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Optimizing Employment and Learning System Using Big Data and Knowledge Management Based on Deduction Graph

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Abstract

In recent years, big data has usefully been deployed by organizations with the aim of getting a better prediction for the future. Moreover, knowledge management systems are being used by organizations to identify and create knowledge. Here, the output from analysis of big data and a knowledge management system are used to develop a new model with the goal of minimizing the cost of implementing new recognized processes including staff training, transferring and employment costs. Strategies are proposed from big data analysis and new processes are defined accordingly. The company requires various skills to execute the proposed processes. Organization's current experts and their skills are known through a pre-established knowledge management system. After a gap analysis, managers can make decisions about the expert arrangement, training programs and employment to bridge the gap and accomplish their goals. Finally, deduction graph is used to analyze the model.

Keywords : Employment, Learning, Big Data, Knowledge Management, Deduction Graph

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1. Introduction

From the earliest developments to the modern data-warehouse era, the human race has always gathered information. However, recent technological advances in the past decades, such as the rise of social media [Ackerman and Guizzo, 2011], internet expansion and sensor development [Grolinger et al., 2016], have led to the production of an overwhelming flow of structured, semi-structured and unstructured data. The massive amount of produced data is usually referred to as "Big Data", generating datasets with sizes and rapid data generation rates being beyond the ability of typical database software tools to handle, store, manage, and analyze [Manyika et al., 2011]. Big data is an offspring of the computer revolution, first appeared in scientific literature in an IEEE paper, "Visually exploring gigabyte data sets in real time", by a group of NASA researchers in 1999 [Bryson et al., 1999], attracting the interests of academia, industry, government and other organizations alike.

There are extensive potentials associated with mining big data, which have shown to be quite useful [Wang et al., 2016]. Traditional analytical methods collect and analyze small data sets from specified sources during specific times and have shown limited performance capabilities. On the other hand, big data sets are constantly growing with online user-generated data and are being necessary for moving towards real-time analysis of the data of large magnitudes. This has facilitated big data analysis, establishing extraordinary results about consumer behaviors and trends; perhaps, the most interesting use of big data analysis was to create new products and services for customers. A company readily arriving at useful insights is expected to gain a competitive advantage and achieve an outstanding leverage against other competitors [Erevelles et al., 2016].

Here, we propose a model using big data and knowledge management information with the purpose of modifying the competence sets in order to meet the future requirements. We also address a case study in which a financial firm is willing to evaluate and expand its service capabilities through big data and knowledge management outputs. Information derived from big data is to help the top management in establishing new strategies and defining or modifying firm's processes. A certain competence set (experts with special skills) is necessary in order to carry out the processes; the information about firm's current competence set can be obtained via a knowledge management system.

Several analytical techniques such as Burbidge's connectance concept, influence diagram, cognitive mapping or induction graph can be used for generating a visual representation of the problem. Burbidge's connectance concept [Burbidge, 1984] uses the cause and effect relationship to create a network of variables. It can connect different variables, tools or objectives and show clear relationships among them; by knowing the different sequences for achieving the target, it can create a whole view of action plans. Burbidge's connectance concept can also make it easy to understand problems and provide additional options for decision making; but, it is a qualitative technique and cannot generally identify the optimal choice.

Influence diagram [Guezguez et al., 2009] is one of the most recognized and used cause-effect diagrams in operations management. It systematically identifies the real causes of the problem and the directions of the effects by breaking down the problem into smaller components. It can make the problem easier to understand. Although quantitative analysis could be applied to the developed model, but efficiency can be lost as the problem gets complicated.

Cognitive mapping [Buzan, 1982] uses statements to build complicated networks for a problem. It allows an individual to acquire, store, recall and decode information about the relative locations and attributes of phenomena in their everyday environments. It is simple to apply for construction of a network from different perspectives, but it may result in very complicated networks, not having a systematic approach for network construction.

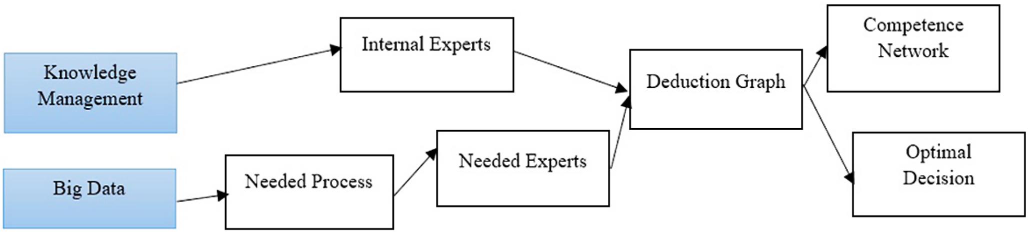
Induction graphs [Zighed et al., 2000] are generalizations of decision trees. In induction graphs, unlike decision trees which do not allow backward links from the leaves to the root, moving from a node to a lower or a higher level node is allowed and the user can introduce links between different level nodes and thus create a graph structure.

