Journal of Organisational Studies and Innovation
Vol. 5, no.1, Spring, 2018

A Model to Optimize Knowledge Flow in Team Working

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Abstract: This paper presents a mathematical model with the necessary variables that can serve to identify employees with right knowledge, skills, and abilities to optimize learning in team working. The paper sets out to achieve a bridging of the fields of human resource development and multi-criteria decision making/operations management. The human resource development implications of supplier management are under-explored. After identifying the factors affecting the knowledge flow, supplier involvement was selected as a human resource development practice to optimize the knowledge flow. Based on the Motivation-Opportunity-Ability framework, selecting appropriate members from among the suppliers and buyers was formulated as a multi-objective decision-making model. Using a meta-heuristic algorithm the model was solved. To reach a high convergence and avoid getting stuck in a local optimum point, the evolutionary algorithms were combined with the classical method. To find the Pareto front for non-dominated solutions, the imperialist competition algorithm was utilized. Then, the multi-attitude decision-making model was applied to prioritize these solutions and find the best solution. The results of applying the proposed method for an industrial company showed its effectiveness in selecting appropriate members for supplier involvement. Organizational managers will be able to select optimum members to exchange between suppliers and inner experts to minimize the cost and maximize the expertise for both supplier and buyer. It will increase the success probability of the joint action; facilitate the maintenance of knowledge acquired during the project lifecycle and lead to supplier development. The paper tries to adopt a mathematical and systematic approach to a human resource selection problem which requires a qualitative approach traditionally.
Keywords: *Human Resource Management; Knowledge Flow, Supplier Development, Meta-Heuristic, Imperialist Competition Algorithm*

Introduction

Human resource development (HRD) deals with the training and development of the employees (Werner, 2014). Supplier involvement that is an activity of supplier development was selected as an HRD practice in this paper. This paper focuses on developing mathematical models that can serve to identify employees with right knowledge, skills, and abilities to optimize learning in cross-functional project team working. A cross-functional project team is formed to design or make a process. A cross-functional project team is a group of experts, having been carefully chosen for complementary skills from different functional areas, and willing to achieve the same aim (Clark and Wheelwright, 1992). Usually, organizations run several projects at the same time, faced with a limitation on human resources, so, employees in different departments are given a particular job in one of the projects and will return to their departments after the completion of the project. This is a chance to create a knowledge flow among members from different departments, that are formed by the teams. Previous studies indicate that knowledge sharing in the team has a great effect on the increasing of expertise level (Love and Roper, 2009). Although the problem is contextualized in supply chain literature, it is simply a team composition problem.

It must be considered that employees have different levels of expertise, abilities, and tendency to share and absorb knowledge in a functional unit (Liao et al., 2007). Therefore, selecting suitable persons for a project team can be dependent on the goals such as improving knowledge sharing or reducing time or cost. There are a number of important criteria considered in the selection of of team members including Technical knowledge, personal trait, workgroup experience, communication abilities, culture, leadership, and willingness Most of the previous studies have emphasized on the desired level of technical knowledge (Zhang and Zhang, 2013). In this paper, the Motivation-Opportunity-Ability framework is utilized to formulate the knowledge flow. Many studies show that motivation is the most important factor for knowledge sharing because staffs start knowledge sharing when they can see its benefits (Brown et al., 2016). Although motivation is an important factor, it is not sufficient. The ability to share knowledge is another important factor because knowledge sharing is a difficult task, especially when it comes to sharing of tacit knowledge. At the end, this ability and willingness must pave the way for the flow of knowledge to take place. Organizational culture and framework create the opportunity or barrier for knowledge sharing. Since this is a time-consuming process, the manager must create necessary environmental circumstances to help employees to capture and share knowledge with others (Radaelli et al., 2014).

The paper defines a problem of knowledge flow optimization in a supply chain with supplier and buyer parties. The paper discusses several reasons that buyer and supplier should communicate with each other and hence, both can benefit from knowledge sharing among experts participating in joint projects. The paper considers two objectives, knowledge maximization flow and minimization of difference between expertise levels. An Imperial Competitive Algorithm is utilized to solve the resultant multi-objective problem. Finally, a TOPSIS approach is applied to select the best solution. This paper is structured in five sections. In the next section, the relevant studies are outlined. Section 3 presents a model for selecting the team members using a knowledge flow approach. Then, the problem formulation and the result of the proposed mathematical model are provided and the best choice of composition is determined. In section 4, discussion and contribution for human resource development are outlined. Ultimately, section 5 concludes the paper and the research recommendations will be presented.

Literature Review

The aim of this paper is to formulate the employee selection for teamwork in order to optimize the knowledge flow in supplier involvement. There are two concepts here: supplier involvement as an HRD practice and teamwork selection.

Supplier Development

A major part of supply chain management (SCM) is supplier development (SD). SD seeks to increase the performance or capability of the supply chain. The aim of SD is to satisfy the buyer's short-term and long-term supply requirements (Scannell et al., 2000). In this matter, it can be an HRD practice that is a part of human resource management (Greer et al., 2006). The aim of SD as an HRD practice is to create and continue the competitive advantage across its suppliers. This goal requires systematic and bi-directional efforts to improve the supplier's performance and/or capability (Sako, 2004). Based on this goal, two intermediate goals are described: performance improvement and capability development. The performance approach concentrates on production problem issues for suppliers and tries to make immediate improvements in the supplier's operations. This action is terminated when the supplier's performance meets accepted level of buyer's requirement. In contrast, the capability approach focuses on continuous improvement by developing the supplier's capabilities such as cost, quality, delivery and technical capability. In addition to identifying and solving the supplier's problems, the buyer's development team can target specific supplier capability which needs to be upgraded for continuous improvement. Sako (2004) states that this approach tries to transfer a few aspects of in-house buyer capabilities out of the organization. These two approaches mentioned above differ in some respects, such as the degree of a buyer's investment and supplier's involvement. However, both are knowledge-based and require the knowledge flow between the buyer and supplier. Development activities in SCM are composed of low-involvement activities, such as creating competitive pressure and evaluating a supplier's performance regularly, or high-involvement activities, such as providing a supplier with specific training programs and involving the supplier in new product development (Chen Liang et al., 2015). SD has been selected as a successful strategy for many companies (Marksberry, 2012). For example, U.S. auto industry utilized the supplier diversity program as an HRD practice (Greer et al., 2006). SD increases a supplier's capabilities such as technical, quality, delivery, and cost capabilities, thus improving its performance such as financial, operational, and market performance (Lawson et al., 2015). Besides, SD leads to the buyer's continuous improvements (Scannell et al., 2000). SD activities are, to a large extent, related to knowledge (Chen Liang et al., 2015). These activities are composed of both tacit and explicit knowledge. The amount of these types may differ depending on the activity. Based on the SECI model proposed by Nonaka and Takeuchi, sharing tacit knowledge takes place through social interactions such as face-to-face communication whereas explicit knowledge flows more easily.

