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Application of PageRank in Virtual Organization Architecture

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ABSTRACT The complexity of open communication stemming from teams' interactions is a fundamental feature of the Global Product Development projects. Design Structure Matrix models and the clustering method are effective approaches for analyzing and optimizing the virtual organization architecture and reducing management complexity. In order to optimize virtual organization architecture, this paper presents a Design Structure Matrix-based spectral clustering approach through identifying core teams and measuring similarity between virtual teams. Firstly, the open communication frequency related to product features is built based on mapping network. Further, this paper proposes a method combining the Information Connectivity Matrix and the Responsibility Measurement Matrix to rank teams and identify core teams based on the PageRank algorithm of Social Network Analysis. In order to measure similarity between virtual teams, this paper presents concepts of Receiver Similarity Index and Sender Similarity Index and utilizes the spectral clustering algorithm to optimize organization architecture. Finally, an industrial example is provided to illustrate the proposed models. The optimization process and comparison test indicate that the proposed method is a more robust clustering algorithm and results provide an integrated managerial insight for reducing management complexity in open communication platforms.

Keywords Design Structure Matrix; Global Product Development, Open Communication Frequency; Organization Architecture; Social Network; Spectral Clustering

I. INTRODUCTION

A key issue in Global Product Development project management is how to establish an effective virtual organization to coordinate and communication between hundreds and even thousands of specialists [1], [2]. An efficient global and open organizational architecture can not only reduce management complexity but also facilitate the communication, coordination and innovation [3], [4].

Usually, some core teams in an organization take key roles depending on their functions in the communication and decision-making process [5]. In order to facilitate the communication, the manager should not only identify core teams which play as connection points in the information flow [6], but also need to optimize the organizational structure according to core teams. The stronger communication strength between Global Product Development teams is required if the stronger dependency between product's technical features exists. Hence, communication strength resulting from product's technical features and an appropriate clustering approach based on core teams in the communication and decision-making process are critical factors for optimizing organization architecture. But sometimes, this new Global Product Development organization may not be properly established, because of the complexity of team's interdependence and task complexity. This may lead to low efficiency and additional risks in communication and coordination between teams [7].

Structured methods are useful tools to explain dependency relationship between elements and reduce management complexity in Global Product Development projects. The Design Structure Matrix proposed by Steward [8] is a powerful structural method to represent the dependency strength of communication between teams. Organizational units (e.g., teams or individuals) with strong dependency can be relocated next to each other, or clustered into the same group [3]. Reducing management complexity is the main benefit of clustering method. Traditional Design Structure Matrix clustering algorithm utilizes the concept of bid to find the clusters (modules) in which any element in Design Structure Matrix has the same probability of being selected into a cluster. Once an element is chosen into in a cluster, the algorithm calculates a bid that can measure how "strongly" dependency of the selected element with other elements in the cluster [9]. But the main disadvantage of the method is that it is difficult to find the global optimized result and the robustness of the algorithm is weak.

Social network analysis technique has been widely applied in different areas and can be used to analyze the information flows in Global Product Development projects and identify the core teams [6], [10]. But the traditional method of Social Network Analysis only considers the features around each node in the network. The PageRank algorithm is one of the most typical sorting algorithms, which considers characteristics of all nodes in the network, and can be used to identify core teams accurately [11]. Furthermore, these core teams can be viewed as the initial clustering center of each group when we optimize the organization. Spectral clustering method is an efficient method to find the global optimized result. Building a similarity matrix is a crucial step to carry out spectral clustering [12]. Therefore, how to identify the core teams and build an appropriate similarity matrix of the Global Product Development project are important issues for optimizing the Global Product Development organization based on spectral clustering method.

In this paper, we use the PageRank algorithm to identify the core teams in the Global Product Development project and use the spectral clustering method to cluster the organization Design Structure Matrix. Thus, this paper seeks to explore the following questions:

1) How to identify core teams depending on team's input and output relationship of technical information with other teams and their role in the process of decision-making?

2) How to evaluate the level of similarity between teams in the Global Product Development project to cluster virtual organization according to core teams and the similarity matrix for reducing the project's coordination complexity?

To address the above issues, we identify the core team within the organization according to their similarity with the application of PageRank algorithm. Further, we use spectral clustering the identify appropriate communities with higher similarity. The rest of the paper is organized as follows. In Section 2, we present an overview of the Design Structure Matrix and Social Network Analysis methods which have been used in virtual product development environments to understand complex information flows. In Section 3, we use a quantitative model to measure technical open communication frequency and find the core teams in the organization network. In Section 4 we define the similarity matrix and utilize the spectral clustering method to cluster the organization Design Structure Matrix. In Section 5, an industrial example is used to verify the proposed model. We conclude the paper in Section 6.

II. LITERATURE REVIEW

A. DESIGN STRUCTURE MATRIX AND CLUSTERING METHOD

Design Structure Matrix models can be utilized to measure the dependency strength between elements in a complex system. They have been used to map and decompose large complex systems into appropriate sub-systems on the basis of a variety of parameter interactions [13]. Measuring the dependencies between the elements in Design Structure Matrix is one of the decisive factors for clustering analysis [14], [15]. To simplify the Design Structure Matrix optimization, initially all dependency strengths were weighted equally (i.e., binary dependency strength). But this binary method is qualitative and dependent on the preference of managers. An extension of binary Design Structure Matrix is the numerical Design Structure Matrix, where numbers, either absolute or relative, are input into the matrix and help in making decisions. The Multi-Domain Matrix is an extension of Design Structure Matrix modeling in which two or more Design Structure Matrix models in different domains are represented simultaneously. Multi-Domain Matrix can be utilized to reveal the relationship between different domains (e.g., product, organization and process) [16].

For organization Design Structure Matrix, redesigning the organization structure can not only strengthen the team communication, but also help to form a creative PD organization and reduce management complexity [4], [17], [18]. Several researchers have explored the clustering method and integrative mechanisms for organizations. Authors studied the integrative mechanisms to reorganize the PD organization and applied it into the development of large projects [23]. Clustering objectives and techniques vary between applications. The common Design Structure Matrix clustering objective is reducing external dependencies or increasing internal dependencies by changing location of elements in Design Structure Matrix [19]. Other clustering objectives include minimizing description length [20], maximizing modularity measure [21] and minimizing coordination cost [17].

Existing Design Structure Matrix's clustering algorithms can't easily find the global optimized results and the robustness of the algorithm is weak. Some methods have been developed to identify a globally optimal clustering [22]. The spectral clustering algorithm has become a popular method for data clustering analysis used in a broad range of applications, due to its solid theoretical foundation, as well as the good performance of clustering compared with some traditional clustering algorithm [23]-[25]. Lee et al. [26] used spectral graph partitioning to advance strategic management and focused on the study of complex systems that contain strongly connected components with interactions that are weighted and directed. Alcácer and Zhao [27] advanced strategic management research by focusing on a density-based cluster algorithm for analyzing the underlying economic activities. Kim et al. [28] used Exponential Random Graph Models to examine multiple interdependent social processes involved in network formation in strategic management research.