The above mentioned analytic infrastructures are designed for general purpose decision makings and thus do not necessarily arrive at optimal solutions. Here, deduction graph is used as proposed by Li [1999]. Tan et al. [2015] developed an analytic infrastructure based on deduction graphs for supply chain innovations harvesting big data.

The rest of our work is organized as follows. In Section 2, the problem is defined in detail and a mathematical formulation of the problem is provided. The performance of the proposed approach is examined through a numerical example in Section 3. Finally, we conclude in Section 4.

2. Model Description

Consider a company revising its strategies according to the output of big data analysis. After defining the new strategies, the action plan is redefined according to the strategies, which in turn results in new processes. The company uses a knowledge management system for knowledge sharing and identification of the experts and skill sets in different fields. Obviously, implementation of new processes will make some changes in the needs of experts and skills in different departments. Some skills can be acquired through association among experts, some new experts with special skill sets should be hired in order to fulfill the needs and some experts with unneeded skills should leave the company. In other words, the company tries to elevate some of its employees using current experts and rotate some experts' workplaces according to the new needs of different departments. Also, as another option, the company can employ new experts instead of teaching or transporting the available ones. Each of these policies has its own benefits and drawbacks for the company. Therefore, the company has to decide which of these three policies or a combination of them should be used for different departments with the goal of minimizing the total cost. <Figure 1> shows the analytic infrastructure framework. According to this figure, the company finds its current



〈Figure 1〉 An Analytic Infrastructure Framework

experts through a knowledge management system. Moreover, new strategies are needed to develop the processes discovered via big data analysis. Also, company's new needs for experts and skill sets can be deducted from the newly modified processes. Finally, a deduction graph can be drawn using the gap of the available skill sets and the needed ones which will be used for defining and optimizing the decision making model.

The following notations and decision variables are used to describe the model :

N : number of the departments $(i, i' = 1, 2, \cdots, n)$

M : number of skills $(j, j' = 1, 2, \cdots, m)$

$x^i_{j,j'}$: number of experts with skill j who learn skill j' from experts with skill j' in department i

$L^i_{j,j'}$: cost per $x^i_{j,j'}$

$y^{i'}_{i,j'}$: number of experts with skill j who are transferred from department i to department i'

$T^{i'}_{i,j}$: cost per $y^{i'}_{i,j}$

A^i_j : number of internal experts with skill j in department i before change

A'^i_j : final needed number of experts with skill j after change

z^i_j : number of experts with skill j who will leave the company

According to the above discussion, the costs associated with each department includes elevation, transferring and employment of new experts. Therefore, the total cost for department i is :

$$Cost_i = \Sigma_{j'}\Sigma_j x^i_{j'j}L^i_{j'j} + \Sigma_{i' \neq i}\Sigma_j y^i_{i'j}T^i_{i'j} + \Sigma_j z^i_j H^i_j. \tag{1}$$

To implement the process, the least number of needed experts for each skill of the processes should be located in each department which offers the following constraint for department i

$$A^i_j + \sum_{j'} x^i_{j'j} + \sum_j z^i_j + \sum_{i' \neq i} y^i_{i'j} - \sum_{j'} x^i_{jj'} - \sum_{i' \neq i} y^{i'}_{ij} \geq A'^i_j, \quad \forall j. \tag{2}$$

Staff elevation through association happens after the relocation of experts. In other words, experts associate or expand their skills in their new departments as shown by :

$$\sum_{i' \neq i} y^{i'}_{ij} \leq A'^i_j - A^i_j, \quad \forall j. \tag{3}$$

The company does not employ new staff unless the required skills cannot be attained through the available staff training. This can be shown as follows :

$$\sum_{j'} x^i_{jj'} \le \sum_{i' \neq i} y^i_{i'j} + A^i_j - \sum_{i' \neq i} y^{i'}_{ij}, \qquad \forall\, j. \qquad (4)$$

Therefore, the final model for the company can be formulated as :

$$Cost = \sum_i Cost_i \qquad (5)$$

s.t.

$$A^i_j + \sum_{j'} x^i_{j'j} + \sum_j z^i_j + \sum_{i' \neq i} y^i_{i'j} - \sum_{j'} x^i_{jj'} - \sum_{i' \neq i} y^{i'}_{ij} \ge A'^i_j, \qquad \forall\, i, j \qquad (6)$$

$$\sum_{i' \neq i} y^{i'}_{ij} \le A'^i_j - A^i_j, \qquad \forall\, i, j \qquad (7)$$

$$\sum_{j'} x^i_{jj'} \le \sum_{i' \neq i} y^i_{i'j} + A^i_j - \sum_{i' \neq i} y^{i'}_{ij}, \qquad \forall\, i, j \qquad (8)$$

3. A Numerical Example

Consider a company consisting of three different departments namely, A, B and C. Using a knowledge management system, the company already has knowledge about its available skills and the number of experts who can handle them. <Table 1> shows the skills and the number of the experts in each department. For example, there are 3 experts with skill "a" in department A.

