A Game-Theoretic Framework to Identify Top-*K* Teams in Social Networks

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Abstract: Discovering teams of experts in social networks has been receiving the increasing attentions recently. These teams are often formed when a given specific task should be accomplished by the collaboration and the communication of the small number of connected experts and with the minimum communication cost. In this study we propose a game theoretic framework to find top-*k* teams satisfying such conditions. The importance of finding top-*k* teams is revealed when the experts of the best discovered team do not have an incentive to work together for any reason and hence we must refer to the next found teams. Finally, the local Nash equilibrium corresponding to the game is reached when all of the teams are formed. The experimental results on *DBLP* co-authorship graph show the effectiveness and efficiency of the proposed method.

1 INTRODUCTION

Finding teams of experts has become one of the most important and interesting subjects in the realm of social network analysis. It is necessary for many companies or departments to detect persons who have enough relevant experiences and expertise to accomplish a given specific task. However the success of the project is not merely defined as the completeness of the task and the project manager must also takes care about the amount of the communication and the collaboration exchanged between the members of team. In addition, it is important to satisfy the minimum possible costs when accomplishing the project.

Game theory is a good tool to capture both the behavior of individuals and strategic interactions among them (Adjeroh and Kandaswamy 2007), because it can model strategic interactions between rational, autonomous and intelligent agents mathematically. In this paper, we modify the game-theoretic framework proposed in (Alvari et al., 2011) to address the problem of forming teams in social networks. Specifically, we assume each node of the underlying social network graph as a rational agent who joins the adjacent groups based on her utilities. The utility of each agent with regards to each of the groups she belongs to is defined as a difference of her gain and loss functions in that team. Finally, the Nash equilibrium of the game results in discovering all of the existing teams.

The most important contribution of our method is that it can find top-*k* teams simultaneously. The importance of finding *k* teams is intensified in two cases. First, when the members of the best found team do not have incentives to form the team and second, when they form the team but suddenly decide to leave the project because of any reason. As a result, in these cases, we must be able to assign the project to other next teams if it is applicable.

The remainder of this paper is organized as follows. Section 2 gives brief reviews on the related works. In Section 3, our proposed framework is introduced in detail. The experimental results are presented in Section 4, and finally we conclude the paper in Section 5.

2 RELATED WORK

A considerable number of works in the literature have been devoted to studying team formation problem. In these works, the authors study the team formation problem by transforming it into an integer programming. Simulated annealing (Baykasoglu et al., 2007), branch-and-cut (Zakarian and Kusiak, 2004), and genetic algorithm (Wi et al., 2009) are used to find an optimal match between individuals and requirements. Chen et al. use a psychological test to form a team by estimating the individuals'

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interpersonal relationship attributes and their personalities (Chen and Lin, 2004). However Gaston et al., show the correlation between different graph structures and performance of a team but they don't consider a computational problem of finding team formation (Gaston et al., 2004). Cheatham et al., consider the structure of social network by collecting the neighbours surrounding each skill in a social-concept graph (Cheatham and Cleereman, 2006). But they don't pay attention to the communication cost among individuals.

The team formation problem in the presence of a social network of individuals by considering the communication cost is first addressed by Lappas et al. (Lappas et al., 2009). They also proved that the problem of finding such teams is NP-hard. In their work, they propose two algorithms *RarestFirst* algorithm and the *EnhancedSteiner* algorithm to solve the team formation problem based on diameter and minimum spanning tree (*MST*) respectively.

In *RarestFirst* approach, the algorithm, first estimates each required skills supporter and the skill with rarest sponsors is determined. Then for each of its candidates, a sub-graph is defined by investigating the closest connected individuals in other support sets. In the last step it selects the sub-graph with minimum communication cost with diameter metric. The *EnhancedSteiner* algorithm consists of two steps. First, it enhances the given graph as follow: it creates the virtual nodes for each of the required skills in the given task and connects them to their supporters by the heavy weighted edge. Second, it can find the solution by searching the Steiner Tree of this enhanced graph. To find a Steiner tree, they use a greedy heuristic algorithm.