It is not only simple, but also easy to find the global optimum, especially for non-convex dataset [29], and very suitable for application in actual problems, such as biological information [30] and image search [31]. Similarity measurement is crucial to the performance of spectral clustering, the classic spectral clustering algorithm with Gaussian kernel function to measure the similarity between two elements.

B. SOCIAL NETWORK ANALYSIS AND PAGERANK ALGORITHM

However, Design Structure Matrix only provides a partial view of the PD project because it lacks the sophistication to uncover the underlying statistical properties of the PD projects, what is more, as the number of elements or relationship between elements increases, the corresponding complexity makes these systems increasingly difficult to analyze. Social Network Analysis techniques provide lots of indicators that describe the statistical properties of networks and can be used to analyze PD information flow [10], [32].

Many researchers have combined Design Structure Matrix and Social Network Analysis to analyze the PD projects [7], [10], [32], [33]. To identify the key nodes is one particular problem in network analysis [28]. Previous studies [6], [10], [34] used traditional metrics of Social Network Analysis which are simple node sorting methods based on network topology, because only the feature around the nodes are taken into consideration. What is more, these constructed networks were based on binary Design Structure Matrix, the different dependency strength between the elements of PD was not considered.

The *PageRank* algorithm was developed by Page and Sergey of Stanford University. PageRank is a way of measuring the importance of website pages which is only generated from the linking structure [35]. The *PageRank* of a node which gives the relative importance degree of the pages can be interpreted as the average portion of time spent at the node by an infinite *random walk* or in other words, it constitutes a global ranking of all Web pages, regardless of their content, based solely on their location in the graph structure. It is traditionally applied for ordering web-search results, but it also has many other applications [36]. Some modifications of this method have been proposed [37], [38]. Agryzkov [11] presented a new method which takes into account not only the connections between the nodes in a network, but also other external factors (e.g. the role in decision-making) for ranking each node in the network.

Although previous research brought considerable insights into measuring dependency strength between teams and clustering PD organization, how to construct a PD organization according to each team's role in technical communication and decision-making [39] and a more robust clustering algorithms is ignored.

There are three key contributions of this paper.

1) In order to manage coordination complexity and improve the robustness and efficiency of Design Structure Matrix clustering methods, this paper use the spectral clustering method for the organization Design Structure Matrix through identifying core teams and measuring similarity between teams in PD projects.
2) This paper builds the *Information Connectivity Matrix and* the *Responsibility Measurement Matrix to* measure the relative importance degree of PD teams for using *PageRank* algorithm of Social Network Analysis to identify the core teams. For characterizing the *Information Connectivity Matrix,* the models of team's information sending connectivity degree and information receiving connectivity degree are built. For characterizing the *Responsibility Measurement Matrix,* the model of involvement degree is built.
3) In order to measure similarity between teams in PD projects, this paper presents the concepts of *Receiver Similarity Index* and *Sender Similarity Index* from the view of information flow. Finally, the spectral clustering algorithm is used to obtain the optimized cluster of organization Design Structure Matrix, which provides a more robust algorithm for obtaining stable results and integrated managerial insight for reducing management complexity.

III. IDENTIFYING CORE PD TEAMS BASE ON MULTI- DOMAIN MAPPING AND PAGERANK ALGORITHM

A. IDENTIFYING CORE TEAMS RELYING ON OPEN COMMUNICATION

In this paper, we use the product-organization architectures to capture the open communication among teams related to product's features.

From Figure 1, teams P_I and P_J are likely to interact to negotiate their component interfaces. This definition assumes that the higher the degree of overlap between activities A_1 and A_2 and the higher the involvement degree of the teams P_1 and P_2 in the redesign of the process, the more these two teams are likely to collaborate each other. This follows the findings of previous research [40], [41].

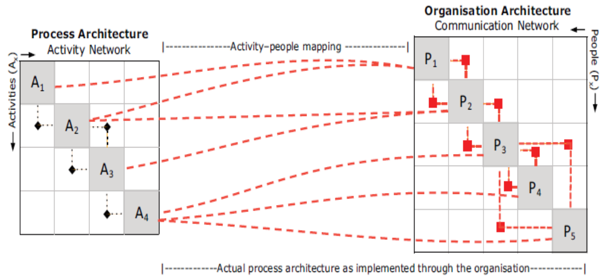


FIGURE 1. Mapping from process to organization architecture from [3, p. 88]

The open communication frequency (OCF (i,j)) allows to determine the pair of teams that could potentially handle indirect changes in the process (i.e., who should talk to whom if a redesign is improved during the process?).

The discontinuous red array from process architecture and organization architecture illustrates a third matrix called the involvement degree matrix, which shows the degree of team's involvement in the product redesign $(ID(i,J))$. In this paper, dependency strengths of process architecture and team's involvement are scaled at four levels [9], [17]: 0 = no relation, 1 = weak relation, 2 = medium relation, 3 = strong relation. These scales are evaluated through analyzing the degree of overlapping between activities and the potential team's involvement degree in the design process respectively, which are judged by groups of the project manager, engineers and experts according to their knowledge and experience [7], [17].

$$OCF(i,j) = \sum_{I=1}^{m} (ID(i,I) \times \sum_{J=1,J\neq I}^{m} (ID(j,J) \times P\_DSM(I,J)) \tag{1}$$

An Open Communication Frequency network of teams could be derived to represent a directed weighted network, in which the nodes represent the teams, the direction of arrow represents the information's input and output and the weighted value of arrow is the Open Communication Frequency between teams.

In order to optimize the organization architecture, we firstly rank all of the Global Product Development teams to identify core teams by evaluating their roles in the information exchange and decision-making. Then the number of core teams in organization can be viewed as the number of groups for clustering the Design Structure Matrix and it is one of input of clustering algorithms. Further, we build *Similarity Index* between teams and then use spectral clustering method to cluster the original Open Communication Frequency of the organization Design Structure Matrix.

B. RANKING CORE TEAMS USING SOCIAL NETWORK ANALYSIS METHOD

In Global Product Development projects, both one team's information connectivity with other team and its role in the decision-making process determine the level of importance of each team in the Global Product Development project. In this paper, the core teams refer to the teams which not only have very important roles in the process of decision making but also have more information connectivity with other teams.

According to the feature that each team sends information to other teams and receives information from other teams, we build *Information Connectivity Matrix* to evaluate the relative importance related to connectivity of information for using the *PageRank* algorithm. In addition, according to the different responsibility of each team in the process of decision-making in Global Product Development projects, we build *Responsibility Measurement Matrix* for describing the role in the process of decision-making.