The flow of knowledge may be from buyer to supplier. In other words, the supplier learns from the buyer. In some cases, the buyer may send its employees to the supplier's facility to offer training or the buyer may set in-house training sessions for the supplier (Carr et al., 2008) or involve the supplier in the buyer's new product design team (Lindgreen et al., 2009). The review of literature indicates several activities are commonly performed for SD such as supplier evaluation, supplier training, direct incentive, performance expectation, financial assistance, physical asset support, technical assistance, managerial assistance, information sharing, supplier rating, supplier involvement, plant visit, invite supplier to visit, dynamic communication, supplier certification, competitive pressure, co-location, supplier council, quality-focused supplier selection, increase supplier intensity, community of suppliers, promise of business, supply rationalization, quality assurance, employee exchange, clear specification, trust building, evaluation feedback, joint action, buyer's involvement (Chen Liang et al., 2015). One approach for learning is employee engagement which is an emerging, motivation-like field in HRM (Shuck et al., 2014). Employee engagement is sensible in some of those activities and takes place in some forms to create knowledge flow between the buyer and supplier. Supplier involvement means involving suppliers in some activities such as new product design. Co-Location assigns support personnel to the supplier's facilities or guest engineers. Joint Action is collaboration/cooperation/work with suppliers in some areas. Buyer's Involvement is collaboration or coordination of the buyer in supplier's business, e.g. process improvements, planning, and goal-setting activities, etc. In supplier involvement, they are able to learn from each other and communicate face-to-face and share even more tacit information during their residence with the other firm (Wagner and Krause, 2009). In some cases, the buyer has been involved in supplier's product development process (Forker, 1997). In this case, the flow of knowledge is from supplier to buyer. in other words, the buyer learns from the supplier.

Learning is categorized into formal, informal, and incidental (van Rooij and Merkebu, 2015). Supplier training which provides training or education to supplier's personnel in any area is a formal form of learning (McGuire and Gubbins, 2010). Sharing resources, social media, and participation in communities are informal learning forms. Team-working on a project or trial-and-error use of a product are examples of incidental learning (van Rooij and Merkebu, 2015).

Teamwork Selection

Teamwork selection process is examined in the HRM literature in order to meet the needs, and reaching organization goals (Sheehan and Anderson, 2015). Table 1 shows some of these efforts. In each research, an aspect of team selection is considered.

Table 1. Criteria for team member selection

Focused area	Reference
The common understanding in the team	(Majchrzak et al., 2012)
- Human and soft factors (such as technical expertise, communication skills, problem-solving abilities, and decision-making skills) - Non-human and hard factors (such as budget and time constraints)	(Baykasoglu et al., 2007)
- Customer requirement - Engineering characteristics	(Zzkarian and Kusiak, 1999)
- Multifunctional knowledge, teamwork capability (including teamwork experience, communication skills, and flexibility in job assignments), - Working relationships (working relationship between the team members based on the Myers-Briggs Type Indicator)	(Chen Shi-Jie Gary and Lin, 2004)
Multi-functional teams in uncertain conditions	(Tseng et al., 2004)
- Multi-functional skill requirements - Innate tendencies :Kolbe Co-native Index (synergy, inertia, and stability)	(Fitzpatrick and Askin, 2005)
talent, strategic integration, cultural relevance, knowledge management, and leadership	(Bozbura et al., 2007)
Work experience, problem-solving ability, technical knowledge, interior organizational collaborative performance, and exterior organizational collaborative performance.	(Fan et al., 2009)
Multi-functional knowledge, teamwork ability, and working relationships	(Mazur and Chen, 2011)
Comprehensive capabilities and interpersonal relationships (expertise and experience, learning and knowledge sharing, communication, and problem-solving by using MBTI to quantitatively predict the collaboration ability of individuals with different personalities	(Zhang and Zhang, 2013)
Knowledge sharing factors (motivation, opportunity, and ability to share)	(Hosseini et al., 2016)

Table 1 shows that the formation of the team is based on the technical knowledge, and psychological / sociological competencies (such as personality, leadership, communication skills, and decision-making ability). However, the goal of team formation may differ in some cases. For example, the previous studies have not considered knowledge flow as a goal. The aim of supplier involvement in the buyer project team is training and developing supplier. Thus in the present study, , the main goal of team formation is knowledge flow.

First, the MOA factors are utilized to model the appropriate selection of team members. The goal is maximizing knowledge flow inside and outside the team. In addition, based on the main goal, the second objective is to reduce the difference of expertise levels in supplier side and buyer. This objective is meant toto balance the expertise in and out of the organization, and to increase learning.

Methodology

The Statement of the Problem

During the project's lifecycle, the members can exchange knowledge in non-expertise domains with other project team members from different departments and suppliers and can share knowledge in expertise domains with their colleagues in their respective departments or suppliers. However, the expertise level, personality trait and technical knowledge of the

employees within a single functional unit may be different. A higher expertise level of the selected person for the project team can increase the level of expertise of the team and create the opportunity for the other member to learn. This triggers the flow of knowledge from external expert member to team. If a lower expertise level person is selected for the project, the team can create the opportunity for him/her to learn from other members. This produces the flow of knowledge from team expert to an external unit (internal departments or suppliers).
Motivation-Opportunity-Ability framework states that team members have different motivations, opportunities, and abilities for knowledge sharing and absorption (Hosseini et al., 2016). A person with high capability of absorbing knowledge may be able to capture more knowledge from other members, or through performing specialized tasks in the project. On the other hand, a person with a greater knowledge-sharing ability will be able to share the knowledge more. Both knowledge sharing and knowledge absorbing will take place if both the sender and the receiver have an opportunity for knowledge sharing or absorption. This sharing/absorbing creates the flow of knowledge. Therefore, four types of knowledge flows may take place. 1) Team members capture knowledge in the domain of expertise by doing specialized tasks in the project. 2) Team members share knowledge among the project in the domains of expertise or knowledge acquisition from other teammates in the domains of non-expertise. 3) Team members share knowledge with their non-member colleagues in their related units (internal departments or suppliers) in the domain of expertise. 4) Team members share knowledge with their non-member colleagues in their respective units in domains of non-expertise.