3 PROPOSED FRAMEWORK

3.1 Problem Statement

Given the social network graph $G(V, E)$, the skill set of individuals and a task T which is composed of the required skills s_i, the team formation problem is formally defined as finding a set of experts $V' \subseteq V$ who best support the required skills. To be specific, a sub-graph $G[V']$ is formed such that: (1) all of the required skills in the given task should be accomplished by team and (2) the total communication cost denoted by $CC(V')$ among selected individuals must be minimized as much as possible.

Additionally, the problem of discovering top-k teams is simply a generalized version of the well-known team formation problem. It is formally defined as finding a set of teams whose experts $V'_1, V'_2, .., V'_k \subseteq V$ best support the given task independently. In this case, a set of sub-graphs $\{G[V_1], G[V_2], \dots, G[V_k]\}$ is formed and the above two conditions for team formation problem must be satisfied for each of these teams.

3.2 Our Approach

The social network is modelled as an undirected and weighted graph $G(V, E)$, where the vertices $V = \{v_1, v_2, \dots, v_n\}$ are experts, and the edges E represent collaborations in co-activities. The edge weight w, describes the cost (distance) between any of two experts. The small-weight edges show that the experts have more frequent collaborations than high-weight edges. Here, we suppose that G is connected, but in the case of graphs with disconnected components (i.e., dissimilar components), we can also add very high-weight edges between every pair of nodes that belong to different disconnected components. This weight is much higher than the sum of all pair-wise shortest paths in each connected component and is used when there are some disconnected teams in the network in addition to connected teams.

The definitions of the necessary symbols for the remaining of the paper are shown in Table 1.

Table 1: Definition of symbols.

SYM.	DEFINITION
$G(V, E)$	Undirected and weighted graph
n, m	Number of individuals and skills
X_i	Set of skills of agent *i*
N_i	Set of neighbours of agent *i*
T	Given task consisting of required skills
S	Set of skills
Φ	Strategies profile
φ_i	Strategy of agent *i*
g^k	Potential group *k* to become one of top teams
$U_i^{g_i^k}$	Utility value for agent *i* corresponding to group *k*
$G_i^{g_i^k}$	Gain value for agent *i* corresponding to group *k*
$L_i^{g_i^k}$	Loss value for agent *i* corresponding to group *k*

Furthermore, assume that we have a set of m skills, $S = \{s_1, s_2, .. s_m\}$ where each expert has a skill set $X_i \subseteq S$. We denote by $s_j \in X_i$ that the individual i has skill s_j. Also, a subset of individuals $V' \subseteq V$ has skill s_j, if there is at least one individual in V' associated with s_j. A task T is simply a subset of skills S required to accomplish the project. The graph distance function for every two nodes $i,j \in V$ is the

weight of the shortest path between them in G, denoted by $d(i,j)$. The distance between node $i \in V$ and a set of nodes $V' \subseteq V$ is then defined by $d(i,V')=min_{j \in V'} d(i,j)$.

The set of all feasible teams of the network is denoted by $[\Psi] = \{1,2,\dots,\Delta\}$ where Ψ is polynomial in n, however the number of our final teams, Δ, may be much smaller than n. As mentioned earlier, we put each vertex down to a rational agent who has a utility function and preserves a vector of group labels that she belongs to as her strategies. Formally, the strategy of each agent is denoted by $\varphi_i \subseteq [\Psi]$ and strategy profile Φ denotes the set of strategies of all agents, i.e. $\Phi = \{\varphi_1, \varphi_2, \dots \varphi_n\}$. The group is considered as a team only if it can accomplish the task.

Naturally, when joining to a new group, each of the agents will be beneficiary, but on the other hand, it must pay some costs (e.g. fees). The utility for agent i who belongs to group k is calculated by:

$$U(\Phi)_i^{g_i^k} = G(\Phi)_i^{g_i^k} - L(\Phi)_i^{g_i^k} \quad (1)$$

Where, $G(\Phi)_i^{g_i^k}$ and $L(\Phi)_i^{g_i^k}$ are respectively, gain and loss functions for agent i:

$$G(\Phi)_i^{g_i^k} = \frac{\alpha}{|T|} \times \left| \bigcup_{j \in g^k \cup \{i\}} (s_j \cap T) \right| \quad (2)$$

$$L(\Phi)_i^{g_i^k} = CC(g^k \cup \{i\}) \quad (3)$$

In equation 2, $s_j \in X_{g^k \cup \{i\}}$ is the number of skills which are covered by both the members of g^k and agent i. However, we consider just the skills which are in the subset of required skills $s_j \subseteq T$ in the task T. Here, α is a coefficient to weight the gain function over the loss function. The main reason for contributing this coefficient is to encourage the agents to form teams. The significance of using α is revealed when the supporters of the required skills are so far from each other or there is not any connected team in our social graph. In equation 3, $CC(V')$ is the communication cost function defined as a diameter of V'.