1) THE INFORMATION CONNECTIVITY MATRIX

In Global Product Development projects, information connectivity refers to the connection between teams related with information exchange, in which each team act as an information receiver or an information sender. So, information connectivity of one team with the other teams is composed of two parts, one is team's *information sending connectivity degree* and another is its *information receiving connectivity degree* compared to other teams. The *Information Connectivity* (IC) *Matrix* can be captured with (2).

$$IC = \Lambda \cdot IC_{out} + (E - \Lambda) \cdot {IC_{in}}^{T} \tag{2}$$

where, ${IC_{in}}^{T}$ is the transpose of IC_{in}, E is the unit matrix, $\Lambda = diag(\lambda_1, \lambda_2, \ldots, \lambda_n)$, $\lambda_i (i = 1,2,..,n)$ are weight coefficients, $\lambda_i = 1$ if team i only plays role as the information sender; and $\lambda_i = 0$ if team i only plays role as the information receiver. Matrix $IC_{out}$and IC_{in}represent information sending connectivity degree and information receiving connectivity degree respectively, which can be captured with (3) and (4).

$$IC(i,j)_{out} = \begin{cases} \dfrac{OCF(i,j)}{\sum_{i=1}^{n} OCF(i,j)} & if\ OCF(i,j) \neq 0 \\ 0 & otherwise, \end{cases} \qquad 1 \leq i,j \leq n \tag{3}$$

$$IC(i,j)_{in} = \begin{cases} \dfrac{OCF(i,j)}{\sum_{j=1}^{n} OCF(i,j)} & if \quad OCF(i,j) \neq 0, \\ 0 & otherwise, \end{cases} \qquad 1 \leq i,j \leq n \tag{4}$$

where $OCF(i,j)$ can be captured by (1). Hence, (2) can be expressed by (5).

$$IC(i,j) = \lambda_i IC(i,j)_{out} + (1 - \lambda_i) IC(j,i)_{in} \tag{5}$$

where, $\lambda_i (i = 1,2,..,n)$ are weight coefficients, $\lambda_i = 1$ if team i only is the information sender; and $\lambda_i = 0$ if team i only is the information receiver; $\lambda_i = 0.5$ if team i is not only the information sender but also the information receiver. In this means, $IC(i,j)_{out}$ will be the ratio between releasing information from team j to team i and information sent by team j to all teams. The bigger value of $IC(i,j)_{out}$ indicates the higher connectivity degree related to releasing information from team i to team *si*milarly, The bigger value of $IC(j,i)_{in}$ indicates the higher connectivity degree of receiving information.

2) THE TEAM'S RESPONSIBILITY MEASUREMENT MATRIX

The team's responsibility refers to the responsibility and duty of each team in the decision-making process of Global Product Development projects. The Global Product Development Process involves concept development, system-level design, detail design, testing and refinement and production ramp-up. In the concept development phase (especially the concept selection sub-phase), the virtual teams are faced with making decision of the best concept for satisfying customer need and further design, refinement, and production [4]. Hence, this paper focus on the design decisions in the process of concept selection, especially the important decisions related with selecting functions and parts. On the other hand, according to distributed teams' previous experience, they can forecast how many important design decisions will be made and how will they be involved in these decisions in a new Global Product Development project. Assuming k decisions are required made by n teams, so, the team and decision-making Domain Mapping Matrix with n column and k row can be built. In the Domain Mapping Matrix, the value of each column j represents the responsibility's level of each team i in decision-making j. The Domain Mapping Matrix indicates the involvement degree of various teams in the process of making decisions for a project or business process. It is especially useful in clarifying roles and responsibilities of each team in cross-functional/departmental activities and processes. The value of involvement degree *Domain Mapping Matrix* can be scaled by 7 levels (i.e., from 0 to 6), and the larger value of *Domain Mapping Matrix* means the higher involvement degree of team i for decision j. The scales of involvement degree are evaluated by groups of the project manager, engineers and experts according to their knowledge and experience.

Because a different decision has a different priority in the project, a weighted vector $\overrightarrow{v_o} \in R^{k \times 1}$can be built to represent the priority of each decision. Then, with *Domain Mapping Matrix* (i,j) and $\overrightarrow{v_o}$, the involvement degree $\vec{v}$ of each team for all the decisions based on the priority of each decision can be captured by (6).

$$\vec{v} = D \cdot \overrightarrow{v_o} \tag{6}$$

Then the normalized vector $\vec{v}_i^*$ can be calculated with (7).

$$\vec{v}_i^* = \left(\frac{v_1}{\sum v_i}, \frac{v_2}{\sum v_i}, \ldots, \frac{v_n}{\sum v_i} \right) \tag{7}$$

Further, we build the *Responsibility Measurement* (RM) *Matrix* $RM \in R^{n\times n}$, in which all elements in the i^{th} column are equal to $\vec{v}_i^*$. In other words, we need to repeat the vector $\vec{v}_i^*$ in every column of the *RM* for *n* times. For instance, for the team and decision-making Domain Mapping Matrix shown in Figure 2, we assume priority vector of each decision $\overrightarrow{v_0} = (0.2, 0.3, 0.5)$, then we obtain $\vec{v} = (3.5, 4.5, 1, 2, 1.2)$ and the normalized $\vec{v}_i^* = (0.29, 0.37, 0.08, 0.16, 0.10)$ which indicates the involvement degree of each team for all the decisions in Global Product Development process.

	Identify customer requirement	Define system scheme	Define product apparence
System design team	6	6	1
Structure design team	3	3	6
Electrical design team	1	1	1
Mechnical design team	1	1	3
package design team	2	1	1

FIGURE 2. Team and decision-making Domain Mapping Matrix

Repeating the vector $\vec{v}_i^*$ n times, we get the team's *RM* matrix as following:

$$RM = \begin{bmatrix} 0.29 & 0.29 & 0.29 & 0.29 & 0.29 \\ 0.37 & 0.37 & 0.37 & 0.37 & 0.37 \\ 0.08 & 0.08 & 0.08 & 0.08 & 0.08 \\ 0.16 & 0.16 & 0.16 & 0.16 & 0.16 \\ 0.10 & 0.10 & 0.10 & 0.10 & 0.10 \end{bmatrix}$$

3) IDENTIFYING CORE TEAMS USING IMPORTANCE DEGREE MATRIX

Because in this paper, we want to find the core teams which not only have very important roles in the process of decision making but also have more information connectivity with other teams. So, the *Importance Degree* (ID) Matrix for ranking the teams can be captured as follows:

$$ID = (1-\alpha)IC + \alpha RM \tag{8}$$

where, α is a weight coefficient. IC represents the Information Connectivity Matrix and RM is the Responsibility Measurement Matrix.

Because the ID matrix is a non-negative, stochastic matrix by columns (i.e., a real square matrix with each column summing to 1), so we can utilize the Perron-Frobenius theorem to analyze the non-negative matrix for ranking teams. For the ID matrix, we can find an eigen vector associated to the eigenvalue 1, and the vector corresponds to the limit vector of a probability distribution of a Markov chain. Besides, as the ID matrix is stochastic and primitive, so its eigenvector is a steady state vector of the Markov chain which can represent the ranking of the teams. The most widely used algorithm for calculating the eigen vector associated to the eigenvalue 1 is the power method [42].