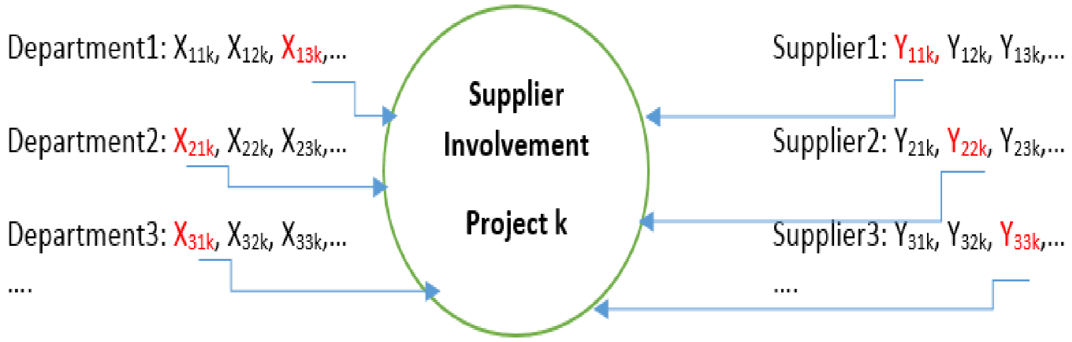

Figure1. Member assignment for supplier involvement project

In Figure 1, three different departments and three suppliers are displayed. In this figure, candidate *j* from the internal department *i* for project *k* is shown by symbol X_{ijk}. For example, candidate 1 from functional department 2 for project 3 has been exposed by symbol X_{213}. Candidate *j* from supplier *i* for project *k* is shown by symbol Y_{ijk}.
The model concentrates on selecting the suitable employee from the suppliers and internal departments to achieve two main objectives: 1) to Maximize the four types of knowledge flows among team members. 2) and to Minimize the different level of expertise in the suppliers and internal departments. In fact, the first objective is the maximization of knowledge flow, which means one has to select experts from the buyer and supplier with the maximum difference between their levels of knowledge. But, the differences between the buyer and suppliers must be controlled to ensure the team is successful in performing the assigned project. For the second objective, the model tries to minimize the difference of expertise. In other words, through the second objective the level of experts are balanced and then, the knowledge flow is minimized, which is in contrast to the first objective. The algorithm finds the best choice for this trade-off in two phases. First, the non-dominated solutions are evaluated by a meta-heuristic approach and then, the best solution is selected by a multi-attitude decision-making approach.

Problem Formulation

Symbols and Assumptions

The symbols related to the decision variables are given in Table 2.

Table 2. The symbols used for variables in the mathematical model

Description	Symbol
=1 if candidate *j* from internal department *i* is selected for the project team *k*; = 0 Otherwise	X_{ijk}
=1 if candidate *j* from supplier *i* is selected for the project team *k*; =0 Otherwise	Y_{ijk}
Knowledge-absorption ability of candidate *j* from unit (internal or external)i.	α_{ij}
Knowledge-sharing ability of candidate *j* from unit *i*.	β_{ij}
Willingness for knowledge sharing of individual *j* from unit *i*.	ω_{ij}
Motivation for knowledge absorption of candidate *j* from unit *i*.	θ_{ij}
Opportunity for knowledge sharing /absorption of individual *j* from unit *i*.	φ_{ij}
Knowledge flow common ability of candidate *j and m* from unit *i* $(m \neq j)$	CC_{ijm}
Expertise level of candidate *j* from unit *i*.	E_{ij}
New expertise level of candidate *j* from unit *i* after doing the task.	nE_{ij}
Expertise level coefficient for the project	λ
The required level of expertise to perform tasks in the domain of *i* in the project *k*.	R_{ik}
The amount of knowledge acquired by candidate *j* (from unit *i*) from other project team members.	KS_{ij}
Cost of doing job of unit *i* in project *k* with mediate expertise level	C_{ik}
Cost of supplier involvement for supplier *i* in project *k*	C'_{ik}
Expertise effect coefficient on cost of doing task for candidate *i* in unit *j*	ρ_{ij}
Expertise effect coefficient on time of doing task for candidate *i* in unit *j*	τ_{ij}
The minimum of workload to delivery task in time for candidate *j* of unit *i* in project team *k*	rwl_{ijk}
The maximum of workload can be assigned to a member	$MAXWL$
Budget for project team *k*	B_k
Extra budget for supplier involvement for project team *k*	B'_k

The Amount of Knowledge Flow

In the supplier involvement teams, there are members from different departments and suppliers with different specialties. They work altogether to achieve particular objectives, while learning from one another. While doing tasks, each member shares the new knowledge gained with other team members. In the flow of knowledge between two nodes, one side is the knowledge provider (sharer) and another side is the knowledge recipient (acquirer). MOA framework states that the amount of knowledge flow between nodes depends on sharer and acquirer. The Sharer should have the sharing ability along eith the willingness to share knowledge, and the acquirer should have the absorption ability and the necessary motivation to capture knowledge. In addition, both sides of the flow should have the chance for knowledge sharing or absorption. The Lack of any of these motivations, opportunities or abilities has a negative impact on the knowledge sharing level (Siemsen et al., 2008). Moreover, if one factor is not present (e.g., there is a lack of opportunity), the existence of the other two factors cannot compensate for the lack of the third. Therefore, to initial the knowledge flow, all requirements (motivation, opportunity, and ability) must be met at the same time. Therefore, the knowledge flow common ability was defined as the minimum of knowledge-absorption ability of acquirer and knowledge-sharing ability of sharer.

$$CC_{ijm} = \text{Min}((\beta_{ij}\omega_{ij}\varphi_{ij}), (\alpha_{im}\theta_{im}\varphi_{im})), j \neq m \tag{1}$$

The team member gains new knowledge and skills in his/her domain of expertise through performing tasks. However, the amount of the knowledge and skills captured depends on his/her initial expertise level and the expertise level coefficient in the project. Thus, the amount of knowledge gained by the project team members via performing tasks can be calculated by:

$$KS_{ij} = \sum_{\substack{m, \\ m\neq j}} \sum_{k} \lambda E_{im} CC_{ijm} (X_{imk} + Y_{imk}), \quad \forall\, i, j \tag{2}$$

While doing the task and after completing the task, the expertise level will be improved by sharing knowledge and new self-experience. New expertise level of candidate *j* from unit *i* was obtained by:

$$nE_{ij} = E_{ij} + \sum_{k} \lambda E_{ij} (X_{ijk} + Y_{ijk}) + \sum_{\substack{m, \\ m\neq j}} \sum_{k} \lambda E_{im} CC_{ijm} (X_{imk} + Y_{imk}), \quad \forall\, i, j \tag{3}$$

3.2.3 *Objective Functions*

The first objective of the model is to maximize knowledge flow inside and outside the team.

$$\text{Max} Z_1 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{\substack{m=1, \\ m\neq j}}^{M} \sum_{k=1}^{K} \lambda E_{im} CC_{ijm} (X_{imk} + Y_{imk}) \tag{4}$$

The second function objective is set to minimize the differences in the expertise level of the internal units and suppliers.

$$\text{Min} Z_2 = \left(\sum_{i} \sum_{j} E_{ij} X_{ij}, - \sum_{i} \sum_{j} E_{ij} Y_{ij}, \right)^2 \tag{5}$$

3.2.4 *Constraints*

The first constraint shows the number of members to do a specific task in a team. In this study, one employee was selected from each internal department and one from each supplier (each supplier considered as one unit).

$$\sum_{j=1}^{J} X_{ijk} = 1, \quad \forall\, i, k, \tag{6}$$

$$\sum_{j=1}^{J} Y_{ijk} = 1, \quad \forall\, i, k,$$

The second constraint is the minimum expertise level needed to do the tasks. There is no constraint for the expertise level of the supplier candidates. They may have every level of expertise. The goal is to maximize the flow. If the supplier expertise is lower than team level, the supplier learns from the buyer. If the supplier expertise is more extensive than team level, the buyer learns from the supplier.

