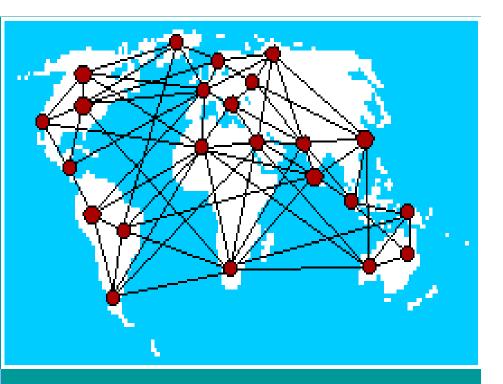
Critical Node Detection Problem

ITALY – May, 2008





Panos Pardalos Distinguished Professor CAO, Dept. of Industrial and Systems Engineering, University of Florida

Outline of Talk

- Introduction
- Problem Definition
- Applications
- Proof NP Completeness
- Formulation
- Heuristics
- Results and Conclusions
- Future Direction





Introduction

- Acknowledgements
- Critical Node Detection
- Centrality
- Prestige
- Prominence
- Key Players





Introduction Acknowledgments

- Coauthors: A. Arulselvan, C. Commander, L. Elefteriadou





Problem Definition

- Given a graph G = (V,E) and an integer
 k
- Goal is to detect (delete) a set |A| ≤ k of critical nodes, or nodes whose deletion results in maximum pairwise disconnectivity
- Disconnectivity → MAX components subject to MIN difference in cardinality
- Example....





Applications

- Assessing vulnerability of a supply chain network by determining the vital nodes
- First of many problems considered involving jamming/suppressing communication on a network
- Breakdown communication in covert networks
- Reduce transmissibility of virus and contagion of epidemic
- Drug design
- Emergency response





Supply Chain Network

- It is essential to estimate the vulnerability of the supply chain network
- The study could be accommodated by maximizing the disconnectivity between supply and demand nodes instead of all pairs of nodes





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Jamming Networks

- Given a graph whose arcs represent the communication links in the graph.
- (Offense) Select at most k nodes to target whose removal creates the maximum network disruption.
- (Defense) Determine which of your nodes to protect from enemy disruptions.
- Arulselvan, C., Pardalos, Shylo. Managing Network Risk Via Critical Node Detection. Risk Management in Telecommunication Networks, Gulpinar & Rustem (eds.), Springer, 2007.





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Covert/Terrorist Network

- Use gathered intelligence to create social network interactions among terrorists
- Target those individuals whose "neutralization" will maximally disrupt the communication. (See example)
- Arulselvan, C., Elefteriadou, Pardalos.
 Detecting Critical Nodes in Sparse Graphs, Computers and Operations Research, 2008.





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Controlling Social Contagion

- Certain social populations have high rates of transmissibility of viruses.
- Mass vaccination is too expensive
- Determine the appropriate set of individuals to vaccinate so that the spread of the disease/virus is minimized
- Arulselvan, C., Elefteriadou, Pardalos. Detecting Critical Nodes in Sparse Graphs, *Computers and Operations Research*, 2008.





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Drug Design

- Examine protein-protein interaction maps.
- Determine which proteins to target in order to destroy the network.
- Last week, University of Florida researchers identify key protein interactions to target to destroy aggressive cancer cells' protective force field, <u>University of Florida</u> scientists reported this week at the <u>American</u> <u>Association for Cancer Research's</u> annual meeting in San Diego.





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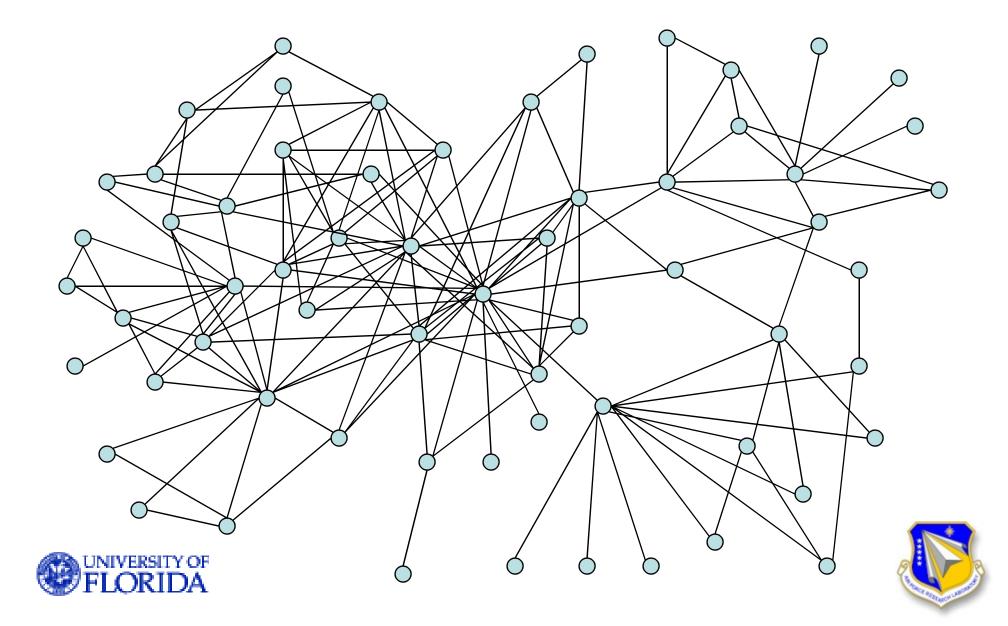