In our framework, the best response strategy of an agent i with respect to strategies Φ_{-i} of other agents is calculated by:

$$arg \max_{\varphi_i' \subseteq [\Psi]} G(\Phi_{-i}, \varphi_i') - L(\Phi_{-i}, \varphi_i') \quad (4)$$

The strategy profile Φ forms a pure Nash equilibrium of the team formation game if all agents play their best strategies. In other words, in Nash equilibrium no agent can improve its own utility by changing its strategy; that is each agent is satisfied with its current utility:

$$\forall i, \varphi_i' \neq \varphi_i,\ U_i(\Phi_{-i}, \varphi_i') \leq U_i(\Phi_{-i}, \varphi_i) \quad (5)$$

We are satisfied with local Nash equilibrium in this game, because reaching global one is not feasible (Lorrain and White, 1971). In other words, the strategy profile Φ forms a local equilibrium if all agents play their local optimal strategies. Here $ls(\varphi_i)$ refers to local strategy space of agent i:

$$\forall i, \varphi_i' \in ls(\varphi_i),\ U_i(\Phi_{-i}, \varphi_i') \leq U_i(\Phi_{-i}, \varphi_i) \quad (6)$$

The *GameTeamFormation* algorithm, shown in the algorithm 1, takes as input, the graph G and the set of required skills $s_j \subseteq T$ to specify the task T. Each agent is selected randomly from a pool of agents. The selected agent searches for its neighbours and what they belong to. After discovering the neighbour groups the agent constructs the virtual relationship with them. So in this step we have a set g_i' consisting of $|N_i| \times \sum_{l \in N_i} |g_l|$ virtual groups, except those which were computed previously. In the next step, the gain function is computed by equation 2. This function is defined as the fraction of covered skills to the required skills in the task T. For the loss function, we calculate the minimum diameter corresponding to these virtual groups. Recall that the diameter of the graph is the largest shortest path between any two nodes in the graph. As it is mentioned before, the utilities of the current agent corresponding to each of these virtual groups are calculated according to equation 1. Then, the maximum utility value for this agent is calculated according to equation 7 and the winner group k' is determined.

$$U_i^{g_i^{k'}} = \max_{c \in g_i'} \{U_i^c\} \quad (7)$$

Finally, the label k' is added to the labels of the current agent according to equation 8 and receives utility $U_i^{g_i^{k'}}$ only if it is greater than the maximum of the previous utilities.

$$\varphi_i \leftarrow \varphi_i \cup \{k'\} \quad (8)$$

On the other hand, if this utility equals the previous utilities or is smaller than them, the agent performs no specific action and remains indifferent.

Since all of the members of the selected group collaborate to do the task, we consider here that they share a common utility and loss values. Therefore, all of the remaining members of this group also update their corresponding utility value to $U_i^{g_i^{k'}}$.

We now consider this group as one of the final

top-k teams if its members are able to accomplish the task. Furthermore, in each stage of detecting teams, if it is revealed that merging some of the existing teams to one team can increase their individual utilities, these teams will be immediately merged. Finally, all of the teams will be discovered when the game reaches the Nash equilibrium. As mentioned before, since reaching global Nash equilibrium is not feasible, we stop the game after reaching the local Nash equilibrium.

In this algorithm, k is the group which is constructed previously, k' is one of the virtual groups and $k^{"}$ is a new group which will be added to the list of current teams.

Algorithm 1: The *GameTeamFormation* algorithm

Input: $G(V,E)$,$\{X_1, X_2, \dots X_n\}$ and T.
Output: *Teams* $G[V'_1], G[V'_2], \dots, G[V'_k]$.