(7)
$$(E_{ij} - R_{ik})X_{ijk} \geq 0, \quad \forall\, i, j, k,$$
Because of the limitation in human resources, an employee can be assigned to more than one team. The next constraint ensures that each candidate should at least be selected by one team.
(8)
$$\sum_{k=1}^{K} X_{ijk} \geq 1, \quad \forall\, i, j,$$
Supplier involvement is costly. The buyer dedicates the budget for this involvement. The below constraint prohibits from the dedicated budget.
(9)
$$\sum_{i=1}^{I}\sum_{j=1}^{J} \rho_{ij}(C_{ik}X_{ijk} + C'_{ik}Y_{ijk}) \leq B_k + B'k, \ \forall k,$$
An employee can be assigned to more than one project. The constraint below ensures that the assigned tasks are not more than the standard level.
(10)
$$\sum_{k=1}^{K} rwl_{ijk}(X_{ijk} + Y_{ijk}) \leq MAXWL, \ \forall\, i, j, \text{Where, } rwl_{ijk} = \frac{\tau_{ij}T_{ik}}{DL_{ik}}$$

T_{ik}, is the time needed to do the job with mediate expertise level, DL_{ik}, is the task delivery time limit and τ_{ij} is expertise level coefficient on duty time. A higher level of expertise brings about a lower time required for the job to be done. Decision-making variables are binary. The last constraints determine the type of the variables.
(11)
$$X_{ijk}, Y_{ijk} \epsilon \{0,1\}, \quad \forall\, i, j, k.$$

Solution Procedure

The Classical problem solution of multi-objective optimization is can be performed through exact and non-exact approaches. The Classic approaches have several problems. Most of these methods consider the local optimal point as the global optimal point in general by mistake, as illustrated in Figure 2.

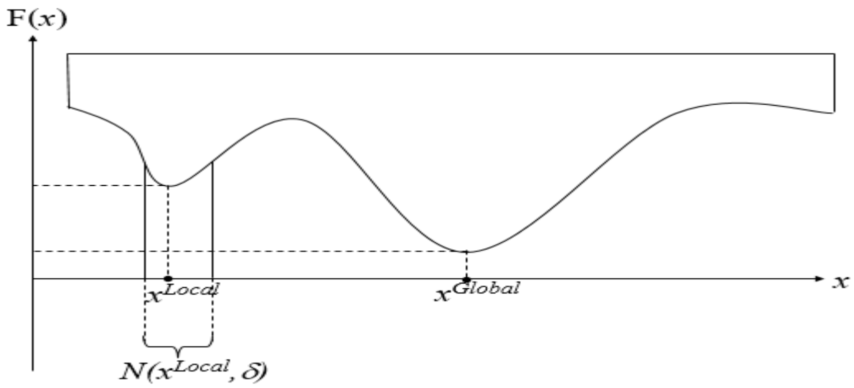

Figure 2. The local optimal point and the global optimal point

Another problem is that each of these techniques is used only for a particular issue. The next point to be considered is the complexity function of the problem. The number of internal departments and suppliers, the number of employees in each department and supplier, and the number of projects determine the answer space in this model. The introduced model is nonlinear, too. By increasing these numbers, the answer space show a rapid growth. The problem could not be optimally solved by an algorithm in a polynomial time. In NP (Non–deterministic Polynomial) issues such as TSP (Travelling salesman problem), knapsack ,Job Shop Scheduling, the increase in in complexity, and the computational models require a lot of time. Recently, evolutionary algorithms proved useful for solving the multi-object optimization models (Leong and Hensher, 2012). Evolutionary algorithms have advantages over traditional techniques. For example, considerations such as the convexity or continuity of functions are not necessary. Evolutionary approaches have the feature of escaping from the local optimum point. In contrary, classical methods have more convergence speed. In order to have a high convergence but no stuck in a local optimum point, one needs to implement a common approach which combines evolutionary algorithms with classical methods, such as the Newton optimization method. In this paper, the imperialist competition algorithm (ICA) is used (Atashpaz-Gargari and Lucas, 2007).

Imperialist Competition Algorithm

The socio-political evolution of human has provided inspiration for imperialist competition algorithm. It has been utilized for solving of some optimization problems successfully (Amiri et al., 2014; Atashpaz-Gargari & Lucas, 2007; Khabbazi et al., 2009; Tavakkoli-Moghaddam et al., 2013; Xu et al., 2014; Yousefi et al., 2011). Usually, evolutionary algorithms start with a number of random initial population. The name of this set may differ. ICA called it "country". Some of the best elements of the population (the equivalent of elites in the genetic algorithm) are selected as imperialists and the rest of the population are considered as the colony. All the imperialists try to take possession of colonies by competition and assimilation policy.

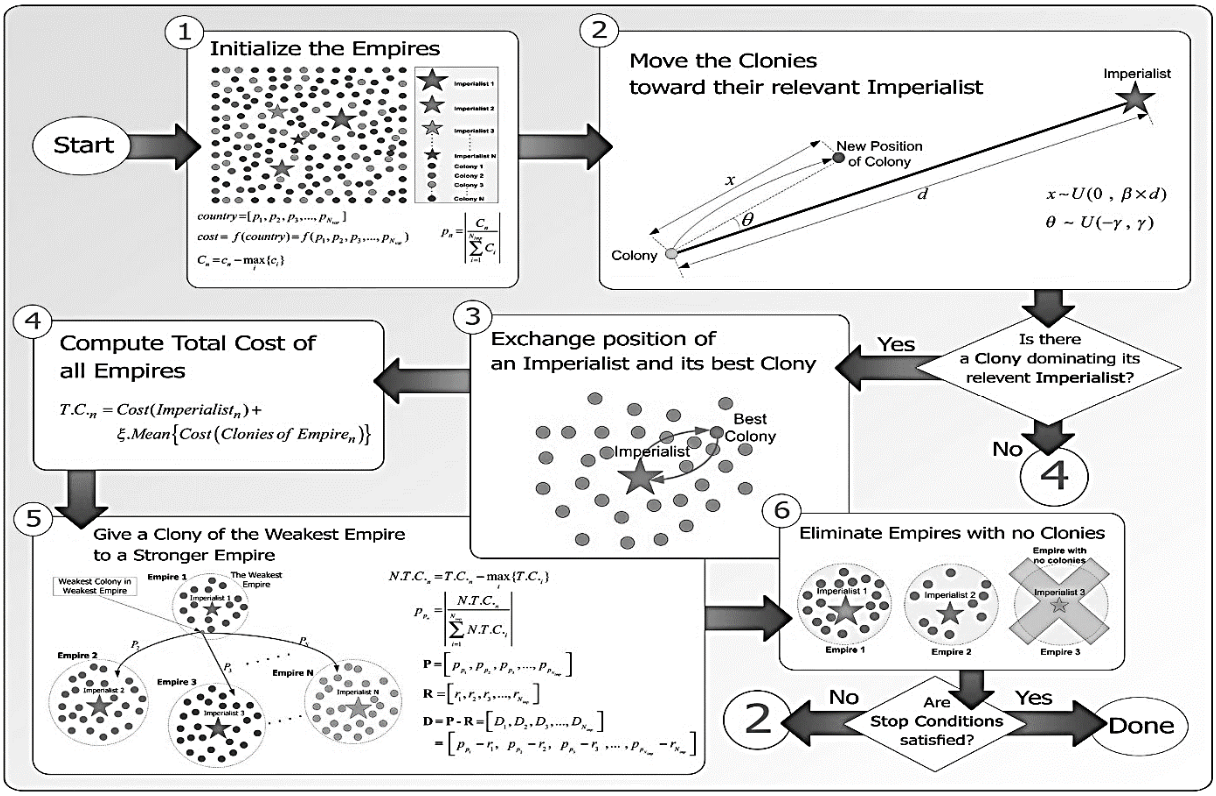

Figure 3. The schematic of imperialist competition algorithm (Atashpaz-Gargari and Lucas, 2007)