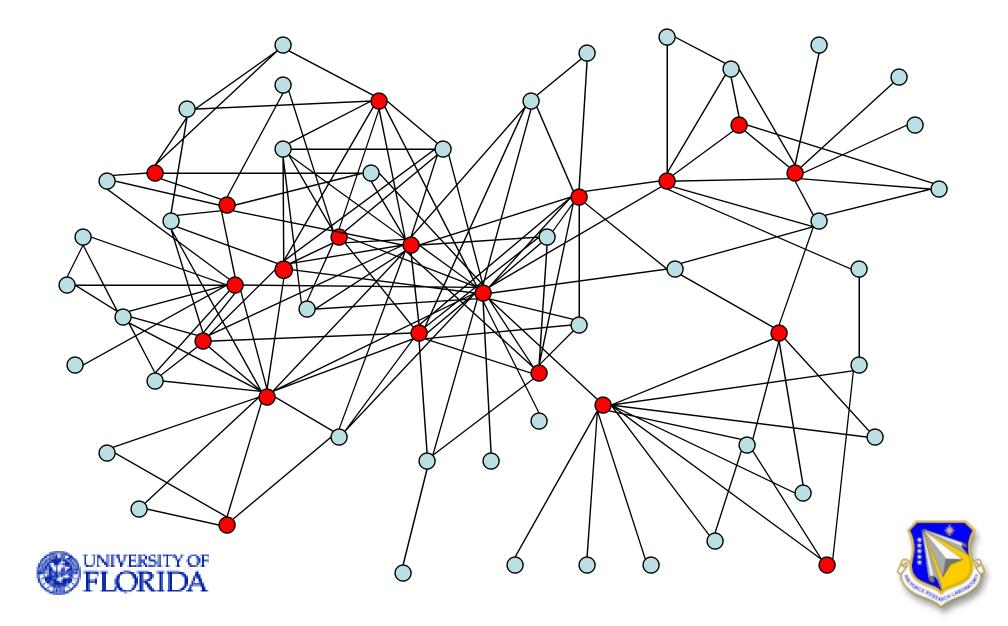
Emergency Response

- Identify roadways to attack to prevent enemy travel.
- Identify key roadways to fortify or repair first in the event of natural disaster.
- Enable mass evacuation (get out) and first responders (get in)
- RE: Hurricane Katrina









Problem Definition

- Decision Version: K-CNP
- Input: Undirected graph G = (V,E) and integer k
- Question: Is there a set *M*, where *M* is the set of all maximal connected components of **G** obtained by deleting *k* nodes or less, such that $\sum_{\forall i \in M} \frac{\sigma_i(\sigma_i 1)}{2} \le K$

where σ_i is the cardinality of component *i*, for all *i* in *M*?





Theoretical Results

 Lemma 1: Let *M* be a partition of G = (V,E) in to *L* components obtained by deleting a set D, where |D| = k Then the objective function

$$\sum_{\forall i \in M} \frac{\sigma_i(\sigma_i - 1)}{2} \ge \frac{(|V| - k)\left(\frac{|V| - k}{L} - 1\right)}{2}$$

with equality holding if and only $\sigma_i = \sigma_j$, for all i,j in M, where σ_i is the size of *i*th component of M.

 Objective function is best when components are of average size.



Theoretical Results

- Lemma 2: Let M_1 and M_2 be a two sets of partitions of G = (V,E) obtained by deleting a set D1 and D2 sets of nodes respectively, where $|D_1| = |D_2| = k$. Let L_1 and L_2 be the number of components in M_1 and M_2 respectively, and $L_1 \ge L_2$. If $\sigma_i = \sigma_j$, for all i,j in M_1 , then we obtain a better objective function value by deleting D_1 .
- THE MORE (components), THE BETTER!!





Proof of NP-Completeness

 NP-complete: Reduction from Independent Set Problem by a simple transformation and the result follow from the above Lemmas.





- Let u_{i,j} = 1, if i and j are in the same component of G(V \ A), and 0 otherwise.
- Let v_i = 1, if node i is deleted in the optimal solution, and 0 otherwise.
- We can formulate the CNP as the following integer linear program





(CNP-1) Minimize

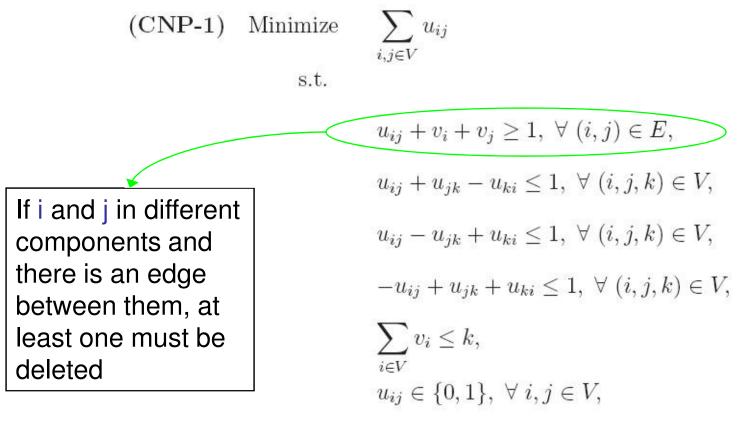
 $\sum u_{ij}$ $i, j \in V$

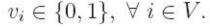
s.t.

$$\begin{split} & u_{ij} + v_i + v_j \geq 1, \ \forall \ (i,j) \in E, \\ & u_{ij} + u_{jk} - u_{ki} \leq 1, \ \forall \ (i,j,k) \in V, \\ & u_{ij} - u_{jk} + u_{ki} \leq 1, \ \forall \ (i,j,k) \in V, \\ & -u_{ij} + u_{jk} + u_{ki} \leq 1, \ \forall \ (i,j,k) \in V, \\ & \sum_{i \in V} v_i \leq k, \\ & u_{ij} \in \{0,1\}, \ \forall \ i,j \in V, \\ & v_i \in \{0,1\}, \ \forall \ i \in V. \end{split}$$



