Proceedings of the 2011 International Conference on Industrial Engineering and Operations Management
Kuala Lumpur, Malaysia, January 22 – 24, 2011

Design of a Creativity Matrix Using Virtual Intelligent Clustering and Knowledge Development Program

Iraj Mahdavi, Hamed Fazlollahtabar*
Department of Industrial Engineering
Mazandaran University of Science and Technology, Babol, Iran
*Corresponding author's email: hamed.hero@gmail.com

Nezam Mahdavi-Amiri
Faculty of Mathematical Sciences,
Sharif University of Science and Technology, Tehran, Iran

Mohsen Arabmaghsudi, Mohammad Hassan Yahyanejad
Mazandaran Gas Company, Sari, Iran

Abstract

Creative organizations needing teams to combine and integrate inputs from other teams, the teams' structure of interaction is an important prerequisite for creativity. Here, we investigate different structural aspects teams' network organization and their creativity within a knowledge development program (KDP). Initially, a pilot group of people in an organization is selected. This group is evaluated through creativity parameters using a questionnaire. Considering the questionnaires' data, a decision maker configures the creativity matrix by a bipolar scoring technique. Applying the creativity matrix, clustering is performed. The pilot group is divided into some research teams. The research subjects are submitted to the teams and their progress in solving the problem is assessed through a comprehensive network interaction assessment method (CNIAM). Finally, an allocated problem is solved and some new research subjects are evolved to be assigned to the next configured teams. This procedure is repeated dynamically for different time periods.

Keywords
Creativity matrix; Intelligent clustering; Knowledge development program (KDP); Comprehensive network interaction assessment method (CNIAM)

1. Introduction
In today's knowledge-intensive environment, Knowledge Development Programs (KDPs) are increasingly employed for executing innovative efforts [1,2]. Researchers and practitioners mainly agree that effective management plays a critical role in the success of such KDPs. Unfortunately, the knowledge and experience base of most managers refer to smaller-scale projects consisting of only a few project teams. This may be responsible for what Flyvbjerg et al. [3] call a 'performance paradox': ''At the same time as many more and much larger infrastructure projects are being proposed and built around the world, it is becoming clear that many such projects have strikingly poor performance records ...".
KDPs employ follow a project-management like approach with the team as the organizational nucleus (e.g., [4]). The information network of these teams defines the opportunities available to them to create new knowledge. As many scholars have argued, networks of organizational linkages are critical to a host of organizational processes and outcomes [5]. New knowledge is the result of creative achievements. Creativity, therefore, molds the foundation for poor or high degree of performance. The extent to which teams in KDPs produce creative ideas depends not only on their internal processes and achievements, but also on the work environment in which they operate (e.g., [6-8]). Since new knowledge is mainly created when existing bases of information are disseminated through interaction

between interacting teams with varying areas of expertise, creativity is couched in interaction networks (e.g., [9-12]).

In the present work, we propose a creativity matrix analyzing creativity parameters of a pilot group in an organization. Then, using an intelligent clustering technique, research teams are configured and research subjects are allocated to them. The teams' progress in solving the problem is evaluated through a knowledge development program by a comprehensive network interaction assessment method. Consequently, the problem is solved and some new research subjects are evolved to be allocated to the next configured teams. This procedure is repeated dynamically for different time periods. A flowchart of our proposed creativity algorithm is shown in Figure 1.