The ICA is based on some concepts: 1) Assimilation: as shown in stage 2 of the figure, imperialist states transfer their attitudes such as the culture in their colonies, for example, by making schools in their own mother language and... 2) Revolution: a sudden change in socio-political characteristics of a country. 3) Exchanging positions of the imperialist and a colony: in stage 3 of the figure, a colony may reach a better position with a lower cost than may imperialist while moving toward it. Here, the imperialist and colony exchange their position. 4) Imperialistic competition: in stage 5, all empires try to take possession of colonies of other empires and control them. The power of the imperialist country has a major effect on the total power of an empire while the power of the colonies of an empire has a mirror effect on the total power of that empire. This is modeled by the total cost function. Primary ICA was developed for numerical function optimization. Some modifications were done to solve discrete problems based on the work by Xu et al. (2014). The effectiveness is verified by standard benchmark instances (Xu et al., 2014). The algorithm can be outlined as below (Atashpaz-Gargari and Lucas, 2007):

i. Initialize the population: create arrays of countries by selecting some random points on the functions. Select some of the best points as the empires calculate the cost of each empire. Set colonies for each imperialist based on its power by random.
ii. Do assimilate: Try to improve an answer to the best-related answer. Create a random generated binary string array, stri, copy cell i of imperialist to cell i of the colony if str i =1).
iii. Exchange the positions of the colony and imperialist in case a colony has a lower cost than the related imperialist.
iv. Compute the total cost of all empires (the total power of an empire is the imperialist power in addition to a portion of their colonies' power).
v. Do competition: Select a colony from the weakest empire. Calculate the normalized total cost of an empire and create P vector, the possession probability of each empire by normalized total cost. Assign the selected colony to an empire based on D vector.
vi. Eliminate the powerless empires: consider an empire as a colony if it loses all of its colonies.
vii. If the algorithm is reached its maximum decades stop, if not go to ii.

Input Parameters, Reliability, and Validity

A case study of a large industrial company is presented in this section. This company has high-level experts and skillful employees. It works with many suppliers who cover a wide variety of expertise and domain. In addition, the employees of this company have received extensive training. There is a competition from the other firms to absorb these experts. Therefore, developing this wide supplier network and losing the knowledge and expertise stored in the mind of internal forces in case of leaving the company are important considerations for managers. If a suitable selection of proper employees is made, it is possible to decrease Knowledge accumulation in the company and, at the same time, increase the flow of knowledge between buyer and supplier. This company intends to involve the suppliers in some projects. The teams consist of members from different internal departments and suppliers.
the data required for each candidate were gathered by a 360-degree assessment instrument (self-assessment, peer-assessment, and supervisory assessment). Questionnaire items utilized the 5-degree Likert Scale. The expertise levels of candidates were classified into novice, beginner, competent, professional, and expert. The required data were gathered through a survey among the experts in the project's specialized domains. In This paper true measurement scales and frameworks developed in the previous studies were implemented. The parameters and measurement scales are shown in Table 3.

Table 3. Measurement scales for the parameters of the model

Parameter	Questionnaire references
Candidates ability for knowledge absorption	Chang Lee et al. (2013)
Motivation of candidates for knowledge absorption	Tsai et al. (2007)
People Ability and willingness for knowledge sharing	Radaelli et al. (2014)

Candidates Opportunity for knowledge sharing /absorption	Siemsen et al. (2008) and Radaelli et al. (2014)
Expertise level of candidates	Dreyfus and Dreyfus (1986)

The full characteristics of the candidates and requirements of the teams are outlined in the attachment. Table 4 summarizes the data just for one department.

Table 4. Characteristics of the candidates

Opportunity for sharing/absorption (φ)	Motivation for absorption (θ)	Willingness for sharing (ω)	Sharing ability (β)	Absorption ability (α)	Expertise level (E)	Candidates	Units (internal departments and suppliers)
0.64	0.69	0.69	0.69	0.68	3.5	Candidate1	Department 1
0.64	0.87	0.88	0.89	0.88	4	Candidate2	
0.82	0.63	0.62	0.62	0.61	3	Candidate3	
0.62	0.70	0.63	0.65	0.63	3.5	Candidate4	

Table 5 shows the data for just one project team. Each project is composed of many tasks and processes. These jobs are divided among groups and each group has been assigned to one employee of a department or one form a supplier.

Table 5. Project requirements

Project budget *(B_K)*	**Task delivery Time** *(DL_{ik})*	**Time to do job with mediate expertise level** *(T_{ik})*	**Cost with mediate expertise level** *(C ,C')*	**Required level of expertise** *(R)*	**Units**	**Teams**
450	100	92	44	3	Department1	Project 1
	105	97	46	4	Department2	
	120	105	50	3	Department3	
	110	103	49	3.5	Department4	
	100	92	44	4	Department5	
	140	130	62	3	Supplier1	
	120	111	53	3.5	Supplier2	
	85	78	37	3.5	Supplier3	
	90	82	39	2.5	Supplier4	
	120	111	53	3	Supplier5	
	115	105	50	3.5	Supplier6	

The coefficient of expertise level was estimated by comparing the current level of expertise and experience of the people based on project management office databases. First, five experts with experience in carrying out the projects were extracted from the database. Each expert has an average of 10 experiences. Therefore, impact factor to increase the level of expertise per project is considered λ=0.1. In order to estimate the impact of the expertise level on the time and cost of tasks, the linear approximation was utilized based on the expert's judgment. Based on the average judgments of experts, it was shown that if the level of expertise is novice the required time of the task and the cost of the task were increased by 8% and 9%, repectively. However, The expertize level can decrease 9% of the required time of the task and decrease 11% of the cost of the task. The management decided to assign the extra budget for supplier involvement equal to 30 (B') for each project.

In order to ensure the reliability of measurement tools, ten researchers in the field of knowledge management investigated the wording of the questionnaire in terms of content, ambiguity, and others. Their feedbacks were used to make the necessary modifications in the final questionnaires. To assess the internal consistency in the questionnaire, some 20 questionnaires were distributed among experts in the fields of study. The gathered data were analyzed by SPSS software. The Cronbach's alpha measures were in the range of 0.724 to 0.813 showing a high reliability of measurement tools, which is far more than the acceptable level of 0.7.