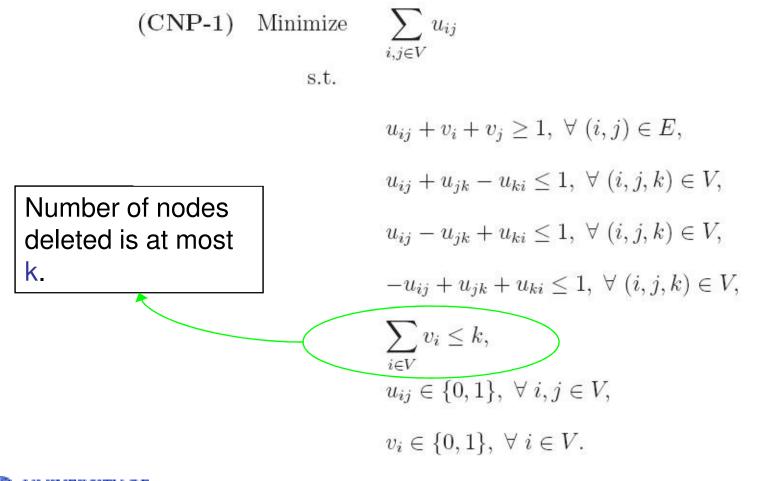
















(CNP-1) Minimize

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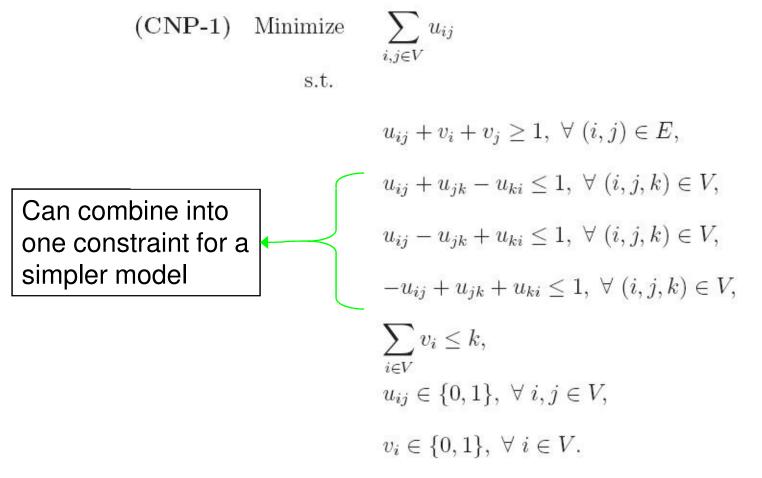
s.t.

For all triplets (i,j,k), if (i,j) in same comp and (j,k) in same comp, then (i,k) in same comp.

$$\begin{split} u_{ij} + v_i + v_j &\geq 1, \ \forall \ (i, j) \in E, \\ u_{ij} + u_{jk} - u_{ki} &\leq 1, \ \forall \ (i, j, k) \in V, \\ u_{ij} - u_{jk} + u_{ki} &\leq 1, \ \forall \ (i, j, k) \in V, \\ -u_{ij} + u_{jk} + u_{ki} &\leq 1, \ \forall \ (i, j, k) \in V, \\ \sum_{i \in V} v_i &\leq k, \\ u_{ij} \in \{0, 1\}, \ \forall \ i, j \in V, \\ v_i \in \{0, 1\}, \ \forall \ i \in V. \end{split}$$

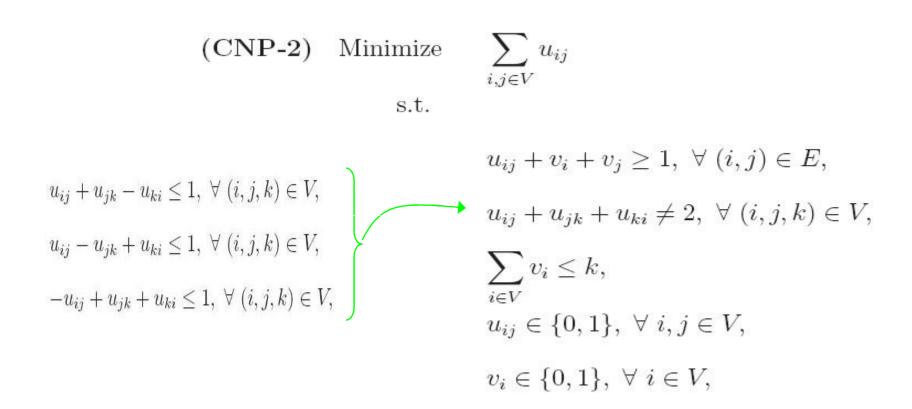
















- Notice if objective was only a function of the number of components then we could use approximation for Max K-Cut by modifying the Gomory-Hu tree
- BUT objective is also concerned with size of components
- Problem is harder...Too bad!





- Recall the objective function:
 - Minimize $\sum_{i,j} u_{ij}$, where $u_{ij} = 1$, if i and j in same component of vertex deleted subgraph.
- We can re-write this as follows:

$$\sum_{i\in S} \frac{s_i(s_i-1)}{2}$$

- Where S is the set of all components and s_i is the size of the i-th component.
- Easily identify with DFS in O(|V| + |E|) time!

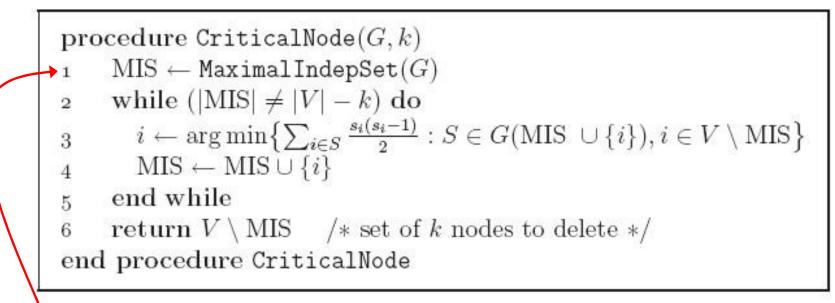




- We implement a heuristic based on Maximal Independent Sets
 - Why? Because induced subgraph is empty
 - Maximum Independent Set provides upper bound on # of components in optimal solution.
- Greedy type procedure
- Enhanced with local search procedure
- Results are excellent
 - Heuristic obtains optimal solutions in fraction of time required by CPLEX
 - Runs in $O(k^2 + |V|k)$ time.