The higher the value of the eigenvector represents a higher integrated connectedness and a critical role in decision-making process. A successful Global Product Development project requires frequent information exchanges and decision-making, so a team's value in the eigenvector indicates the capability that it becomes the core team in the Global Product Development organization.

In summary, in order to rank the teams and identify the core teams in Global Product Development project, the process requires the following steps:

Step 1: Obtain the matrix IC from organization Design Structure Matrix using (2).

Step 2: According to the team-decision Domain Mapping Matrix and the weight vector of decision $\overrightarrow{v_0}$ to calculate the RM matrix by the (6) and (7).

Step 3: According to (8), the ID matrix can be achieved. Then, we compute the eigenvector $\vec{u}$ whose eigenvalue equal to 1 of the ID matrices using the power method. The eigenvector $\vec{u}$ represents the ranking vector for each team.

Finally, according to $\vec{u}$ (i.e., the ranking of teams), we can identify the core teams depending on experience and priority of the project manager.

IV. SPECTRAL CLUSTERING APPROACH FOR GLOBAL PRODUCT DEVELOPMENT TEAMS

A. BUILDING THE SIMILARITY MATRIX FOR GLOBAL PRODUCT DEVELOPMENT TEAMS

Identifying the similarity matrix S in which the value of $S(i,j)$ represents the level of similarity between elements i and j is the first step of spectral clustering method. The clustering method uses the similarity matrix to find a set of clusters (i.e., groups) for the elements (i.e., individuals or teams), so that similarity of intra-cluster is maximized while similarity of inter-cluster is minimized. The Gaussian kernel function is widely adopted as the similarity measure [29]. The similarity matrix IS in our paper is not a sparse matrix, and a similarity matrix calculated by Gaussian kernel function is not sparse [42]. Therefore, the Gaussian kernel function is used as the benchmark case to evaluate our IS results. Given a dataset $X = \{x_1, x_2, \ldots, x_n\}$ with k clusters, we can define a similarity matrix A whose element $A_{i,j}$ can be viewed as the weight on the edge connecting the i^{th} and j^{th} data-points. The element A_{ij} of the similarity (affinity) matrix is measured by a typical Gaussian kernel function $A_{ij} = exp(-d^2(x_i,x_j)/\sigma^2)$, where $d(x_i,x_j)$ is Euclidean distance, σ is the scale parameter which controls the width of the neighborhoods.

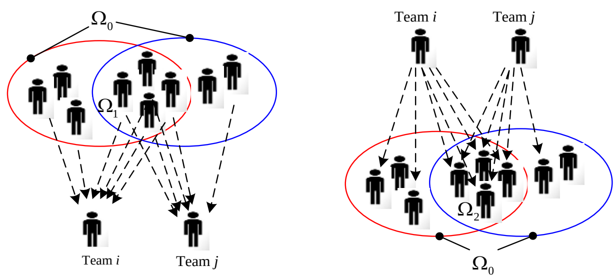
Usually, the level of similarity between finite sample sets A and B can be measured by the Jaccard similarity coefficient, which is defined as the size of the intersection divided by the size of the union of the sample sets:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \tag{9}$$

Because the Jaccard coefficient can be used as an accuracy measure for sparse matrix [42], and Design Structure Matrix is sparse matrix, so this paper builds quantitative models to measure the similarity matrix for Global Product Development teams based on the Jaccard coefficient and further the spectral clustering method is utilized based on the similarity matrix.

For any team in an organization (see Figure 3), it is probably either an information receiver or an information sender. From the view of team i and team j receiving information from other teams (see Figure 3(a)), the bigger amount of input-linked information from same teams indicates they have the higher similarity level. On the other hand, if team i and team j release technical information to other teams (see Figure 3(b)), the number of output-linked teams that release technical information to same teams reflects the level of similarity from the view of information's sender. The bigger number of output-linked teams indicates the higher similarity level is shared between teams i and j. The teams share high similarity level with both the received information and released information should be clustered into the same group.

By using spectral clustering, it can make the teams with high level of similarity (i.e., strong information exchange) are clustered in one group and simultaneously the interaction relationship between group become weak, which will reduce the management complexity. In the extreme case even though the information exchange between teams is very limited, they still will be clustered in one group if they have high level similarity. For example, in the system design of a new airplane, teams performing design the front cabin and back cabin have limited communication, but both of them have strong information exchange with teams responsible for mechanics and electric circuit, so they can be clustered in one group.



(a) Information receiver (b) Information sender

FIGURE 3. Measuring the similarity between teams

In order to measure similarity between the teams i and j, we define sets $\Omega_0, \Omega_1, \Omega_2$ and $\Omega_0, \Omega_1, \Omega_2$: Ω_0 is the set of all teams in the project.

Ω_1 is the set of common teams from which both teams i and j receive technical information. In the organization Design Structure Matrix, Ω_1 represents the set of column k in which both the value of row i and j is non-zero.

Ω_2 is the set of common teams, which both teams i and j send technical information to them. In the organization Design Structure Matrix, Ω_2 represents the set of row k which both the value of column i and j is non-zero.

Hence, this paper presents the concept of *Receiver Similarity Index* (RSI) to measure similarity between teams i and j from the view of information's receiver. RSI is defined as the ratio of the total value of organization architecture in the Ω_1 to the total value in the Ω_0 and it can be calculated with (10):

$$S_r(i,j) = exp\left(\frac{\sum_{k \in \Omega_1}(OCF(i,k) + OCF(j,k))}{\sum_{k \in \Omega_0}(OCF(i,k) + OCF(j,k))}\right) \tag{10}$$

$$\sum_{k\in\Omega_1}(OCF(i,k) + OCF(j,k)) = \sum_{k=1}^{n}(OCF(i,k) + OCF(j,k)) \tag{11}$$

if $OCF(i,k) \times OCF(j,k) \neq 0$

$$\sum_{k\in\Omega_0}(OCF(i,k) + OCF(j,k)) = \sum_{k=1}^{n}(OCF(i,k) + OCF(j,k)) \tag{12}$$

where $\sum_{k=1}^{n}(OCF(i,k) + OCF(j,k))$ is the sum of value of row of i and $OCF(i,k) \times OCF(j,k) \neq 0$ denotes the situation that both i and j receive information from k.