ICA Results

After the input parameters were collected, the fixed internal parameters of the ICA algorithm were regulated according to the best choices in solving problems by this algorithm (Tavakkoli-Moghaddam et al., 2013). Pareto optimum answers from the implementation of the algorithm were listed in Table 6. The algorithm is trying to reach the Pareto optimum different solution. The old methods have some drawbacks; including not finding the several optimal answers during a time of the algorithm, does not guarantee to find the different optimal answers and the impossibility of the application in issues with discrete variables.

Table 6. List of the alternatives for team selection

<table>
<tr><th>Z_2^*</th><th>Z_1^*</th><th>Option</th><th>$X^* = [X_{1j1}^* \dots X_{1j5}^* \vert X_{2j1}^* \dots X_{2j5}^* \vert \dots \vert X_{11j1}^* \dots X_{11j5}^*]$</th></tr>
<tr><td>0.966</td><td>11.949</td><td>ALT 1</td><td>[2 2 4 3 1 | 3 1 2 3 1 | 1 4 3 1 3 | 1 3 3 2 2 | 3 2 3 3 1 | 3 2 3 4 1 | 4 2 2 3 1 | 1 3 1 2 4 | 3 1 2 1 3 | 4 1 2 1 3 | 1 2 1 2 3]</td></tr>
<tr><td>0.275</td><td>16.363</td><td>ALT 2</td><td>[4 2 2 3 1 | 1 3 2 1 2 | 4 1 3 2 4 | 3 2 3 2 1 | 1 2 3 1 3 | 3 1 1 4 2 | 2 4 2 1 3 | 1 4 2 3 3 | 1 3 2 3 1 | 2 1 4 3 4 | 2 2 3 1 2]</td></tr>
<tr><td>0.224</td><td>17.224</td><td>ALT 3</td><td>[1 3 3 4 2 | 3 3 2 1 1 | 2 4 4 1 3 | 1 2 2 3 1 | 1 2 3 1 3 | 3 1 4 4 2 | 1 3 4 2 3 | 3 1 4 2 4 | 3 3 2 1 2 | 1 2 4 2 3 | 1 1 2 2 3]</td></tr>
<tr><td>1.833</td><td>10.179</td><td>ALT 4</td><td>[4 1 4 2 3 | 3 3 2 1 1 | 2 4 4 1 3 | 2 2 3 1 3 | 1 2 3 3 2 | 3 2 2 1 4 | 2 1 3 3 4 | 1 3 2 3 4 | 1 3 2 2 1 | 2 1 4 3 2 | 1 2 2 1 3]</td></tr>
<tr><td>1.193</td><td>11.334</td><td>ALT 5</td><td>[2 1 4 3 3 | 3 3 2 1 1 | 4 1 3 2 4 | 3 2 3 2 1 | 1 2 3 1 1 | 3 1 4 4 2 | 1 4 1 3 2 | 3 4 3 2 1 | 2 1 2 3 2 | 3 2 4 1 3 | 1 2 2 2 3]</td></tr>
<tr><td>0.033</td><td>27.706</td><td>ALT 6</td><td>[2 1 4 4 3 | 3 3 2 1 1 | 2 4 4 1 3 | 3 2 1 2 3 | 1 2 3 1 3 | 3 1 4 4 2 | 1 3 4 2 3 | 3 1 4 2 4 | 3 2 2 1 1 | 2 1 4 3 2 | 1 2 2 1 3]</td></tr>
<tr><td>0.026</td><td>29.384</td><td>ALT 7</td><td>[2 1 4 4 3 | 3 3 2 1 1 | 2 4 4 1 3 | 1 2 3 2 3 | 1 2 3 3 2 | 3 1 2 3 4 | 2 1 3 3 4 | 1 3 2 2 4 | 1 3 2 2 1 | 2 1 4 3 2 | 1 2 2 1 3]</td></tr>
<tr><td>0.851</td><td>12.331</td><td>ALT 8</td><td>[1 3 2 4 2 | 3 3 2 1 1 | 4 1 3 2 4 | 1 2 3 2 3 | 1 3 2 3 3 | 3 2 1 4 3 | 4 3 2 2 1 | 1 1 3 2 4 | 3 3 2 1 1 | 4 1 2 1 3 | 1 1 2 2 3]</td></tr>
<tr><td>1.382</td><td>10.924</td><td>ALT 9</td><td>[1 3 2 4 2 | 3 3 2 1 1 | 2 4 4 1 3 | 1 2 3 2 3 | 1 2 3 3 3 | 3 2 1 4 3 | 4 3 2 2 1 | 1 1 3 2 4 | 3 3 2 1 1 | 4 1 2 1 3 | 1 1 2 2 3]</td></tr>
</table>

Table 6 shows nine different alternatives for team formation. It is very difficult to show all binary variables in the table. The model has five internal departments and six suppliers (eleven units) and five project teams. All eleven units are divided by | symbol in the table. For example, ALT 1 ([2 2 4 3 1 |) shows that the second employee of the first unit is assigned to the first project team. The second employee of the first unit is assigned to the second project team again. The forth employee of the first unit is assigned to the third project team. The third employee of the first unit is assigned to the fourth project team and the first employee of the first unit is assigned to the fifth project team. Values for two objective functions were calculated. None of the answers was dominated. The primary defined model was Max-Min. To better coding and presentation, the model was changed to Max-Max form by reversing the second objective function in order to have a better coding and a clear presentation.