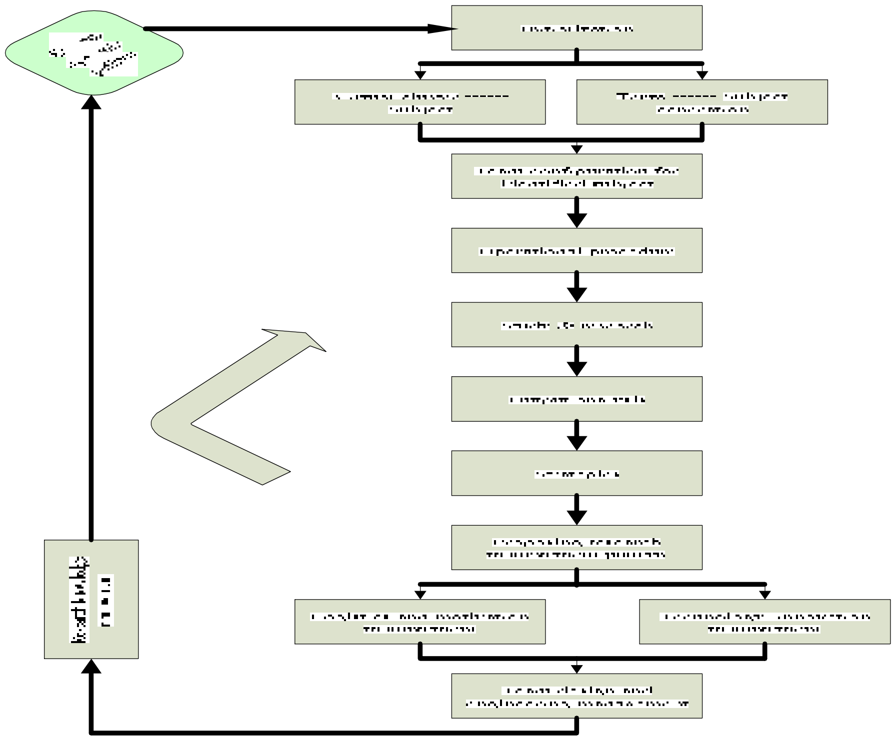

Figure 1: A flowchart of our proposed creativity algorithm

2. Creativity Parameters and Matrix

To conceptualize creativity in an organization, we need to identify the creativity parameters. Any person can be analyzed using the creativity parameters via a questionnaire. A typical questionnaire is shown in Table 1.

Table 1: A questionnaire of creativity parameters

No	Activity	How many?
1	Writing book	
2	Writing research papers in English	
3	Writing research papers in languages except English	
4	Invention	
5	Innovation	
6	Lectures in international congress	
7	Lectures in workshops	
8	Attending international conferences	
9	Attending national conferences	
10	Attending workshops	
11	Attending special fairs	
12	Having general computer proficiency certificates	

13	To be familiar with special computer software	
14	Having special proficiency certificates (quality, management, …)	
15	Experience in team works	

After completing the questionnaire by a pilot group in an organization, the creativity matrix is configured. Scoring in this matrix is done based on decision maker's viewpoint. The mathematical indices and notations used in the creativity matrix are:

Indices:

i Index for human resource, $i=1,...,m$,

j Index for creativity parameter, $j=1,...,n$.

Notations:

H_i i^{th} human resource,

P_j j^{th} creativity parameter,

S_{ij} Score of i^{th} human resource with respect to j^{th} creativity parameter, $S_{ij} \in \{1,...,9\}$.

The proposed creativity matrix is given in Table 2.

Table 2: Creativity matrix

Creativity parameters / Human resources	P_1	...	P_j	...	P_n
H_1					
.					
.					
.					
H_i			S_{ij}		
.					
.					
.					
H_m					

Using the scores obtained in a creativity matrix, an intelligent clustering is performed to configure research teams.

3. Intelligent Clustering

Here, we use a clustering technique to classify our human resources to teams having more similarity. An important component of a clustering algorithm is the distance measure being used for the data points. If the components of the data instance vector all have the same physical unit, then the simple Euclidean distance metric would be adequate to successfully group the similar data instances. However, even in this case the Euclidean distance can sometimes be misleading. For higher dimensional data, a popular measure is the Minkowski metric,

$$d_p(x_i, x_j) = \left(\sum_{k=1}^{d} \left| x_{i,k} - x_{j,k} \right|^p \right)^{\frac{1}{p}},$$

where d is the dimension of the data. The Euclidean distance is a special case, where $p=2$, while Manhattan metric has $p=1$. However, there are no general theoretical guidelines for selecting a measure in any given application. A clustering Q means partitioning a data set into a set of clusters Q_i, $i=1,...,C$. In crisp clustering, each data sample belongs to exactly one cluster. A widely adopted definition of optimal clustering is a partitioning that minimizes distances within and maximizes distances among clusters. However, this leaves much room for variation: within- and between-cluster distances can be defined in several ways; see Table 3. The selection of the distance criterion depends on the application. The distance norm $\|.\|$ is yet another parameter to consider. Here, we use the Euclidean norm. We utilize local criteria in clustering data. Thus, S_{nn} and d_s in Table 3 are based on distance to nearest neighbor. In Table 3, $x_i, x_{i'} \in Q_k$, for $i \neq i'$, $x_j \in Q_l$, $k \neq l$, N_k is the number of samples in cluster Q_k, and $c_k = \frac{1}{N_k} \sum_{x_i \in Q_k} x_i$.