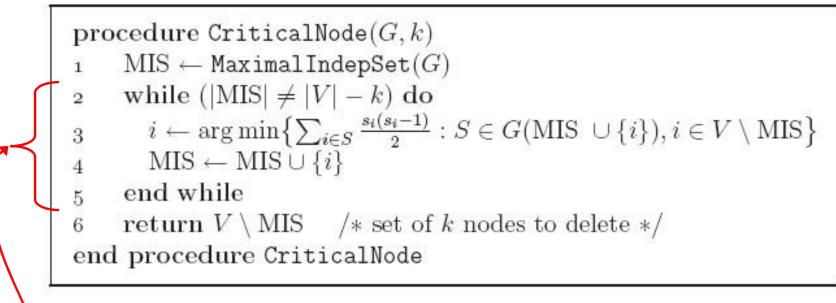


1) Find Maximal Independent Set (MIS)

- 2) Repeat until we have found k critical nodes
- 3) Find node which returns best objective function value (GREEDY)
- 4) Add to MIS







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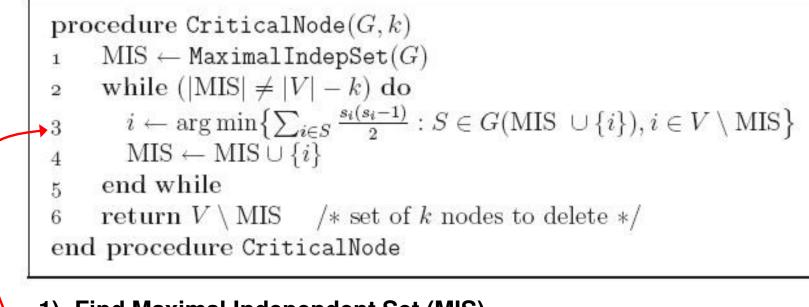
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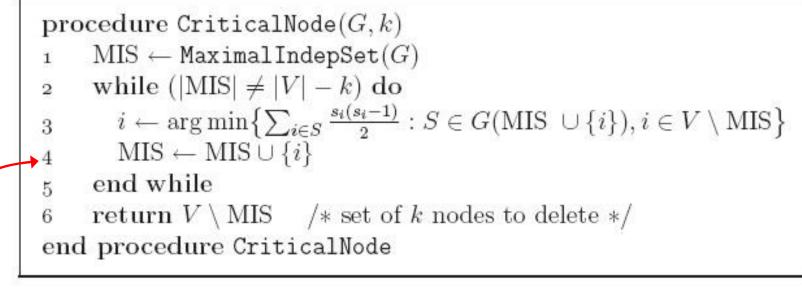




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procedure CriticalNodeLS(G, k) $X^* \leftarrow \emptyset$ 1 $f(X^*) \leftarrow \infty$ 2 for j = 1 to MaxIter do 3 $X \leftarrow \texttt{CriticalNode}(G, k)$ 4 $X \leftarrow \text{LocalSearch}(X)$ if $f(X) < f(X^*)$ then 56 $X^* \leftarrow X$ 7 end if end 9 **return** $(V \setminus X^*)$ /* set of k nodes to delete */ 10 end procedure CriticalNodeLS

- Same procedure as before
- Insert local search
 - 2-exchange method
- Return best overall solution





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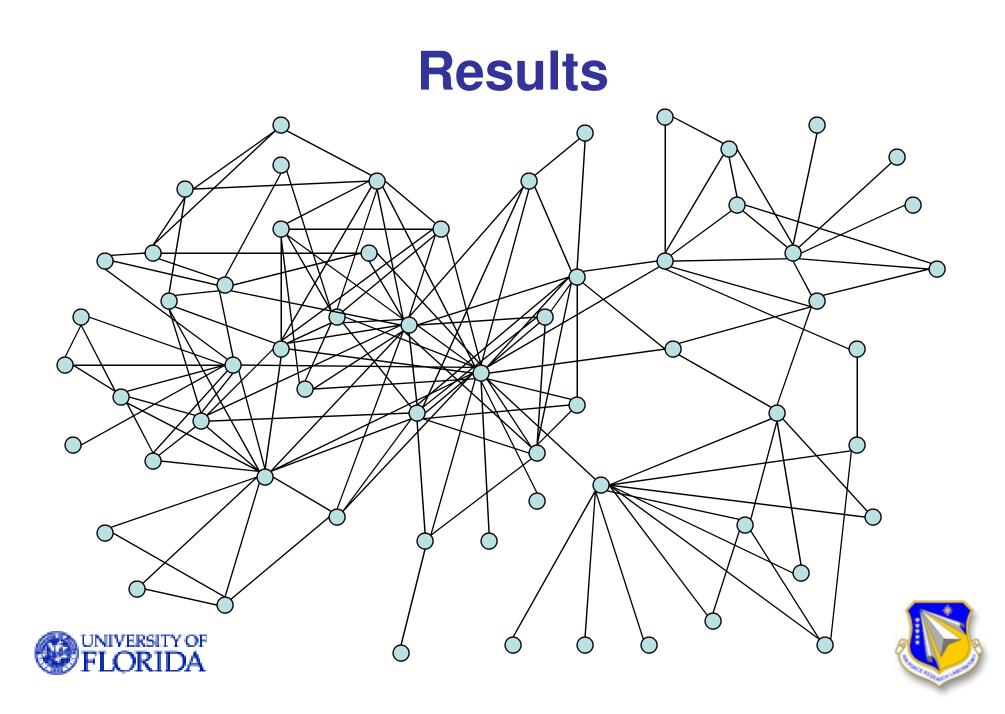


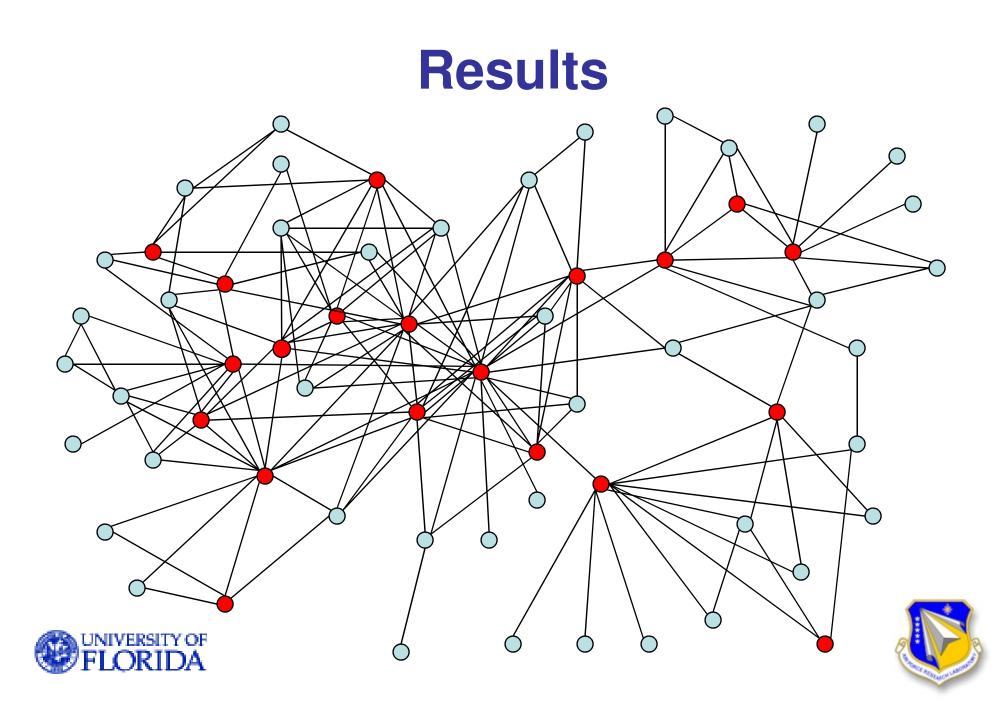
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Instance	IP N	Iodel	Heuristic		
Nodes	Objective	Execution	Objective	Execution	
Deleted (k)	Value	Time (s)	Value	Time (s)	
20	20	12.69	20	0.01	
15	61	277.77	61	0.01	
10	169	3337.06	169	0.02	
9	214	2792.33	214	0.02	
8	282	15111.94	282	0.01	
7	327	10792.08	327	0.01	