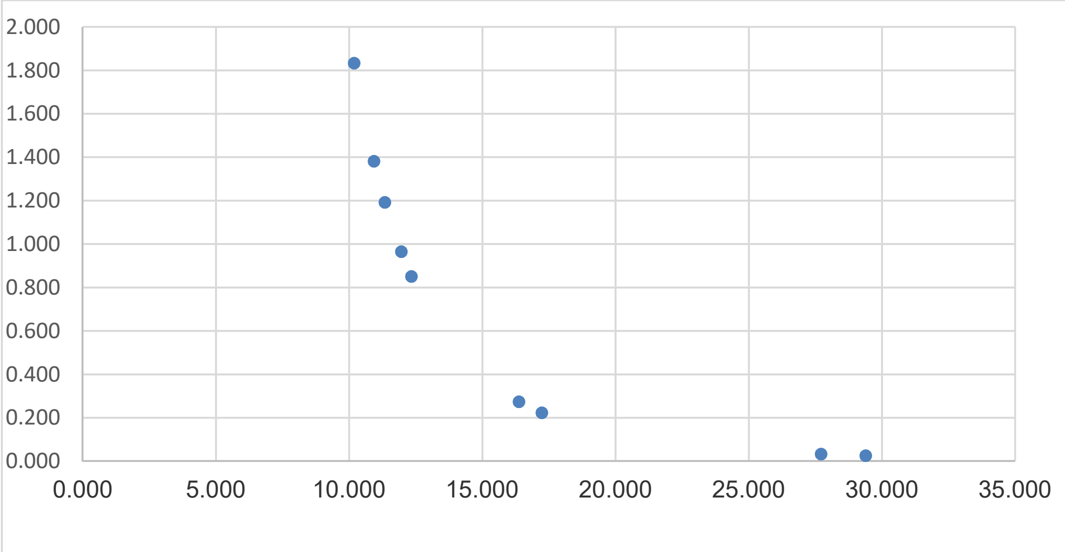

Figure 4. Pareto front for non-dominated solutions in Max-Max form

Multi Attitude Decision-Making Process

Multi-objective decision-making (MODM) methods are utilized to explore the effect of different factors on the objectives. The objective of this paper is to maximize knowledge flow in and out of the organization, and to minimize the difference of expertise levels in the supply chain. So, the problem of selecting team members was formulated as a bi-objective optimization model in this paper. Nine options were calculated in the previous section. Pareto answers were created that shows different combinations of the workforce to participate in the teams. Managers can weigh the goals with regard to their preferences, then a suitable combination for partnership could be specified. Multi-attribute decision-making (MADM) methods are employed to evaluate the different alternatives such as simple additive weighting (SAW) or pairwise comparisons of alternatives like AHP. Multi attitude decision-making process was conducted as follows.

Alternatives, Indices and Decision-Making Methods

In the diagnosis and evaluation phase, options and indicators of decision - making, and methods for prioritizing options or final choice are selected. In the final stage, options are evaluated in front of indicators by decision–makers (Hajkowicz et al., 2000). There are three qualitative and quantitative indicators with both negative and positive aspects. The first index is maximizing the objective function. It is a quantitative index with a positive aspect (the greater value is desirable). The second index is minimizing the difference in expertise level. It is a quantitative index with a negative aspect but this paper utilized the reversed function**.** So, the greater value is, the more desirable. Another index was added to each option. as mentioned before, ability and willingness must pave the way for the flow of knowledge to take place. Organizational culture, framework and other circumstances create the opportunity or barrier for knowledge sharing. Although The ability and motivation were calculated, there are other risks in team working based on the cultural and structural attributes. These risks may vary from organization to organization . So, the paper declared an index as the consistency risk of choice. It is a qualitative index with a negative aspect. Nine Pareto answers were selected as options (alternatives). For each option, the third index was calculated. The TOPSIS method was selected to prioritize the options. The Decision matrix along with the index values for each option is presented in Table 7. Consider that the second objective was reversed to have the Max-Max form. So, the greater value in IX2 is considered desirable.

Table 7. Matrix decision to evaluate the options against characteristics

Options	Maximizing knowledge flow(IX1)	Minimizing the difference in expertise level – reversed (IX2)	Consistency risk of choice (IX3)
ALT1	11.949	0.966	Very much
ALT2	16.363	0.275	Very much
ALT3	17.224	0.224	Very much
ALT4	10.179	1.833	much
ALT5	11.334	1.193	much
ALT6	27.706	0.033	mediate
ALT7	29.384	0.026	low
ALT8	12.331	0.851	Very low
ALT9	10.924	1.382	Very low

Scale of Measuring Indicators and Changing a Qualitative Index to Quantitative

In this study, there are both a quantitative index (maximum of knowledge flow and minimize the difference of expertise level) and a qualitative index (consistency risk of choice). This paper converts the qualitative into a quantitative index through a bipolar distance scaling (Shojaefard et al., 2016). In the decision matrix index, IX3 was quantitated based on the bipolar scale (9, 7, 5, 3 and 1).

Normalization of Measures

The scales for measuring indices are different. One index calculates the amount of shared knowledge. Another index calculates the difference of expertise level. the normalization of the scales is required before mathematical operations. There are some methods for normalization such as linear or vector. In the linear method, for an index with a positive aspect, the equation 12 is used while, for an index with a negative aspect, the equation 13, is utilized.

$$n_{ij} = \frac{r_{ij}}{r_j^* = \max_i r_{ij}} \tag{12}$$

$$n_{ij} = \frac{\left(\frac{1}{r_{ij}}\right)}{\max_i \left(\frac{1}{r_{ij}}\right)} = \frac{\min_i r_{ij}}{r_{ij}} = \frac{r_j^{\min}}{r_{ij}} \tag{13}$$

$$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}} \tag{14}$$

In vector normalization, the equation 14 is utilized for both an index with a positive, and an index with a negative aspect. Topsis approach uses vector normalization. The result for these normalizations is shown in Table 8.

Table 8. Decision matrix after linear and vector normalization

	Linear normalization			Vector normalization		
	IX1(+)	IX2(+)	IX3(-)	IX1(+)	IX2(+)	IX3(-)
ALT1	0.407	0.527	0.111	0.224	0.332	0.464
ALT2	0.557	0.150	0.111	0.307	0.094	0.464
ALT3	0.586	0.122	0.111	0.323	0.077	0.464
ALT4	0.346	1.000	0.143	0.191	0.63	0.361
ALT5	0.386	0.651	0.143	0.213	0.41	0.361
ALT6	0.943	0.018	0.200	0.52	0.011	0.258
ALT7	1.000	0.014	0.333	0.551	0.009	0.155
ALT8	0.420	0.464	1.000	0.231	0.292	0.052
ALT9	0.372	0.754	1.000	0.205	0.475	0.052

Weighing the Indices

Two common methods are used for weighting indicators: entropy based on objective information and the least squares weighty decision based on subjective preferences (Mousseau et al., 2003), In this study due to a lack of the matrix of judgment, decisions about comparing the relative importance of indicators are based on expert judgment (Zavadskas et al., 2016). In this step, the AHP technique was used to weigh the indices. The experts utilized the equal weight for these indices.

Top Choice or Prioritizing Options

At this stage, the TOPSIS method was utilized for prioritizing options. It is based on the smallest distance from the positive ideal and far from negative ideal choice. In this way, *m* options can be assessed by *n* indices. After the calculation of the weight of indices (matrix $\overline{W}$), and the normalization of the decision matrix ($\overline{N}_D$), the weighted scaled matrix $\overline{V}$ is produced by (15).

$$\overline{V} = \overline{N}_D * \overline{W}_{n*n} \tag{15}$$

Went on, the ideal solution (A^+) and negative ideal solution (A^-) are calculated, respectively, according to the relations (16) and (17).

$$\begin{cases} A^+ = \left\{(\max_i V_{ij} \mid j \in J), (\min_i V_{ij} \mid j \in J') \mid i = 1,2,\dots,m\right\} = \left\{V_1^+, V_2^+, \dots, V_j^+, \dots, V_n^+\right\} \\ J = \left\{j = 1,2,\dots,n \mid j \xrightarrow{for} Positive\ Attribute\right\} \\ J' = \left\{j = 1,2,\dots,n \mid j \xrightarrow{for} Negative\ Attribute\right\} \end{cases} \tag{16}$$

$$\begin{cases} A^- = \left\{(\min_i V_{ij} \mid j \in J), (\max_i V_{ij} \mid j \in J') \mid i = 1,2,\dots,m\right\} = \left\{V_1^-, V_2^-, \dots, V_j^-, \dots, V_n^-\right\} \\ J = \left\{j = 1,2,\dots,n \mid j \xrightarrow{for} Positive\ Attribute\right\} \\ J' = \left\{j = 1,2,\dots,n \mid j \xrightarrow{for} Negative\ Attribute\right\} \end{cases} \tag{17}$$

Table 9 shows the ideal and negative ideal for the criteria.