Table 3: Within-cluster and between-clusters distances

Within-cluster distance	$S(Q_k)$
Average distance	$S_a = \frac{\sum_{i,i'} \lVert x_i - x_{i'} \rVert}{N_k (N_k - 1)}$
Nearest neighbor distance	$S_{nn} = \frac{\sum_i \min_{i'} \{\lVert x_i - x_{i'} \rVert\}}{N_k}$
Centroid distance	$S_c = \frac{\sum_i \lVert x_i - c_k \rVert}{N_k}$
Between-clusters distance	$D(Q_k, Q_l)$
Single linkage	$d_s = \min_{i,j} \{\lVert x_i - x_j \rVert\}$
Complete linkage	$d_{co} = \max_{i,j} \{\lVert x_i - x_j \rVert\}$
Average linkage	$d_a = \frac{\sum_{i,j} \lVert x_i - x_j \rVert}{N_k . N_l}$
Centroid linkage	$d_{ce} = \lVert c_k - c_l \rVert$

We are looking for clusters so that the within-cluster distance is minimized and between-clusters distances are maximized. This way, the similarity within members of a cluster is high, and thus the members can be perceived to work as a team easily.

4. The Networks of KDP

In spite of the growing consensus that networks matter [13], the specific effects of different elements of network structure on creativity remain widely unclear. In the network literature, a debate has arisen over the network structures that can appropriately be regarded as beneficial. According to one view, close networks with many strong connections linking teams are seen as advantageous. The alternative view, however, states that advantages derive from the opportunities created by an open social structure. Teams can build contacts with multiple disconnected clusters of teams and use these connections to obtain the right information at the right time. From a theoretical point of view, these arguments have different, even contradictory, implications. The closeness of a team's network is described by its 'network range' and 'tie strength'. Openness is captured by 'network efficiency'. In this KDP, a performance assessment stage is considered. We conduct a comprehensive network interaction assessment method (CNIAM) for evaluating the performance of the team's network interactions in intelligent information exchange. The CNIAM consists of three elements: network range, tie strength, and network efficiency.

5. Measuring CNIAM

We make use of the following entities.

Network range: Network range is measured by the fraction of all contacts each team maintains with the other teams at least with a monthly frequency.

Tie strength: Tie strength represents the proportional strength of contacts a team maintains on the scales of 0 = no interaction, 1 = (at least) monthly interaction, 2 = (at least) weekly interaction, and 3 = (at least) daily interaction.

Network efficiency: For calculating the efficiency of the team's network we use the efficiency measure.Network efficiency is calculated as the proportion of a team's non-redundant relationships.
The measures employed in this work are summarized in Table 4.

Table 4: The CNIAM measures

Network range	
NR(n_i)=percentage of contacts of item *i* to all other teams *j* *N*= Number of teams $x_{ij} = \begin{cases} 1 & \text{if } i \text{ is connected to } j \\ 0 & \text{if } i \text{ is not connected to } j \end{cases}$	$NR(n_i) = \dfrac{\left(\sum_{\forall j \neq i} x_{ij}\right) \times 100}{N}$
Tie strength	
TS(n_i)= proportional tie strength of team *i* to all other contacts *j* S_{max}= maximum tie strength 3 $x_{ij} = \begin{cases} 1 & \text{if } i \text{ is connected to } j \\ 0 & \text{if } i \text{ is not connected to } j \end{cases}$ $s_{ij} = \begin{cases} 1 & \text{if } i \text{ is connected to } j \text{ at least monthly} \\ 2 & \text{if } i \text{ is connected to } j \text{ at least weekly} \\ 3 & \text{if } i \text{ is connected to } j \text{ at least daily} \end{cases}$	$TS(n_i) = \dfrac{\left(\sum_{\forall j \neq i} x_{ij} \times s_{ij}\right) \times 100}{\sum_{\forall j \neq i} x_{ij} \times s_{\max}}$
Network efficiency	
$i \neq j$ and $q \neq i, j$ *NE(n_i)*= network efficiency of team *i* p_{iq}= proportion of *ith* team's tie strength to *qth* team's tie strength (interaction with *qth* team divided by the sum of *ith* contacts) m_{jq}= marginal strength of *jth* team's contact in relation with *qth* team's contact (interaction with *qth* contact divided by the strongest of *jth* relationship with anyone)	$NE(n_i) = \sum_j \left[1 - \sum_q p_{iq}.m_{jq}\right]$