•This is the case you just saw!!

•Optimal solutions computed for all values of k for this terrorist graph

- The solutions are computed very quickly
- •Wait...it gets better!





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•Random instances from 75-150 nodes

•Various values of k for each set

•Optimal solution found for each instance

•Average CPLEX time: 289.44 seconds

•Average Heuristic time: 0.33 seconds

	Insta	nce	IP N	fodel	Heu	ristic
Nodes	Arcs	Deleted Nodes (k)	Objective Value	Execution Time (s)	Objective Value	Execution Time (s)
75	140	20	36	66.7	36	0.03
75	140	25	18	33.28	18	0.03
75	140	30	7	4.23	7	0.04
75	210	25	26	93.71	26	0.04
75	210	30	8	3.57	8	0.05
75	210	35	2	4.36	2	0.04
75	280	33	26	749.19	26	0.04
75	280	35	20	164.34	20	0.06
75	280	37	13	83.98	13	0.11
100	194	25	44	151.14	44	0.09
100	194	30	20	59.66	20	0.11
100	194	35	10	8.51	10	0.12
100	285	40	23	136.47	23	0.11
100	285	42	17	263.82	17	0.17
100	285	45	11	16.78	11	0.23
100	380	45	22	128.13	22	0.15
100	380	47	16	243.07	16	0.16
100	380	50	10	228.72	10	0.11
125	240	33	62	5047.51	62	0.30
125	240	40	29	118.92	29	0.24
125	240	45	16	17.09	16	0.39
150	290	40	40	41.6	40	0.47
150	290	50	12	26.29	12	0.831
150	290	60	1	24.92	1	0.851
150	435	61	19	29.55	19	0.741
150	435	65	13	31.45	13	1.952
150	435	67	11	37.91	11	0.801





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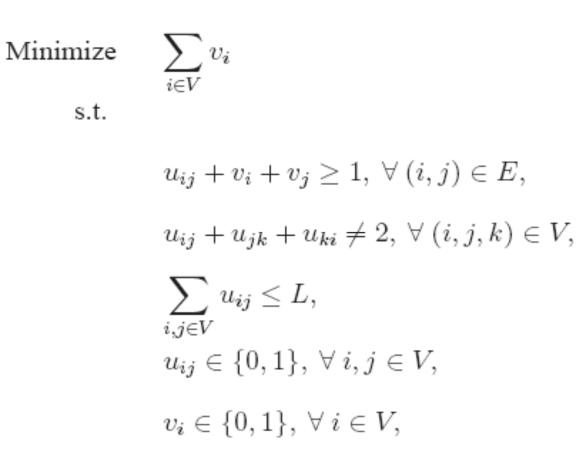
Cardinality Critical Node Problem (CCNP)

- Alternate Formulation:
 - Suppose now, we want to limit the connectivity of the agents.
 - We can impose a constraint for this.
 - Now, we minimize the number of nodes deleted to satisfy this constraint.
 - We have the CARDINALITY CONSTRAINED CRITICAL NODE PROBLEM