Teams={}
Repeat
  i = Random_Select(*Agents*)
  for every $j \in N_i$
    for every $c \in g_j$
      $G_i^{g_i^c} \leftarrow \frac{\alpha}{|T|} \times \left|\bigcup_{k \in g^c \cup \{i\}} (s_k \cap T)\right|$
      R={ Diameter(a) | $a \in g^c$}
      $L_i^{g_i^c} = min_a R$
      $U_i^{g_i^c} = G_i^{g_i^c} - L_i^{g_i^c}$
  $U_i^{g_i^{k'}} = \max_C U_i^{g_i^c}$
  if $(U_i^{g_i^{k'}} > \max_{k \in g_i} U_i^{g_i^k})$
    if $(g_i^{k'} \in Teams)$
      $g^{k"} \leftarrow g^{k'} \cup \{i\}$, $\varphi_i \leftarrow \varphi_i \cup \{k"\}$, $U_i^{g_i^{k"}} \leftarrow U_i^{g_i^{k'}}$
    else
      $g^{k'} \leftarrow g^{k'} \cup \{i\}$, $\{U_j^{g_j^{k'}} \leftarrow U_i^{g_i^{k'}}, \forall j \in g^{k'}\}$
  if $(G_i^{g_i^{k'}} == 1)$
    $Teams \leftarrow g^{k'}$
Until local equilibrium is reached
Sort(*Teams*)

4 EXPERIMENTS

4.1 Dataset

For our experiments, we use the *DBLP* dataset as a benchmark dataset which is publicly available from the *DBLP* portal. The snapshot of this dataset was taken on April 12, 2006, while the data is related to papers which are published in areas of *Database (DB)*, *Data mining (DM)*, *Artificial intelligence (AI)*, and *Theory (T)* conferences. They are used in order to balance the necessity of covering the diverse fields of study (including 19 venues as follows: {*SIGMODE*, *VLDB*, *ICDE*, *ICDT*, *EDBT*, *PODS*, *WWW*, *KDD*, *SDM*, *PKDD*, *ICDM*, *ICML*, *ECML*, *COLT*, *UAI*, *SODA*, *FOCS*, *STOC* and *STACS*}).

We construct the expert social network using co-authorship graph in the following way. First, to collect the experts, the authors who have less than three papers in *DBLP* are discarded. Then, the skill set X_i of each author i is filled with the terms that appear in at least two titles of their papers in the co-authorship graph. For the skill extraction, we use the terms extracted from Bibsonomy tag tools to avoid noisy tags. Two authors are called connected if they co-authored in at least two papers. The weights on edges are computed by equation 9:

$$w(i,j) = 1 - \frac{|p_i \cap p_j|}{|p_i \cup p_j|} \quad (9)$$

Where P_i is a set of papers published by author i. The graph distance between two nodes in graph G_{dblp} is computed by using the shortest path distance. In this graph, the total number of authors is 5508 where there are 1792 distinct skills and 5588 edges.

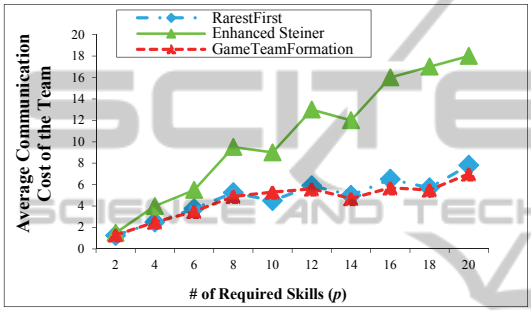
The preliminaries for performing our method are as follow. Each task *T=(p,q)* is characterized by two parameters: (1) p, the number of required skills in task T; (2) q, the minimum required number of experts to accomplish each skills of *T*. Specifically, a task T is generated as follows: first, p skills are picked randomly from the terms appearing in published papers. In all experiments reported in this section, we use $p \in \{2,4,\dots,20\}$ and $q = 1$. Then, for every (p, q) configuration, we generate 100 random tasks for all of the algorithms and take the average performance achieved by different methods.

