9	17	3	22
E_T	7492	6957	6823	6921	6692	7219	6556
T_{arr}	4.54	4.14	4	4.14	3.87	4.38	3.73

Table 7 Nodal payoffs, total energy usage of the system, and average packet arrival time in the case of various coalition formations, applying CLB and net reward. ∅ means the all singleton coalition, in other cases only non-singleton coalitions are enumerated. All values are positive: This means that in this case even the cooperating nodes benefit from coalition formation. Every result is an averaged value of 10 simulations.

Coalitions	v(2)	v(3)	v(4)	v(5)	v(6)	v(7)	v(8)	v(15)	v(17)	E_T	T_{arr}
{2, 6, 15}, {3, 5, 7},{4, 8, 17}	105	104	97	231	291	101	143	39	129	5931	3.32
{2, 6}, {3, 5, 7},{4, 8, 17}	109	104	100	234	307	108	140	39	131	5883	3.29
{2, 15}, {3, 5, 7},{4, 8, 17}	112	71	86	141	255	61	119	26	120	6278	3.63
{6, 15}, {3, 5, 7},{4, 8, 17}	116	81	89	165	252	79	125	24	125	6202	3.54
{3, 5, 7},{4, 8, 17}	98	64	87	131	231	39	105	26	113	6401	3.71
{2, 6, 15}, {3, 5},{4, 8, 17}	53	80	83	184	181	130	118	30	124	6335	3.68
{2, 6, 15}, {3, 7},{4, 8, 17}	72	58	92	244	217	113	125	31	124	6186	3.56
{2, 6, 15}, {5, 7},{4, 8, 17}	75	95	92	171	237	85	131	36	126	6129	3.45
{2, 6, 15},{4, 8, 17}	32	60	80	166	124	104	111	25	119	6524	3.82
{2, 6, 15}, {3, 5, 7},{4, 8}	105	106	78	214	288	97	120	37	70	6040	3.37
{2, 6, 15}, {3, 5, 7},{4, 17}	100	103	82	203	281	94	106	36	85	6059	3.38
{2, 6, 15}, {3, 5, 7},{8, 17}	108	99	71	218	296	99	125	39	100	5985	6.03
{2, 6, 15}, {3, 5, 7}	97	101	66	212	275	94	123	39	100	6033	3.38

Table 8 Nodal payoffs in various coalitional structures. The values are averaged results of 10 simulations.

Partition	Coalitional values
{2,6,15}	435
{2,6}, {15}	416, 39
{2,15}, {6}	138, 255
{2},{6,15}	116, 276
{2},{6},{15}	98, 231, 26

Table 9 Partition function of coalition $\{2,6,15\}$

Regarding $\{3,5,7\}$ and $\{4,8,17\}$ we find that in both cases the grand coalitions are stable as depicted in Fig. 6 and 7. Again we can see in Table 8 that the partitions in which $\{3,5,7\}$ and $\{4,8,17\}$ form the grand coalition are the most efficient.

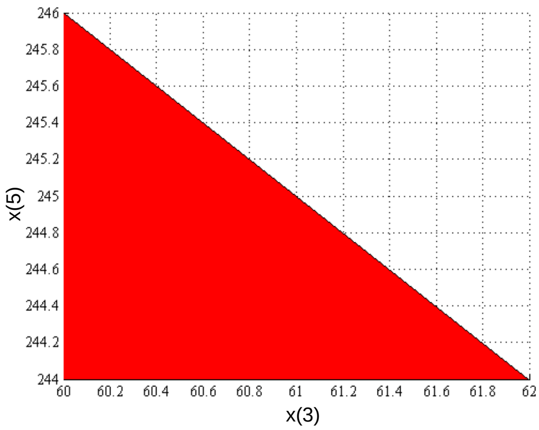

Fig. 6 Recursive core of coalition $\{3,5,7\}$ in the payoff space. As the equality $x(3)+x(5)+x(7)=436$ holds in the case of the recursive core, the stable payoffs forma hyperplane in the space of x_3, x_5, x_7. The figure depicts the projection of this hyperplane onto the plane of x_3, x_5 - x_7 may be determined for every feasible $x_3 - x_5$ pair via the equation.

Appendix B holds further data underlining the trend that stable coalitional configurations correspond to the most efficient operation modes of the network.