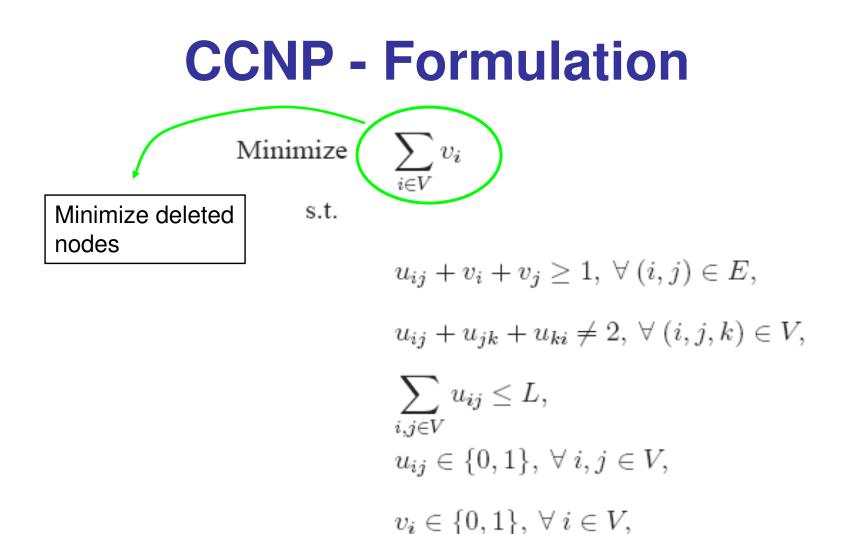


CCNP - Formulation





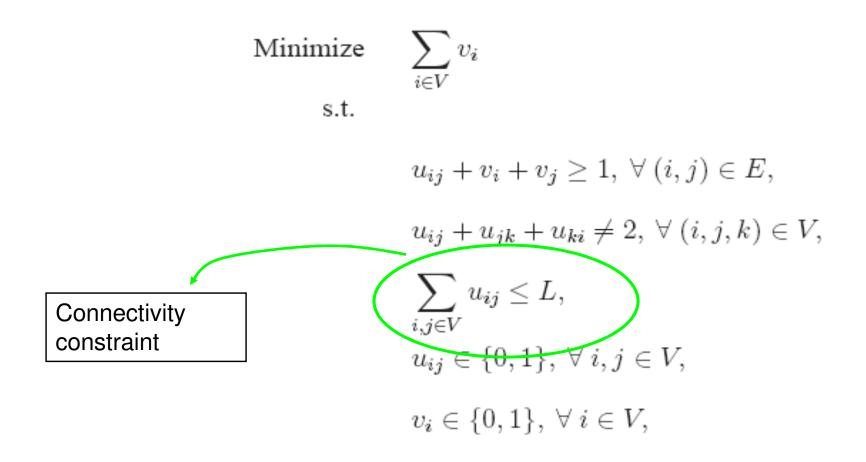






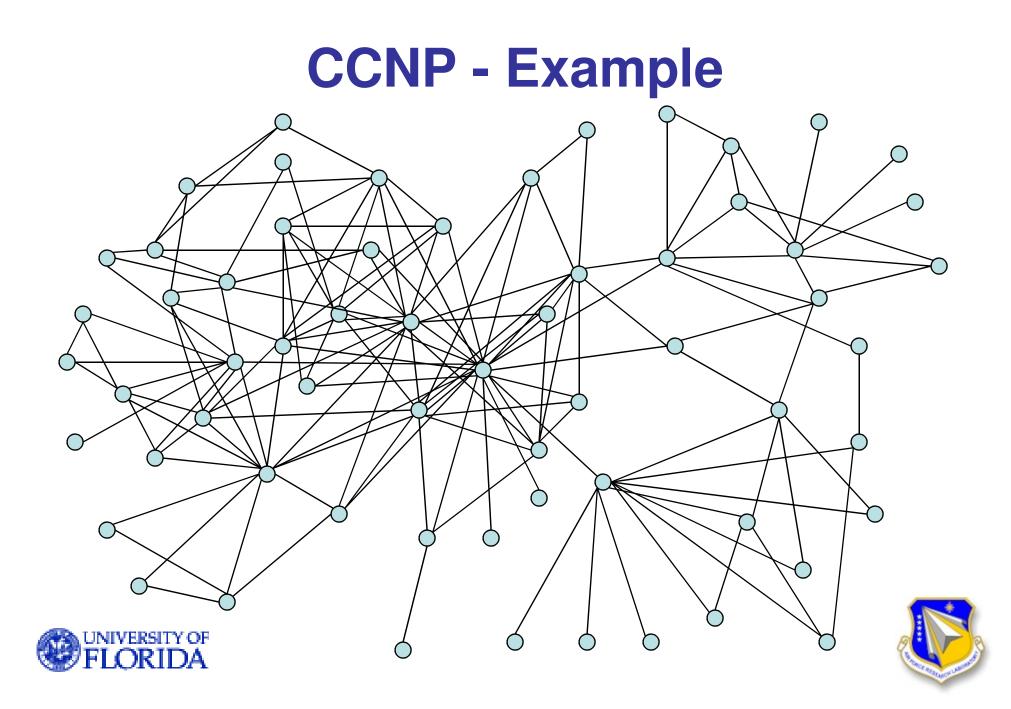


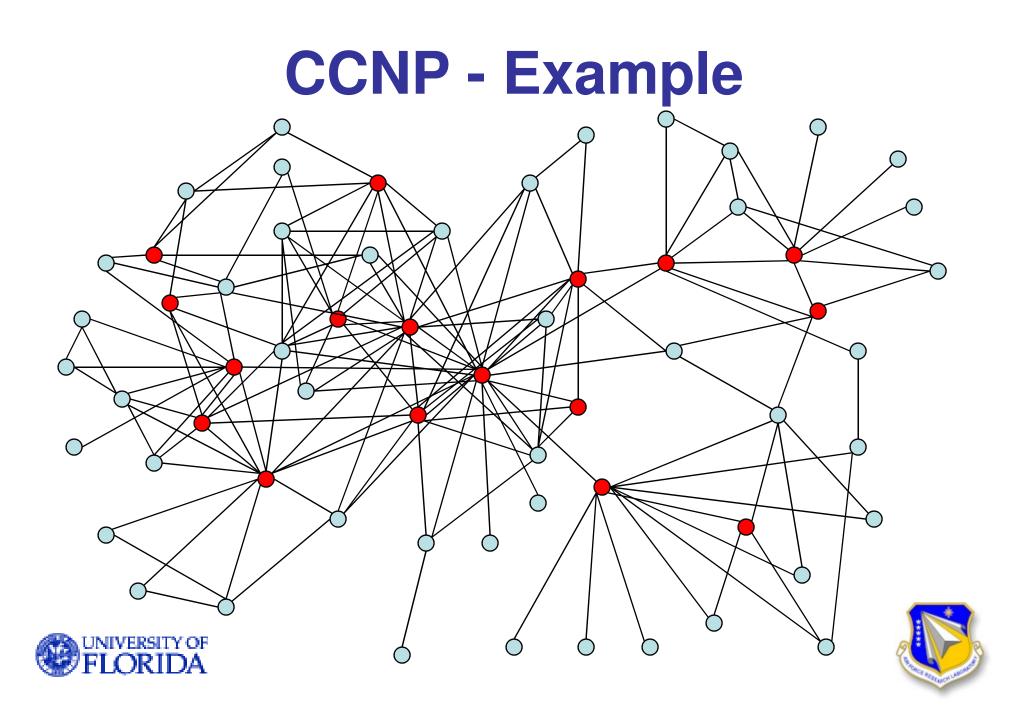
CCNP - Formulation









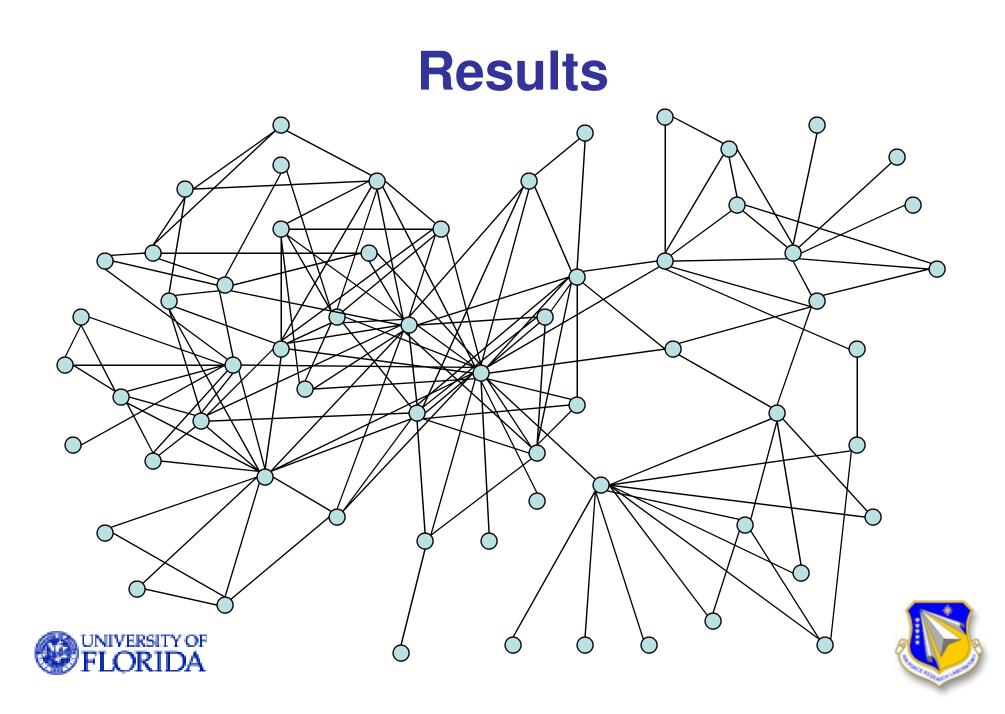


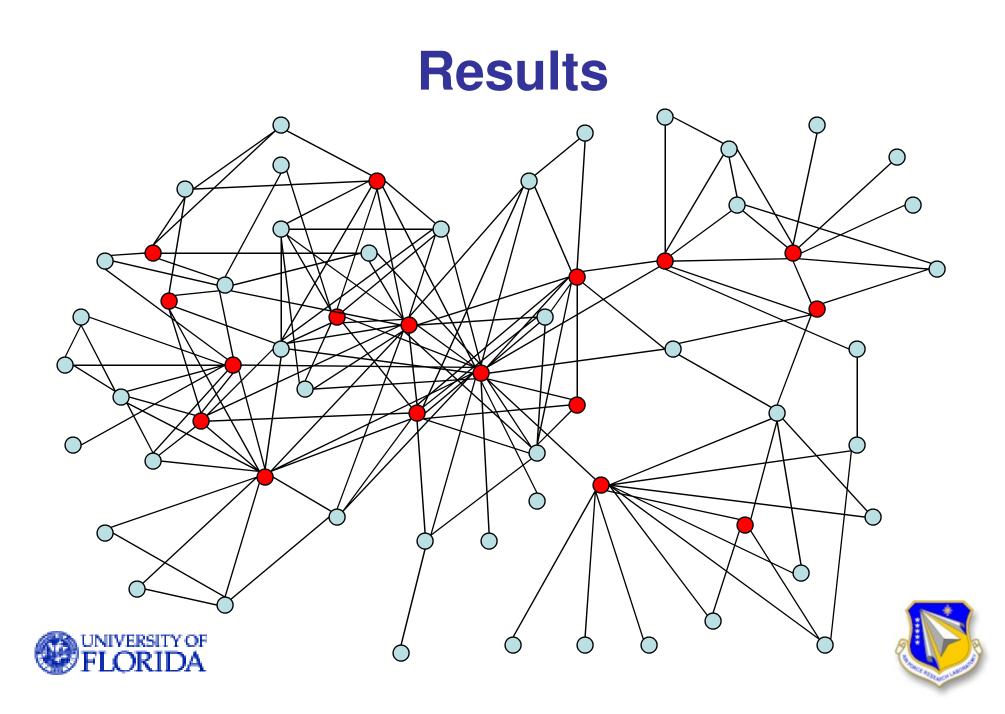
CCNP - Heuristics

- We modified the MIS heuristic for this problem, but it is easy to create pathological instances. So...
- We also implemented a Genetic Algorithm for the CC-CNP.
- The GA was able to find optimal solutions for all instances tested.
- Example (again). Here L = 4. Opt Soln









Instance	IP Model		Ger	Genetic Alg		ComAlg		Alg+LS
Max Conn.	Obj	Comp	Obj	Comp	Obj	Comp	Obj	Comp
Index (L)	Val	Time (s)	Val	Time (s)	Val	Time (s)	Val	Time (s)
3	21	188.98	21	0.25	22	0.01	21	0.1
4	17	886.09	17	0.741	19	0.01	17	0.45
5	15	30051.09	15	0.871	20	0.18	25	1.331
8	—	—	13	0.39	14	0.05	13	0.07
10	—	—	11	0.741	12	0.07	11	0.05

`•This is the case you just saw!!

•Optimal solutions computed for all values of L for this terrorist graph

The solutions are computed very quickly