Similarly, this paper presents *Sender Similarity Index* to measure similarity between teams i and j from the view of the information's sender. This index is defined as the ratio of the total value of organization architecture in the Ω_2 to the total value in the Ω_0 and it can be captured with (13):

$$S_s(i,j) = exp\left(\frac{\sum_{k\in\Omega_2}(OCF(k,i) + OCF(k,j))}{\sum_{k\in\Omega_0}(OCF(k,i) + OCF(k,j))}\right) \tag{13}$$

$$\sum_{k\in\Omega_2}(OCF(k,i) + OCF(k,j)) = \sum_{k=1}^{n}(OCF(i,k) + OCF(j,k)) \tag{14}$$

if $OCF(k,i) \times OCF(k,j) \neq 0$

$$\sum_{k\in\Omega_0}(OCF(k,i) + OCF(k,j)) = \sum_{k=1}^{n}(OCF(k,i) + OCF(k,j)) \tag{15}$$

Therefore, the *Integrated Similarity Index* between teams i and j which refers to the integration of *Receiver Similarity Index* and *Sender Similarity Index* between the teams can be captured with (16):

$$IS(i,j) = \frac{1}{2}(S_r(i,j) + S_s(i,j)) \tag{16}$$

The integrated similarity matrix (i.e., IS matrix) is a symmetric matrix, and $0 \leq IS(i,j) \leq 1$.

B. SPECTRAL CLUSTERING METHOD

Spectral clustering is a clustering method based on algebraic graph theory. In multivariate statistics and the clustering of data, spectral clustering techniques make use of the spectrum (i.e., eigenvalues) of the data's similarity matrix to perform dimensionality-reduction before clustering in fewer dimensions. The similarity matrix is provided as an input and consists of a quantitative assessment of the relative similarity of each pair of points in the dataset.

One of spectral clustering technique is the NJW algorithm introduced by [44]. It utilizes the Laplacian matrix which is a simple normalization of the similarity matrix to optimize the normalized cut criterion according to the eigenvector associated with the largest eigenvalues. The optimal partition makes the similarity of the elements in the cluster (or subgraph) maximized and the similarity between the elements of different clusters minimized. As for the choice of a specific spectral method, [42] provided a comparative overview of the different methods of spectral clustering and recommends the use of normalized spectral clustering. Researchers found that the NJW algorithm-normalized spectral clustering has more robust performance compare to other clustering algorithms [44].

In summary, use the organization Design Structure Matrix to derive a team similarity matrix, which is then used in conjunction with knowledge of the core teams as inputs to a spectral clustering algorithm to optimize the organization architecture, to identify clusters that minimize the total coordination cost among the teams. Third, we model teams' information connectivity, and combine this with additional data on the teams' responsibility in meeting key PD objectives, in order to identify and rank the core teams with the PageRank algorithm from social network analysis. These steps are currently suitable to emphasize virtual work success [45], [46].

The procedure of NJW spectral clustering for Global Product Development organization is as following:

Step 1: Build the similarity matrix IS using (16).

Step 2: Compute the normalized Laplacian matrix of IS.

Step 3: Calculate Laplacian matrix's eigenvalue and eigenvector. Then choose the k value (i.e., the number of core teams) which corresponds to the number of groups at a specific level of hierarchy so as to generate a low dimensional vector space for describing IS.

Step 4: Set the core teams resulted from (8) as the original clustering center, then the k-means clustering algorithm is used to obtain the optimized cluster of organization architecture.

V. AN ILLUSTRATIVE EXAMPLE

An industrial example, customer plate from at L'ORÉAL Paris (CPOP) project is utilized to verify the proposed concepts and model. The IT project involves 20 project teams and each team performs a unique task. We interviewed more than 20 persons including the project manager and other core project team members from the R&D department, production department and marketing department. During the interviews, some main questions are involved: 1) How to optimize the project's organization regarding communication and coordination between technical teams? 2) How much the influence of one component change on other components and what the involvement degree of one team in the process of one component? The overall early design stage is sophisticated, and we select 4 main decision-making processes.

Firstly, we build the process architecture and the process-organization mapping. Using (1), we calculate the open communication frequency relying on the degree of overlap and customer requirements and obtain the original organization architecture (see Figure 4(a)), in which each numerical interaction represents the Open Communication Frequency. It is clear that obvious complexity management exits because there are a lot of interaction marks in original organization Design Structure Matrix. Figure 4(b) is the team and decision-making Domain Mapping Matrix showing the involvement degree between each team and different decisions (a, b, c, d represent four main decisions). We developed the clustering algorithm using MATLAB 16 software.

	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*N*	*O*	*P*	*Q*	*R*	*S*	*T*
A	*A*	.83		.81	.73			.81	.10								.70			
B	.86	*B*		.90	.70			.80									.82			
C			*C*			.81		.10		.31			.82		.31		.10	.73		
D	.80	.81		*D*	.71	.10		.71		.15							.70	.13		
E	.73	.81		.73	*E*			.73	.33			.24					.73			
F			.80	.20		*F*		.10		.17			.82					.73		
G			.30				*G*					.13		.32			.12		.82	.80
H	.72	.82	.10	.81	.73	.13		*H*									.91			
I	.11				0.2				*I*		.70	.91		.91	.82					
G			.30	.11		.16				*G*			.51					.11		
K									.81		*K*	.82		.90			.82			
L	.13				.30				1.0		.91	*L*		.82	1.0		.73			.13
M			.73			.72				.62			*M*							.20
N							.20		.91		.82	.80		*N*	.91	.82				
O									.82			.91		.90	*O*	.80				
P											.73	.70		.82	.73	*P*				
Q	.70	.82		.70	.82			1.0	.12		.10						*Q*			
R		.20	.73	.10		.71			.23	.16								*R*		
S							.91												*S*	.82
T							.73					.21					.15		.73	*T*

(a)

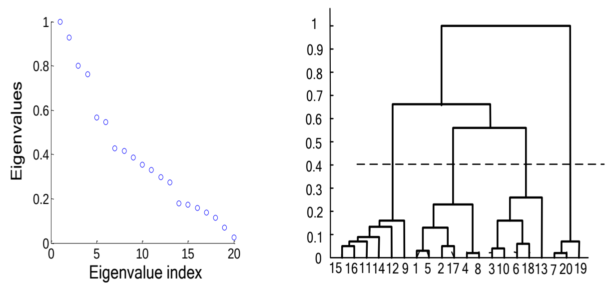
	a	*b*	*c*	*d*
A	6	2	0	3
B	1	3	1	0
C	2	1	3	1
D	1	3	1	4
E	4	1	6	1
F	1	2	0	1
G	1	2	3	4
H	3	1	1	0
I	1	1	0	1
J	1	4	1	0
K	0	1	2	1
L	5	6	1	3
M	1	0	1	5
N	2	1	0	1
O	1	0	1	1
P	3	1	0	1
Q	1	2	1	0
R	5	1	0	3
S	1	0	4	1
T	1	2	1	0

(b)

FIGURE 4. The original organization Design Structure Matrix (a) and Domain Mapping Matrix (b)

Based on the original organization Design Structure Matrix and the team and decision-making Domain Mapping Matrix, we build the *Importance Degree* (ID) Matrix with (2)-(8) and utilize the power method to calculate the ID matrix's eigenvector (see Table. 1), which indicates the teams' ranking in the Global Product Development project. In this case, all teams are both information senders and information receivers, $\lambda_i = 0.5, (i = 1,2,\ldots,n)$ in (2). In (6) and (8), $\overrightarrow{v_0} = (0.2, 0.3, 0.1, 0.4)$ and $\alpha = 0.15$ respectively, which are collected from the project manager and experts in the project.