4 Conclusions and future work

We introduced a game theoretic model to describe coalitional formation in wireless networks with fixed communication structure and analyzed the implied phenomena on scale-free topology. Cooperation was interpreted as exchange of local topological information. The effect of cooperation has been analyzed, and it has been found that percentage of coalition-covered nodes affects efficiency significantly more than the size of coalitions. We have shown that if

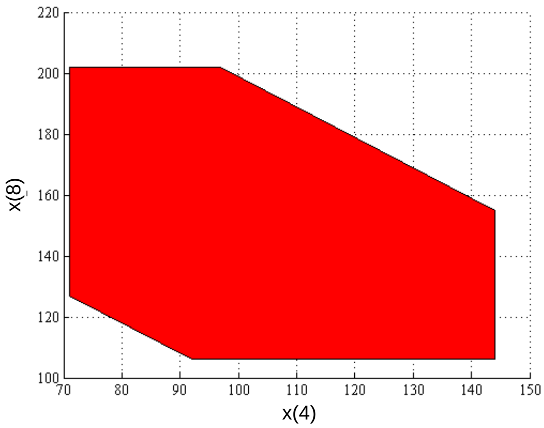

Fig. 7 Recursive core of coalitions $\{4, 8, 17\}$ in the payoff space. The equality $x(4)+x(8)+x(17) = 369$ holds

we define the payoffs of the nodes exclusively by the energy saving compared to the non-cooperative case, players are not motivated to form coalitions, since the traffic of such cooperating agents increase. To enhance coalitional stability and retain positive externalities we introduced coalitional load balancing and net reward, and calculated the payoff of nodes according to these assumptions. This means that these modifications allow us to motivate the players for cooperation and to enhance network performance in the same time. Furthermore we have shown that increasing levels of cooperation ease network congestion.

There are several directions in which the current concept may be extended. First, as we consider a wireless environment, it is straightforward to assume that the nodes (or at least some of the nodes) are moving. In this case the stability of coalitions may be subject to change due to change in the transmission costs. Second, in the current model we assumed that the exchange of local topological information is free, or it can be neglected compared to the energy cost of packet forwarding. To make the model more realistic one may assume that the exchange of local topological information itself takes place via packet forwarding, thus its energy cost may be incorporated in the model. Third, the concept of net reward may be refined as well. E.g. it can be assumed that the network operator holds a few high degree nodes (e.g. with fixed position - base stations), and is able to redistribute only the energy savings corresponding to these nodes among the players.

5 acknowledgments

This work was supported by the Hungarian National Fund (OTKA NF-104706) and by the Funds KAP15-079-1.2 and KAP16-71009-1.2-ITK.

Appendix A

A game in partition function form (Thrall and Lucas, 1963) is a pair (N, V), where $V : \mathcal{E} \to \mathbb{R}$ is the partition function, which assigns a real payoff to each embedded coalition. Each partition is composed of coalitions, e.g. the partition $\{1,2\}\{3,4,5\}$ of $\{1,2,3,4,5\}$ is composed of coalitions $\{1,2\}$ and $\{3,4,5\}$.

We define the *residual game* over the set $R \subsetneq N$ as follows. $\Pi(S)$ denotes the set of partitions of S. Assume $\overline{R} = N \setminus R$ have formed $\overline{\mathcal{P}_R} \in \Pi(\overline{R})$. Then the residual game $(R, V_{\mathcal{P}_{\overline{R}}})$ is the partition function form game over the player set R with the partition function given by $V_{\mathcal{P}_{\overline{R}}}(C, \mathcal{P}_R) = V(C, \mathcal{P}_R \cup \mathcal{P}_{\overline{R}})$.

Definition 1 ((Pessimistic) Recursive Core (Kóczy, 2007b)) *For a single-player game the (pessimistic) recursive core is trivially defined. Now assume that the (pessimistic) recursive core $C(N, V)$ has been defined for all games with $|N| < k$ players. We call a pair $\omega = (x, \mathcal{P})$ consisting of a payoff vector and a partition $\mathcal{P} \in \Pi(N)$ an outcome. Let us denote the set of outcomes in (N, V) by $\Omega(N, V)$. Then for an $|N|$-player game an outcome $(x, \mathcal{P})$ is dominated if there exists a coalition Q forming partition $\mathcal{P}_Q$ and a feasible payoff vector $y_Q \in \mathbb{R}^Q$, such that for all $(y_Q, y_{\overline{Q}}, \mathcal{P}_Q \cup \mathcal{P}_{\overline{Q}}) \in \Omega(N, V)$ we have $y_Q > x_Q$ and if $C(\overline{Q}, V_{\mathcal{P}_Q}) \neq \varnothing$ then $(y_{\overline{Q}}, \mathcal{P}_{\overline{Q}}) \in C(\overline{Q}, V_{\mathcal{P}_Q})$. The* pessimistic recursive core *$C(N, V)$ of (N, V) is the set of undominated outcomes.*