6. Conclusions

We investigated different structural aspects of teams' network organization and their creativity within a knowledge development program (KDP). Initially, a pilot group of people in an organization was selected. This group was evaluated through creativity parameters using a questionnaire. Considering the questionnaires' data, a decision maker configured the creativity matrix by a scoring technique. Applying the creativity matrix, the clustering was performed. The pilot group was divided into some research teams. The research subjects were submitted to the teams and their progress in solving the problem was assessed through a comprehensive network interaction assessment method (CNIAM). As a result, the problem was solved and some new research subjects were evolved to be allocated to the next configured teams. This procedure was repeated dynamically in different time periods. The advantages of such programs are continuous monitoring, gradual problem solving in an organization, involvement of organization's employees in the problem solving process, updating employees creativity parameters, intelligent clustering of employees into research teams, and a comprehensive network interaction assessment method to guarantee continuous improvement.

Acknowledgments

The first two authors thank Mazandaran University of Science and Technology, the third author thanks Research Council of Sharif University of Technology, the fourth and fifth authors thank Mazandaran Gas Company for supporting this work.

References

1. Oxley, J.E., Sampson, R.C., 2004. The scope and governance of international R&D alliances. Strategic Management Journal 25, 723– 749.
2. Smith, P.G., Blanck, E.L., 2002. From experience: leading dispersed teams. Journal of Product Innovation Management 19, 294–304.
3. Flyvbjerg, B., Bruzelius, N., Rothengatter, W., 2003. Megaprojects and Risk: An Anatomy of Ambition. Cambridge University Press.
4. Van Engelen, J.M.L., Kiewiet, D.J., Terlouw, P., 2001. Improving performance of product development teams through managing polarity. International Studies of Management and Organization 31, 46–63.
5. Reagans, R., McEvily, B., 2003. Network structure and knowledge transfer: the effects of cohesion and range. Administrative Science Quarterly 48, 240–268.
6. Amabile, T.M., Schatzel, E.A., Moneta, G.B., Kramer, S.J., 2004. Leader behaviors and the work environment for creativity: perceived leader support. Leadership Quarterly 15, 5–32.
7. Perry-Smith, J.E., Shalley, C.E., 2003. The social side of creativity: a static and dynamic social network perspective. Academy of Management Review 28, 89–1073.
8. Reiter-Palmon, R., Illies, J.J., 2004. Leadership and creativity: understanding leadership from a creative problem-solving perspective. Leadership Quarterly 15, 55–77.
9. Leenders, R.T.A.J., Van Engelen, J.M.L., Kratzer, J., 2003. Virtuality, interaction, and new product team creativity: a social network perspective. Journal of Engineering and Technology Management 20, 69–92.
10. Ingram, P., Robert, P., 2000. Friendships among competitors in the Sydney hotel industry. American Journal of Sociology 106, 387–423.
11. Reagans, R., Zuckerman, E., 2001. Networks, diversity and performance: the social capital of R&D teams. Organization Science 12, 502–517.
12. Tsai, W., 2001. Knowledge transfer in intraorganizational networks: effects of network position and absorptive capacity on business team innovation and performance. Academy of Management Journal 44, 996–1004.
13. Ahuja, G., 2000. Collaboration networks, structural holes, and innovation: a longitudinal study. Administrative Science Quarterly 45, 425–455.