Then, we calculate the similarity matrix using (10)-(16) and carry out the spectral clustering for the original organization, in which the k-means clustering algorithm is used. In the process of spectral clustering, first of all, we obtain the result of eigenvalue of normalized Laplacian matrix (see Figure 5 (a)). The choice of the k value (i.e., the number of core teams) is guided by the findings on the separation of large eigen values of the normalized Laplacian matrix. The k value corresponds to the number of groups at a specific level of hierarchy, particularly, the value of k equal to the number of groups in a perfectly clustering network. Figure 5 (a) shows that a big separation exists between eigenvalue index 4 and 5, so the optimal number of clusters (i.e., groups) in the Global Product Development organization is 4. Then, we take the top 4 as the core teams which are the input of the k-means cluster algorithm. Further, Figure 5(b) shows that a dashed line can be drawn across the cluster tree so that 4 groups are formed, and corresponding teams in each group are [O, P, K, N, L, I], [A, E, B, Q, D, H], [C, J, F, R, M], [G, T, S]. The number of x-axis in Figure 5(b) represents the corresponding team.



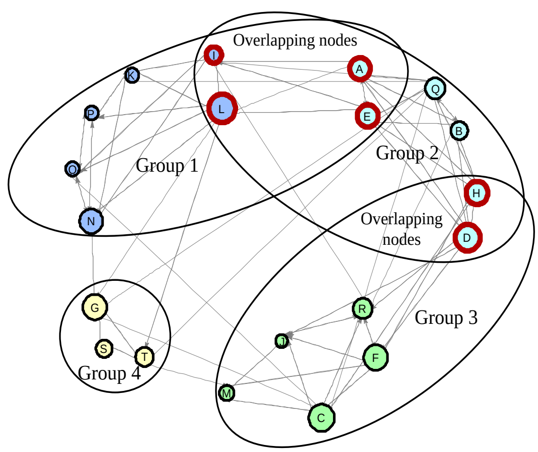
(a) Eigenvalue (b) Cluster tree

FIGURE 5. Results of eigenvalue and cluster tree using spectral clustering

Figure 6 (a) shows that the clustered organization has been decomposed into four groups of teams according to Figure 5 (b). The clustered Design Structure Matrix indicates that teams with strong interactions are clustered, so the organization complexity is reduced significantly. Additionally, we note that some overlapping teams that are shared by two groups exist, such as [L, I, A, E] and [D, H]. Figure 6 (b) shows the corresponding Global Product Development organization network of Figure 6 (a).

	O	*P*	*K*	*N*	*L*	*I*	*A*	*E*	*B*	*Q*	*D*	*H*	*C*	*J*	*F*	*R*	*M*	*G*	*T*	*S*
O	*O*	.80		.90	.91	.82														
P	.73	*P*	.73	.82	.70															
K		.82	*K*	.90	.82	.81														
N	.91	.82	.82	*N*	.80	.91												.20		
L	1.0	.73	.91	.82	*L*	1.0	.13	.30											.13	
I	.82		.70	.91	.91	*I*	.11	.20												
A						.10	*A*	.73	.83	.70	.81	.81								
E					.24	.33	.73	*E*	.81	.73	.73	.73								
B							.86	.70	*B*	.82	.90	.80								
Q			.10			.12	.70	.82	.82	*Q*	.70	1.0								
D							.80	.71	.80	.70	*D*	.71		.15	.10	.13				
H							.72	.73	.82	.91	.81	*H*	.10		.13					
C	.31									.10		.10	*C*	.31	.81	.73	.82			
J											.11		.30	*J*	.16	.11	.51			
F											.20	.10	.80	.17	*F*	.73	.82			
R						.23			.20		.10		.73	.16	.71	*R*				
M													.73	.62	.72		*M*		.20	
G				.32	.13					.12			.30					*G*	.80	.82
T					.21					.15								.73	*T*	.73
S																		.91	.82	*S*

(a) Clustered Organization Design Structure Matrix



(b) Network showing technical communication

FIGURE 6. Clustered organization Design Structure Matrix and network using spectral clustering

By using spectral clustering, it can make the teams with high level of similarity (i.e., strong information exchange) are clustered in one group and simultaneously the interaction relationship between group become weak, which will reduce the management complexity. In the case, even though there is no information exchange between teams R and M, they are still clustered in one group because other teams (e.g., teams C, J, F) have strong information exchange with R and M, which can lead most communication occur in one group and meanwhile the communication cross-groups is reduced. In contrast, if R and M are separated in different group, the information exchange between teams C, J, F with R or M with will occur across-groups which will increase the management complexity.

We adapt Numerical Dependency Density (as described in (17)) [17] to evaluate the degree of clustering, which is the ratio of the total interaction strength (i.e., TIS in the equation) for non-zero elements outside the block (cluster) to the total number of cells outside the block (cluster):

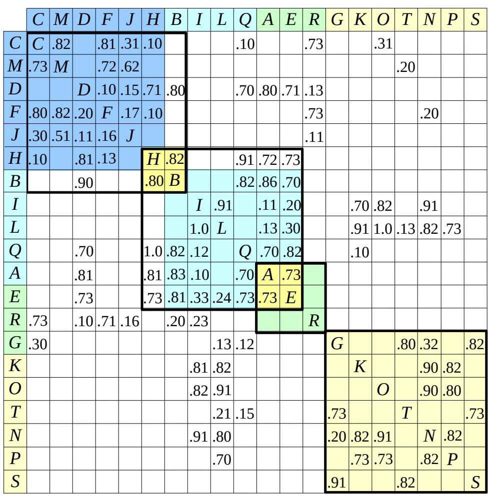
$$NDd = TIS/\mathrm{cell\_out} \tag{17}$$

Table 1 shows the experimental results in which the total coordination cost is used to evaluate the management complexity of Global Product Development project.