•Wait...it gets better!





nstance IP Model		Genetic Alg		ComAlg		ComAlg + LS	
Obj	Comp	Obj	Comp	Obj	Comp	Obj	Comp
Val	Time (s)	Val	Time (s)	Val	Time (s)	Val	Time (s)
21	188.98	21	0.25	22	0.01	21	0.1
17	886.09	17	0.741	19	0.01	17	0.45
15	30051.09	15	0.871	20	0.18	25	1.331
_	_	13	0.39	14	0.05	13	0.07
_	—	11	0.741	12	0.07	11	0.05
	Val 21 17	Val Time (s) 21 188.98 17 886.09	Obj Comp Obj Val Time (s) Val 21 188.98 21 17 886.09 17 15 30051.09 15 - - 13	Obj Comp Obj Comp Val Time (s) Val Time (s) 21 188.98 21 0.25 17 886.09 17 0.741 15 30051.09 15 0.871 - - 13 0.39	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $

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Instance	IP Model		Gen	etic Alg	C	omAlg	Com	Alg+LS
Max Conn.	Obj	Comp	Obj	Comp	Obj	Comp	Obj	Comp
Index (L)	Val	Time (s)	Val	Time (s)	Val	Time (s)	Val	Time (s)
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Instance	IP Model Genetic Alg		ComAlg		ComAlg + LS			
Max Conn.	Obj	Comp	Obj	Comp	Obj	Comp	Obj	Comp
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Considered randomly generated instances with various values of L.