The number of experts with specific skills may be more than the department needs, and therefore, some experts can be transferred to other departments. The cost of transferring experts with skill set {*a*, *m*, *n*} is estimated to be \$7 and the costs for sets {*c*, *b*, *h*} and {*d*, *e*, *g*, *f*} is expected to be \$8 and \$5, respectively.

〈Table 1〉 Available Experts in Various Departments

After generating new strategies by analyzing the data warehouse, the company decides to implement 4 new processes in the departments. These processes and the least needed experts for implementing them are shown in <Table 2>. As an example, the process develops product needs with at least 2 experts with skill *a*, 2 experts with skill *c*, 1 expert with skill *d* and 2 experts with skill *g* for implementation.

Department	Skills									
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*m*	***n***
Department A	3	0	1	4	0	2	1	4	2	1
Department B	0	3	1	1	3	2	0	2	2	1
Department C	1	4	1	0	2	0	0	3	1	1

〈Table 2〉 Processes and their Expert Needs

<Table 3> notes the processes to be implemented in each department. For example, all the processes except "manage changes" are going to be implemented in department A.

Process	Skills									
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*m*	***n***
Ⅰ : Development of product/service design	2	0	2	1	0	0	2	0	0	0
Ⅱ : Management of customer service	1	2	0	1	2	1	0	2	0	0
Ⅲ : Management changes	0	1	1	1	0	1	1	0	0	0
Ⅳ : Performance planning and management accounting	1	0	2	1	1	0	0	1	0	0

Although training and transferring experts are made prior to employment, in some cases the company needs to employ new experts due to lack of experts in some departments. On the other hand, some experts may leave the company because there is no further need for their skills. <Table 4> indicates the cost of employment of each skill in each department.

<Table 3> Processes of departments.

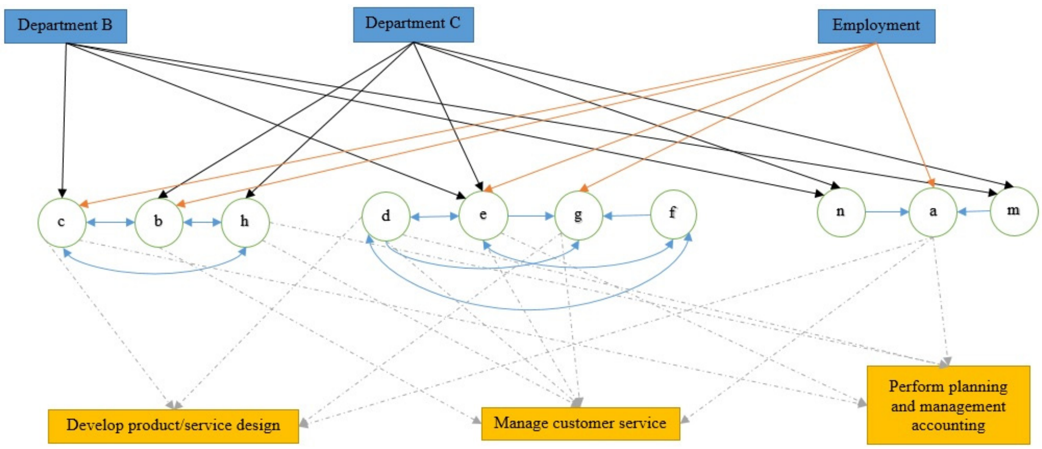
Skills *a*, *n*, *m* can be learned from each other because the experts who use these skills have the same field of study. Skills *c*, *b*, *h* and skills *d*, *e*, *g*, *h* are two other skill sets which can be learned from each other. The company estimated a cost of approximately $10 for each skill training.