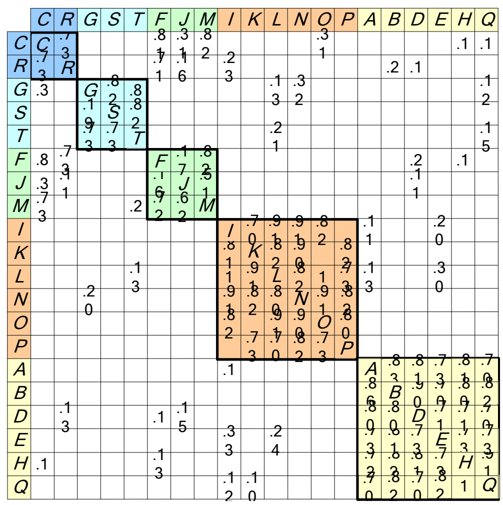
TABLE I. Experimental Results

	Original Design Structure Matrix	Proposed Design Structure Matrix spectral clustering method	Comparison test 1: Sarkar's Design Structure Matrix spectral method	Comparison test 2: minimizing Total Coordination Cost
NDd	-	0.012	0.086	0.036
Number of clusters	-	4	4	5
Marks of outside the cluster	-	14	40	42
Total coordination cost	1281.2	444.7	919.2	516.5

We also compare our proposed clustering methods with two alternative methods: 1) the classic spectral clustering algorithm which uses Gaussian kernel function to measure the similarity between two elements [22]; 2) and a typical Design Structure Matrix clustering method which use the two-stage clustering criteria for minimizing the total coordination cost (TCC) to cluster teams in organization Design Structure Matrix [7], [22]. Firstly, we apply traditional Design Structure Matrix spectral clustering method to original numerical Design Structure Matrix and the results show that many elements can't be clustered in any module (see Figure 7(a)), which indicates that it is inefficient to cluster numerical Design Structure Matrix using traditional spectral clustering method. Further, we apply the minimization of the total coordination cost to cluster the Design Structure Matrix. Results (see Figure 7(b)) show that several clusters are created but there are more external marks (external coordination) outside the clusters than those in the case when we apply our proposed clustering method (see Figure 6 (a)).



(a) Comparison test 1



(b) Comparison test 2

FIGURE 7. Results of comparison test

Through comparing Figure 6 (a) with Figure 7 (a), it indicates our method of measuring similarity index can reflect the Global Product Development process more precisely than traditional spectral clustering method. Our similarity matrix can avoid selecting the scale parameter artificially. Therefore, it is important for project managers to identify an appropriate similarity measurement method for practical situation.

Experimental results are shown in Table 1. Comparing to those in comparison test 1 when traditional spectral clustering method is applied for original numerical Design Structure Matrix, the total marks of outside the clustered numerical Design Structure Matrix is decreased by 65% and the NDd is decreased by 87%, total coordination cost is decreased by 51.6%. Comparing to those in comparison test 2 when the minimization of the total coordination cost is applied for clustering the Design Structure Matrix, the NDd of clustered Design Structure Matrix is reduced by 67% and number of marks of outside the clustered Design Structure Matrix is reduced by 67%, total coordination cost is decreased by 14%. It is clear that the spectral clustering method for organization Design Structure Matrix proposed by this paper outperforms the alternatives.

VI. CONCLUSIONS

A systematic method for integrating Design Structure Matrix (Design Structure Matrix) and spectral clustering method has been presented in this paper. This paper provides a framework for Global Product Development project managers to form a high-efficiency new distributed product development organization using Design Structure Matrix (Design Structure Matrix) and spectral clustering method. In order to optimize a Global Product Development organization, this paper develops a more robust clustering method to improve our understanding and analysis of Global Product Development projects, especially while dealing with open communication within the virtual organization.

Another significant contribution of this paper is that we used the *PageRank* algorithm to identify the "core teams", and then define the integrated similarity matrix so as to utilize the spectral clustering method for clustering the organization Design Structure Matrix. Firstly, technical communication Design Structure Matrix related to product features based on MDM and the corresponding directed weighted network are built. Then a *PageRank* algorithm in which the feature of information flow between teams (i.e., team's information sending/receiving connectivity degree) and team property in Global Product Development projects (i.e., the role in the process of decision making) are taken into account to rank the teams and identify the core teams. Further, we propose concepts of *Receiver Similarity Index* and *Sender Similarity Index* to measure the integrated similarity matrix of Global Product Development teams. Finally, the spectral clustering method with the core teams as the initial clustering center is used to find the global optimal solution, which provides a more robust algorithm and integrated managerial insight for reducing management complexity of the Global Product Development organization.

Several aspects of the model presented in this paper merit further examination. First, the concept of entropy is worth for future research to analyze similarity between activities. Second, this paper's model about identifying core teams involving information connection and the team's role in the decision-making process, which can be more refined. Other factors that influence a teams' position in organization structure can future be researched. Moreover, we use component interface to derive team technical interactions, which is then used to design an organizational architecture. However, organizations are relatively static and should be reorganized after the change of products. We can further research how other factors (e.g., the dependency relationship between activities) influence the technical communication and organization architecture.

REFERENCES

[1] E. Bonjour, J. P. Micaelli, "Design core competence diagnosis: a case from the automotive industry", *IEEE. Trans. Eng. Manag.*, vol. 57, no. 2, pp. 323-337, 2010.

[2] T. Yan, K. J. Dooley, "Communication intensity, goal congruence, and uncertainty in buyer–supplier new product development," *J. Oper. Manag.*, vol. 31, pp. 523–542, 2013.

[3] S. D. Eppinger, T. R. Browning. *Design structure matrix methods and applications*. MIT, Press Cambridge: MA, 2012.

[4] A. Tripathy, S. D. Eppinger, "Structuring Work Distribution for Global," Prod. Oper. Manag., vol. 22, no. 6, pp. 1557–1575, 2013.

[5] R. J. Slotegraaf, K. Atuahene-Gima, "Product development team stability and new product advantage: The role of decision-making processes," *J. Marketing.*, vol. 75, no. 1, pp. 96-108, 2011.

[6] D. A. Batallas, A.A.Yassine, "Technical information Leaders in Product Development Organizational Networks: Social Network Analysis of the Design Structure Matrix," *IEEE. Trans. Eng. Manag.*, vol. 4, pp. 570-582, 2006

[7] S. Kherbachi, "Trust room's of manoeuvre lasting communication in distributed product development projects,"*Econ. & Manag. Res. J.*, vol. 13, no. 2, pp. 129-144, 2020.

[8] D. V. Steward, "Design structure system: a method for managing the design of complex systems," *IEEE Trans. Eng. Manag.*, vol. 28, no. 3, pp. 71-74, 1981.

[9] S. Kherbachi, Q. Yang, "Predicting technical communication in global product development projects related change propagation," *J. Modern Proj. Manag.*, vol. 4, no. 2, pp. 85-89, 2016

[10] M. E. Sosa, S. D. Eppinger, C. M. Rowles, "A network approach to define modularity of components in complex products," *J. Mech. Design*, vol. 129, no. 11, pp. 1118-1129, 2014.

[11] T. Agryzkov, J. L.Oliver, L. Tortosa, J. F. Vicent, "An algorithm for ranking the nodes of an urban network based on the concept of PageRank vector," *Appl. Math. Comput.*, vol. 219, no 4, pp. 2186-2193, 2012.

[12] L. Wang, B. O. Lie-Feng, L. C. Jiao, "Density-sensitive spectral clustering," *Acta Electronica Sinica*, vol. 35, no. 8, pp. 1577–1581, 2007.

[13] S. Kherbachi, "Managing risk of product development projects with similarity of propagation effects," *Eco. Researcher Rev.*, vol. 7, no. 11, pp. 128-146, 2019.