4.2 Quantitative Results

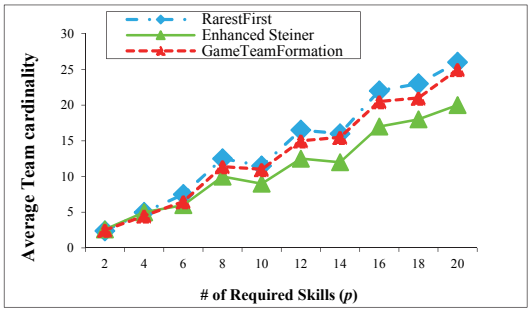
In this section, our results compared with two well-known algorithms, *RarestFirst* and *EnhancedSteiner* (Lappas et al., 2009) are presented. The comparisons are done with respect to the communication cost, team cardinality, the number of disconnected teams, stability and scalability.

Figure 1, compares the average communication cost, team cardinality and the number of disconnected teams on the *DBLP* dataset. The following observations are achieved from the analysis of Figure 1. As we can see in Figure 1(a), by increasing the number of required skills, the communication costs of the algorithms grow considerably, since in this case, the search space which is needed to be explored, will be expanded. In

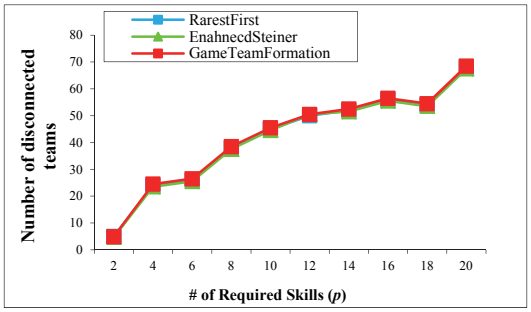
other words, because of the sparsity of the underlying graph, the probability of the existence of experts who are capable to do the required skills decreases. Our final evaluation is in term of the number of disconnected teams. In the real world projects, the employees who are in the same department can communicate and collaborate more easily than other employees who are in the outside. Therefore, it is of great importance to detect connected teams to minimize the communication cost. As it is depicted in Figure 1(c), the *GameTeamFormation* algorithm as well as *EnhancedSteiner* and *RarestFirst* algorithms first try to find the connected teams, and if these teams are not available, they determine the disconnected ones.



(a)



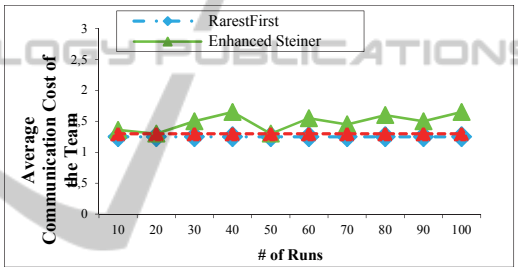
(b)



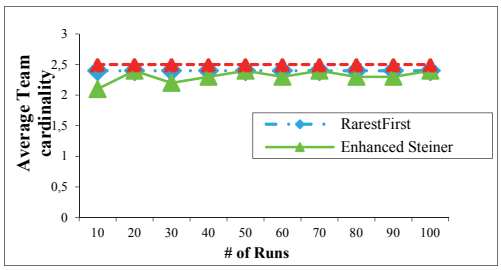
(c)

Figure 1: Average effective measures for k=1 is reported by *GameTeamFormation*, *RarestFirst*, *EnhancedSteiner* algorithms: (a) Average communication cost. (b) Average cardinality. (c) Average number of disconnected teams.

The stability status of the algorithm for each specified task is depicted in Figure 2. The results show that although each of the agents is selected randomly from the pool of the agents, this does not affect our final results and this shows that our method is stable. As it is mentioned before, this is due to the fact that in each run of our method, it finally reaches its equilibrium, meaning that the agents will not change their strategies. However, the fact of getting the average of 100 runs for each p in Figure 1 does not imply the instability of our method and it is for thwarting the effect of randomness of the selected p required skills in each run. On the other side, although *RarestFirst* algorithm demonstrates stability in its runs, *EnhacedSteiner* algorithm is somehow sensitive to the random selection which is done in the greedy heuristic algorithm used in its Steiner Tree algorithm. Therefore, *EnhacedSteiner* algorithm outputs its results with fluctuation in each run for the specific skills.



(a)



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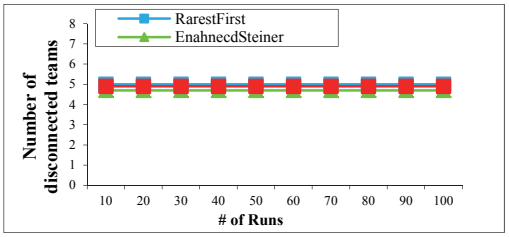

(c)

Figure 2: The stability of *GameTeamFormation* algorithm for p=2, k=1, the two specified required skills. (a) Communication cost. (b) Team cardinality. (c) Average number of disconnected teams.