- Solution Quality:
 - GA: optimal solutions found for 100% of cases.
 - MIS Heuristic: optimal solutions found for 87.5%



Instance			IP Model		Genetic Alg		ComAlg + LS	
Nodes	Arcs	Max Conn.	Obj	Comp	Obj	Comp	Obj	Comp
		Index (L)	Value	Time (s)	Value	Time (s)	Value	Time (s)
20	45	2	9	0.04	9	0.02	9	0.03
20	45	4	6	0.13	6	0.04	6	0.862
20	45	8	5	0.39	5	0.04	5	1.482
25	60	2	11	0.07	11	0.49	11	0.08
25	60	4	9	14.1	9	2.113	10	0.01
25	60	8	7	26.64	7	0.05	8	0.06
30	50	2	11	0.07	11	0.06	11	0.01
30	50	4	8	0.1	8	0.05	8	0
30	50	8	6	1152.15	6	0.09	6	0
30	75	4	10	18.77	10	0.14	10	0.02
30	75	6	9	442.41	9	0.09	9	0.04
30	75	10	7	64.94	7	0.18	8	0
35	60	2	12	0.13	12	0.14	12	0.14
35	60	4	8	29.89	8	0.711	8	0
35	60	6	7	31.61	7	0.31	7	0.01
40	70	2	15	0.17	15	0.1	15	0.101
40	70	4	11	341.97	11	0.06	11	0
40	70	6	8	78.94	8	0.2	8	0.04
45	80	2	16	0.24	16	0.06	16	0.1
45	80	4	11	48.17	11	0.05	11	0.02
45	80	6	8	118.23	8	0.09	8	0.071
50	135	2	19	0.36	19	0.27	19	0.05
50	135	4	15	165.18	15	0.63	15	0.291
50	135	6	14	5722.88	14	0.721	14	0.03
Total (Sum)			24	8257.58	24	6.705	27	3.417



Considered randomly generated instances with various values of L.

- Solution Quality:
 - GA: optimal solutions found for 100% of cases.
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Instance			IP Model		Genetic Alg		ComAlg + LS	
Nodes	Arcs	Max Conn.	Obj	Comp	Obj	Comp	Obj	Comp
		Index (L)	Value	Time (s)	Value	Time (s)	Value	Time (s)
20	45	2	9	0.04	9	0.02	9	0.03
20	45	4	6	0.13	6	0.04	6	0.862
20	45	8	5	0.39	5	0.04	5	1.482
25	60	2	11	0.07	11	0.49	11	0.08
25	60	4	9	14.1	9	2.113	10	0.01
25	60	8	7	26.64	7	0.05	8	0.06
30	50	2	11	0.07	11	0.06	11	0.01
30	50	4	8	0.1	8	0.05	8	0
30	50	8	6	1152.15	6	0.09	6	0
30	75	4	10	18.77	10	0.14	10	0.02
30	75	6	9	442.41	9	0.09	9	0.04
30	75	10	7	64.94	7	0.18	8	0
35	60	2	12	0.13	12	0.14	12	0.14
35	60	4	8	29.89	8	0.711	8	0
35	60	6	7	31.61	7	0.31	7	0.01
40	70	2	15	0.17	15	0.1	15	0.101
40	70	4	11	341.97	11	0.06	11	0
40	70	6	8	78.94	8	0.2	8	0.04
45	80	2	16	0.24	16	0.06	16	0.1
45	80	4	11	48.17	11	0.05	11	0.02
45	80	6	8	118.23	8	0.09	8	0.071
50	135	2	19	0.36	19	0.27	19	0.05
50	135	4	15	165.18	15	0.63	15	0.291
50	135	6	14	5722.88	14	0.721	14	0.03
Total (Sum)		24	8257.58	24	6.705	27	3.417	



Considered randomly generated instances with various values of L.

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Instance			IP Model		Genetic Alg		ComAlg + LS	
Nodes			Obj	Comp	Obj	Comp	Obj	Comp
INDUES	AICS	Index (L)	Value	Time (s)	Value	Time (s)	Value	Time (s)
20	45	2	9	0.04	9	0.02	9	0.03
20	45 45	4	9 6	0.04	6	0.02	9 6	0.862
20	45 45	4 8	5	0.13	5	0.04	5	1.482
20	45 60	2	5 11	0.39	11	0.49	11	0.08
	60 60	2 4	9		9		10	
25				14.1		2.113		0.01
25	60	8	7	26.64	7	0.05	8	0.06
30	50	2	11	0.07	11	0.06	11	0.01
30	50	4	8	0.1	8	0.05	8	0
30	50	8	6	1152.15	6	0.09	6	0
30	75	4	10	18.77	10	0.14	10	0.02
30	75	6	9	442.41	9	0.09	9	0.04
30	75	10	7	64.94	7	0.18	8	0
35	60	2	12	0.13	12	0.14	12	0.14
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Total (Sum)		24	8257.58	24	6.705	27	3.417	



- Contributions of the chapter
- K-CNP
 - Propose math program based on integer linear programming.
 - Proof of computational complexity
 - Implement an efficient heuristic based on maximal independent sets
 - Heuristic finds optimal solutions for all instances tested in fraction of time required by CPLEX
- CC-CNP
 - Math Programming formulation
 - Genetic Algorithm implemented finds optimal solutions for all instances tested.
- Current Work
 - Weighted version of the problem
 - Approximation of the problem
- Papers:
 - A. Arulselvan, C.W. Commander, L. Elefteriadou, P.M. Pardalos. Detecting critical nodes in social networks. *Computers and Operations Research*, 2008.
 - A. Arulselvan, C.W. Commander, P.M. Pardalos, O. Shylo. Managing network risk via critical node identification. *Risk Management in Telecommunication Networks*, N. Gulpinar and B. Rustem (editors), Springer, to appear 2008 (in process)





Conclusions and Future Directions

- Identified nodes of sparse
- Breakdown communication
- Integer Programming and Heuristics
- Approximation algorithms
- Weighted version of the problems





THANK YOU!!!!!

QUESTIONS?