Table 9. The ideal and negative ideal

Criteria	Ideal	Negative ideal
IX1	0.138	0.048
IX2	0.158	0.002
IX3	0.026	0.232

Then the size of the separation measure of the ideal solution for option $i(d_i^+)$, as well as the separation measure of the negative ideal solution for option i (d_i^-) using Euclidean method are calculated, respectively, according to the relations (18) and (19).

$$d_{i+} = \left\{ \sum_{j=1}^{n} (V_{ij} - V_j^+)^2 \right\}^{0.5} \quad ; \quad i = 1, 2, \ldots, m \tag{18}$$

$$d_{i-} = \left\{ \sum_{j=1}^{n} (V_{ij} - V_j^-)^2 \right\}^{0.5} \quad ; \quad i = 1, 2, \ldots, m \tag{19}$$

Finally, the relative closeness for option ALT_i to ideal solution cl_i^+ was calculated according to (20).

$$cl_{i+} = \frac{d_{i-}}{(d_{i+} + d_{i-})} \quad ; \quad 0 \le cl_{i+} \le 1 \quad ; \quad i = 1, 2, \ldots, m \tag{20}$$

Closeness rating is a number in [0, 1], with 0 being the worst possible and 1 the best possible solution. Table 10 shows the relative closeness of ideal solution for each option.

Table 10. The relative closeness for option ALTi to ideal solution

Options	Separation measure to the ideal solution	Separation measure to the negative ideal solution	Relative closeness
ALT1	0.234	0.081	**0.257**
ALT2	0.253	0.036	**0.125**
ALT3	0.255	0.037	**0.127**
ALT4	0.178	0.164	**0.480**
ALT5	0.185	0.113	**0.379**
ALT6	0.186	0.132	**0.415**
ALT7	0.164	0.178	**0.520**
ALT8	0.117	0.218	**0.651**
ALT9	0.095	0.237	**0.714**

Base on Table10, the ninth option (ALT9) is the best combination and the second option (ALT2) is the worst.

Discussion

The human resource development implications of supplier management are under-explored. The paper set out to achieve a bridging of the fields of human resource development and multi-criteria decision making/operations management. This study has focused on learning in supplier and buyer relation. HRD practice through employee engagement was done here.

First, knowledge flow has an effect on capability enhancement. Competitive advantage depends on not only internal but also external resources and capabilities acquired from chains (Mathews, 2003). Firms with the ability to absorb knowledge across partners have improvement in capabilities such as anticipating potential market opportunities, rapidly commercializing new innovations, anticipating surprises and crises, quickly adapting its goals and objectives to industry changes, decreasing market response times, being responsive to new market demands, streamlining its internal processes, and promoting just-in-time principles. There are tools such as the FAQ (Frequently asked questions), news and policies via electronic portals, email, and blogs or physical media for exchange supplier knowledge. Content management systems for contract management, reporting systems, and catalogs' library are other formal channels of explicit knowledge exchange. Social interactions such as face-to-face techniques are suggested to tacit knowledge exchange. Supplier involvement in projects, visit of supplier's factory, invite supplier to visit the plant, employee exchange, setting regularly sessions to find out needs in the future, doing in-house research on future products, polling participants regularly to assess the quality of supply chain services, and reviewing the likely effect of changes in chain can be utilized for tacit knowledge exchange. The result showed that both buyer and supplier benefit from knowledge interacting. Walter et al. (2007) introduced the supply chain as a valuable source of knowledge and best practices.

Further, there is a relation between knowledge flow and competitiveness that was examined by other studies. A model was developed and validated by Lee and Choi (2003). It introduces seven developing enablers related to knowledge creation processes. They were related to the firm's overall performance positively. The relation between human resource capabilities and competitive advantage is examined by Chuang (2004). The finding showed human resource capabilities are significantly associated with competitiveness positively. Chen Yue-Yang and Huang (2012) showed just a mixed model of information technology and human resource approach to knowledge flow can have a significant influence on financial performance and competitiveness. Learning may occur in a specific level but may affect another level. For example, communication takes place between employees but the effect on performance occurs in the organization.

Finally, the selected MOA framework implies some contributions to HRD. Organizational culture and framework create the opportunity or barrier for HRD. Kimbrough and Componation (2009) surveyed the role of organizational culture across an enterprise. A HRD scholar should identify potential cultural strengths and barriers prior to implementing knowledge sharing projects (Akhavan and Shahabipour, 2014). Cultural attributes such as fairness and trust are more important than other cultural orientations to implement such projects. Open communications between employees, teams and units are suggested to encourage the supportive culture. An implication for managers is to identify the specific mechanisms for closer communication. In another note, modes of governance have a great impact on knowledge processes rates at the organizational level (Squire et al., 2009). Management commitment has a major role in HRD to support the procedures and policies. Focus on encouragement, affiliation, achievement, and self-actualization has a positive effect on the success of HRD projects. Based on the work of Lord and Farrington (2006), the more investment in motivation and trait considering has more effect on decreasing the risk of the project. Motivational systems and pay system based on performance have a positive impact on the creation and dissemination of knowledge. The manager should help build a sense of self-efficacy, self-worth theory, self-determination theory and self-verification theory. When selecting experts and engineers for HRD process, both skills in the task domain and the intrinsic motivation must be considered. Personally challenged qualified people produce more knowledge than qualified people with no motivation. Based on Jungian theory, there are four dimensions to divide persons into sixteen different types. Four dimensions are extroversion-introversion, feeling-thinking, judging-perception, and intuition-sensing. Typical uses of the theory are for career counseling, team building and for general self-awareness. Other notes that must be considered for appropriate HRD project manager assignments are the importance of a project, the match between project requirements and the competency of a project manager, and the assignment constraints that can mitigate assigning a particular project to a project manager (Pota et al., 2014; Sonnenberg, 2001).

Conclusion

The paper proposed a mathematical model and solution for selecting appropriate candidates (i.e., employees) who will conduct the joint project with the firm's suppliers. The paper tried to adopt a mathematical and systematic approach to a human resource selection problem which requires a qualitative approach traditionally. Supply chain management is a successful strategy to improve the chain performance and competitive advantages. Supplier development as an HRD practice is an important part of this relation. It includes several activities with differences in some aspects. However, all of them are heavily knowledge based. Supplier involvement was selected as an SD activity. This paper determined the factors affecting the knowledge flow in this relation. A multi-objective integer nonlinear programming model was developed to maximize learning in the supplier involvement teamwork. The MODM model was solved by ICA that is a meta-heuristic evolutionary algorithm to find non-dominated solutions. The TOPSIS approach that is a MADM model was utilized to prioritize the options and find the best choice for selection of the team members to achieve particular goals.

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