Finally, Figure 3 shows the scalability of our

method. First, as we can see in this figure, by increasing the number of k, the running time of our method remains constant. This is because after reaching the Nash equilibrium, all of the applicable teams are always detected regardless of the value of k. Furthermore, since we use local Nash equilibrium in our method, the time complexity of our method to discover all of the applicable teams is comparable with other methods considering that they are extended to support finding all of the teams instead of just finding the best team. Second, the average running time increases when the number of required skills grows. The main reason is that, here, the underlying social network's graph is very sparse w.r.t the given task. Therefore, to satisfy the task with low communication cost, when the number of the required skills increases, the agents have to explore their neighbourhoods more.

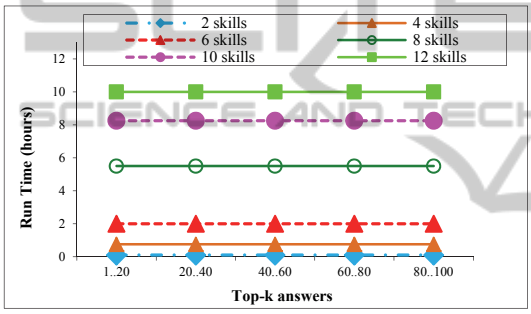

Figure 3: The scalability of GameTeamFormation algorithm.

Totally, it can be seen that our proposed framework is capable of forming finer top-k teams of experts. The analysis of the experiments shows that our method performs well in the terms of communication cost, team cardinality of the selected teams and the number of disconnected teams, stability and scalability.

5 CONCLUSIONS

In this paper, the problem of finding top-k teams which can independently accomplish a specific given task with minimum communication cost is studied and the game-theoretic framework is presented for finding these teams.

The experimental results on *DBLP* show that the effective teams can be found with minimum communication cost and cardinality. Also the stability and scalability of the proposed method is studied.

For the future works, more constraint teams can be considered. Furthermore, the generalized tasks can be studied and defined with the required skills which should be supported with the minimum number of experts.

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REFERENCES

Adjeroh, D., Kandaswamy, U, 2007. Game-Theoretic Analysis of Network Community Structure. Vol.3, No.4, pp. 313-325, doi:10.5019/j.ijcir.2007.112.

Alvari, H., Hashemi, S., Hamzeh, A, 2011. Detecting Overlapping Communities in Social Networks by Game Theory and Equivalence Concept. *AICI 2011, Part II, LNAI 7003, pp.620 - 630, Springer-Verlag.*

Baykasoglu, A., Dereli, T., Das, S., 2007. Project Team Selection Using Fuzzy Optimization Approach. *Presented at Cybernetics and Systems, pp.155-185.*

Cheatham, M., Cleereman, K., 2006. Application of Social Network Analysis to Collaborative Team Formation. *In Proc. of Intl. Symposium on Collaborative Technologies and Systems, pp.306–311.*

Chen, S.-J., Lin, L., 2004. Modeling team member characteristics for the formation of a multifunctional team in concurrent engineering. *IEEE Transactions on Engineering Management, pp.111-124.*

Gaston, M., Simmons, J., Desjardins, M., 2004. Adapting Network Structures for Efficient Team Formation. *In Proceedings of the AAAI Fall Symposium on Artificial Multi-agent Learning.*

Lappas, T., Liu, K., Terzi, E., 2009. Finding a Team of Experts in Social Networks. *In Proc. of ACM Intl. Conference on Knowledge Discovery and Data Mining (KDD'09), pp.467-476.*

Lorrain, F., White, H. C., 1971. Structural equivalence of individuals in social networks. *The Journal of Mathematical Sociology 1(1): 49–80.*

Wi, H., Oh, S., Mun, J., Jung, M., 2009. A Team Formation Model Based on Knowledge and Collaboration. *Expert Syst. Appl., vol. 36, pp.9121-9134.*

Zakarian, A., Kusiak, A., 2004. Forming Teams: An Analytical Approach. *IIE Transactions, 31:85-97.*