[14] Q. Yang, Y. Lu, S. Kherbachi, "Multi-domain integration of team-product-function and organization clustering in product development project [in Chinese]," *Sys. Eng.-Theory & Practice*, vol. 38, no. 6, pp. 1557-1565, 2018.

[15] S. Kherbachi, Q. Yang, "Multi-domain matrix as a framework for global product development project process," *Proceed. 16th Intern. Dependency & Structure Modeling Conf.*, 2014, July 2-4, pp. 257-265.

[16] M. Maurer, U. Lindemann, "The Application of the Multiple-Domain Matrix," *IEEE Int. Conf. Sys. Man. and Cybernetics*, pp. 2487-2493, 2008.

[17] Q. Yang, S. Kherbachi, Y. S.Hong, C. Shan, "Identifying and managing coordination complexity in global product development project," *Int. J. Proj. Manag.*, vol. 33, no. 7, pp. 1464-1475, 2015.

[18] M. E. Sosa, F. Marle, "Assembling creative teams in new product development using creative team familiarity," *Soc. Sc. Electron. Pub.*, vol. 135, no. 8, pp. 1885-1886, 2013.

[19] R. I., Whitfield, J. S. Smith, A. H. B. Duffy. (2002). Identifying component modules. *Proc. 7th Int. Conf. on Artif. Intell. Design*, Cambridge, UK., pp. 571-592.

[20] T. L. Yu, A. A. Yassine, A. Goldberg, "An information theoretic method for developing modular product architectures using genetic algorithms," *Res. Eng. Des.*, vol. 18, no. 2, pp. 91-109, 2007.

[21] X. Lai, J. K. Gershenson. Representation of similarity and dependency for assembly modularity. *Int. J. Adv. Manuf. Tech*., vol. 37, pp. 803-827, 2008.

[22] S. Sarkar, A. Dong, J. A. Henderson, P. A. Robisnon, "Spectral characterization of hierarchical modularity in product architectures," *J. Mech. Design*, vol.136, no. 1, pp. 249-256, 2014.

[23] M. C. Nascimento, A. C. De Carvalho. Spectral methods for graph clustering–a survey. *Eur. J. Oper. Res.*, vol. 211, no. 2, pp. 221-231, 2011.

[24] L. Shi, J. Malik., "Normalised cuts and image segmentation," IEEE Trans. Pattern Anal.Mach. Intell., vol. 22, no. 8, pp. 888-905, 2000.

[25] S. E. Schaeffer, "Survey: graph clustering," *Comput. Sci. Rev.*, vol. 1, no. 1, pp. 27-64, 2007.

[26] C., Lee, M. N. Hoehn-Weiss, S. Karim, "Grouping Interdependent Tasks: Using Special Graph Partitioning to Study Complex Systems," *Strat. Mgmt. J.*, vol. 37, no. 1, pp. 177-191, 2016.

[27] Alcácer, M. Zhao, "Zooming in: a practical manual for identifying geographic clusters," *Strat. Mgmt. J*., vol. 37, no. 1, pp. 10-21, 2016.

[28] J. Y. Kim, M. Howard, E. C.Pahnke, W. Boeker, "Understanding network formation in strategy research: exponential random graph models," *Strat. Mgmt. J.*, vol. 37, no. 1, pp. 22–44, 2016.

[29] S. Ding, H. Jia, L. Zhang, F. Jin, "Research of semi-supervised spectral clustering algorithm based on pairwise constraints," *Neural Comput. Appl.*, vol. 24, no. 1, pp. 211-219, 2014.

[30] Z. Yu, J. You, L. Li, H. S. Wong, G. Han, "Representative distance: a new similarity measure for class discovery from gene expression data," *IEEE Trans. Nanobiosci.*, vol. 11, no. 4, pp. 341-351, 2012.

[31] Z. Lu, X.Yang, W.Lin, H.Zha, X. Chen. "Inferring user image-search goals under the implicit guidance of users," *IEEE Trans. Circ. Syst. Vid.*, vol. 24, no. 3, pp. 394-406, 2014.

[32] S. T. Collins, J. A.Bradley, A. A. Yassine, "Analyzing product development task networks to examine organizational change," *IEEE Trans. Eng. Manag.*, vol. 57, no 3, pp. 513-525, 2010.

[33] M. E. Sosa, "Linking cyclicality and product quality," *M&SOM-Manuf. Serv. Op.*, vol. 15, no. 3, pp. 473-491, 2012

[34] C. L. Storto, "A Four-Stage Framework for the Identification of Information Flow Inefficiencies in the Manufacturing Environment," *App. Mech. Mater.*, vol. 309, pp. 335-341, 2013.

[35] L. Page, S. Brin, R. Motwani, T. Winograd, "The PageRank Citation Ranking: Bringing Order to the Web," Stanford Info. Lab., vol. 9, pp. 1-14, 1998.

[36] C. Fan, "A brief survey of pagerank algorithms," *IEEE Trans. Netw. Sci. Eng.*, vol. 1, no. 1, pp. 38-42, 2014

[37] D. J. Higham, "Google PageRank as mean playing time for pinball on the reverse web," *Appl. Math. Lett*., vol.18, no. 12, pp. 1359-1362, 2005.

[38] H. Ishii, R. Tempo, "Distributed randomized algorithms for the pagerank computation," IEEE Trans. Automat. Contr., vol. 55, no. 9, pp. 1987-2002, 2010.

[39] K. Lakkaraju, G. Sukthankar, R. T. Wigand, *Social interactions in virtual worlds: an interdisciplinary perspective*, Cambridge University Press, 2018.

[40] S. Kherbachi, "Managing risk of product development projects with similarity of propagation effects," *Econ. Researcher Rev*., vol. 7, no., 11, pp. 128-146, 2019.

[41] S. Kherbachi, Q. Yang, "Modeling change propagation Design Structure Matrix for optimizing product's change". Proceed. of the 3rd Conf. on Comp. Sc. Networks & Infor. Tech., 2017, pp. 105-109.

[42] U. V. Luxburg, "A tutorial on spectral clustering," Stat. Comput., vol. 17, no. 4, pp. 395-416, 2007.

[43] A. Paiement, M. Mirmehdi, X. Xie, M. C. K. Hamilton, " Integrated segmentation and interpolation of sparse data," *IEEE Trans. Image. Process*., vol. 23, no. 1, pp. 110-125, 2014.

[44] A. Y. Ng, M. I. Jordan, Y. Weiss, "On spectral clustering: analysis and an algorithm," *Adv. Neural Inf. Proc. Syst.*, vol. 14, pp. 849–856, 2002.

[45] O. Scekic, M. Riveni, H. L. Truong, S. Dustdar, *Social interaction analysis for team collaboration*. In: Alhajj R., Rokne J. (eds) Encyclopedia of Soc. Netw. Analysis & Mining. Springer, NY: New York, 2018.

[46] C. Y. Lee, H. Y. Chong, P. C. Liao, X. Wang, "Critical review of social network analysis applications in complex project management," J. of Manag. In Eng., vol. 34, no. 2., 2018.

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