Appendix B

To give some further impression into coalitional stability of the model we analyze some more cases. Let us consider the coalitions $\{5, 7, 9\}$, $\{10, 13, 14\}$ and $\{11, 18, 23\}$ and the values summarized in Table 10.

Coalitions	v(5)	v(7)	v(9)	v(10)	v(11)	v(13)	v(14)	v(18)	v(23)	E_T	T_{arr}
$\{5,7,9\}$, $\{10,13,14\}$,$\{11,18,23\}$	236	116	36	215	81	56	57	117	47	5999	3.35
$\{5,7\}$, $\{10,13,14\}$,$\{11,18,23\}$	244	129	38	217	79	58	59	123	47	5961	3.33
$\{5,9\}$, $\{10,13,14\}$,$\{11,18,23\}$	229	138	22	164	62	42	40	79	41	6305	3.66
$\{7,9\}$, $\{10,13,14\}$,$\{11,18,23\}$	233	137	30	159	63	44	41	82	40	6274	3.63
$\{10,13,14\}$,$\{11,18,23\}$	181	101	24	110	50	35	29	57	33	6593	3.85
$\{5,7,9\}$, $\{10,13\}$,$\{11,18,23\}$	224	113	36	206	78	45	73	116	47	6046	3.41
$\{5,7,9\}$, $\{10,14\}$,$\{11,18,23\}$	195	102	32	182	72	42	32	102	43	6203	3.51
$\{5,7,9\}$, $\{13,14\}$,$\{11,18,23\}$	180	86	30	191	71	47	40	101	43	6266	3.54
$\{5,7,9\}$, $\{11,18,23\}$	193	94	31	196	68	49	41	102	42	6232	3.51
$\{5,7,9\}$, $\{10,13,14\}$,$\{11,18\}$	222	108	36	204	73	54	55	116	41	6052	3.4
$\{5,7,9\}$, $\{10,13,14\}$,$\{11,23\}$	179	84	34	183	66	48	45	113	35	6229	3.51
$\{5,7,9\}$, $\{10,13,14\}$,$\{18,23\}$	185	86	34	191	64	52	48	111	36	6207	3.49
$\{5,7,9\}$, $\{10,13,14\}$,	184	90	35	178	65	50	48	111	34	6221	3.51

Table 10 Nodal payoffs in various coalitional structures. The values are averaged results of 10 simulations.

Considering $\{5,7,9\}$, the stability analysis shows that $\{5,7\},\{9\}$ is the stable partition with $x(5)+x(7)=373$, $x(9)=38$ and $233<x(5)<235$. Considering $\{10,13,14\}$ and $\{11,18,23\}$ the grand coalitions are stable, with payoffs depicted in Fig. 8. Again, it can be seen that stable partitions correspond to the most efficient network operation modes.

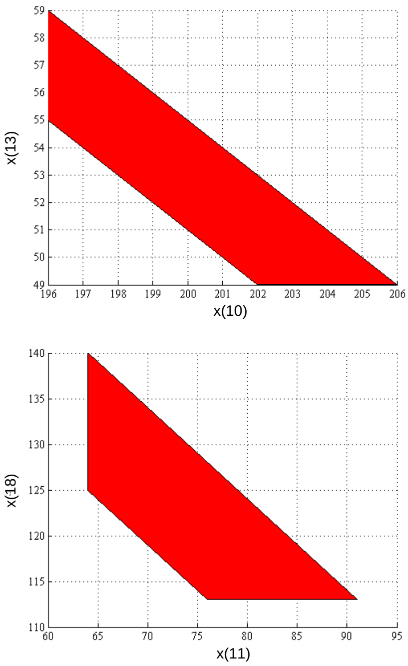

Fig. 8 Recursive cores of coalitions $\{10,13,14\}$ and $\{11,18,23\}$ in the payoff space. Equality $x(10)+x(13)+x(14)=328$ holds.

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