Department	Process			
	I	II	III	IV
Department A	☑	☑		☑
Department B		☑	☑	
Department C	☑		☑	☑

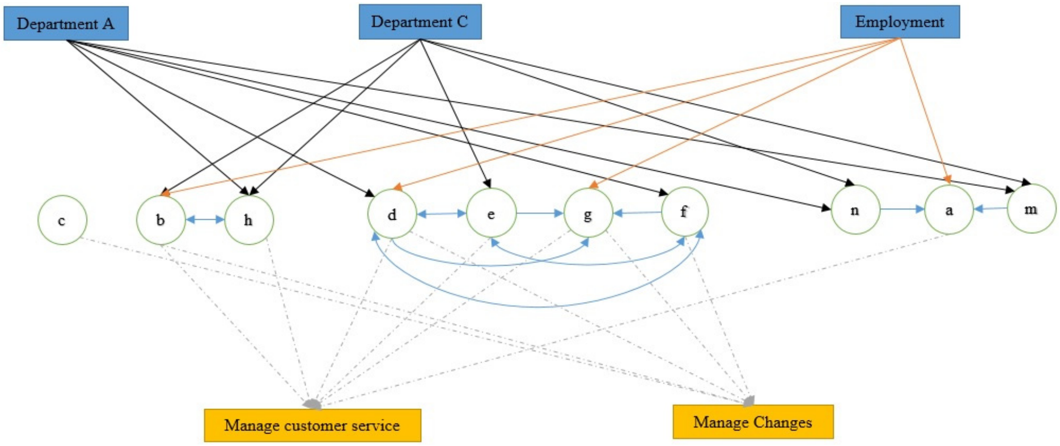
<Table 4> Cost of Employment for Each Skill

<Figure 2>, <Figure 3> and <Figure 4> show the expanding process of departments A, B and C, respectively. Each node represents one skill, and arcs indicate the possibility of learning skills based on the current skill set; for example, the arc $m \rightarrow a$ means that skill *a* is attainable for an expert with skill *m*. Based on the developed networks and according to the model described in the previous section, the linear programming problem can be formulated as follows. At first, the cost function is written according to (1) considering the cost of different departments. Then, constraints 6 to 8 will be developed for each department separately.

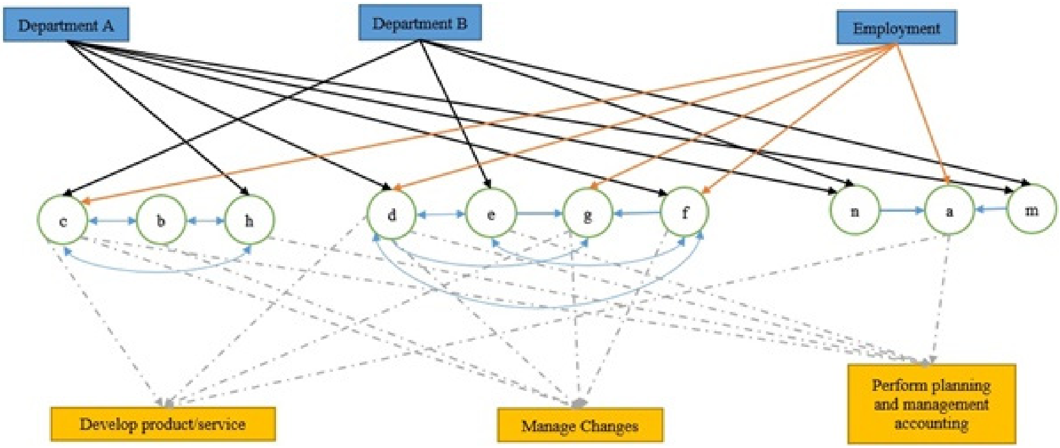
Department	Skills									
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*m*	*n*
Department A	20	15	20	10	15	22	22	22	22	22
Department B	10	20	20	10	20	10	20	20	20	20
Department C	15	20	20	18	18	20	18	18	20	18



<Figure 2> Expanding Process for Department A



〈Figure 3〉 Expanding Process for Department B



〈Figure 4〉 Expanding Process for Department C

$$
\begin{aligned}
Cost = \; & ((10x^A_{na} + 10x^A_{ma} + 20z^A_a) \\
& + (7y^A_{Bn} + 7y^A_{cn} + 7y^A_{Bm} + 7y^A_{cm}) \\
& + (10x^A_{cb} + 10x^A_{hb} + 15z^A_b + 8y^A_{cb}) \\
& + (10x^A_{bc} + 10x^A_{hc} + 20z^A_c + 8y^A_{Bc}) \\
& + (10x^A_{bh} + 10x^A_{ch} + 8y^A_{ch}) + (10x^A_{ed} + 10x^A_{fd}) \\
& + (10x^A_{de} + 10x^A_{fe} + 15z^A_e + 5y^A_{Be}5 + y^A_{Ce}) \\
& + (10x^A_{eg} + 10x^A_{eg} + 10x^A_{fg}22 + z^A_g) + (10x^A_{ef} + 10x^A_{df})) \\
& + ((10x^B_{na} + 10x^B_{ma}) + (7y^B_{cn} + 7y^B_{An} + 7y^B_{Cm} + 7y^B_{Am}) \\
& + (10x^B_{hb} + 20z^B_b + 8y^B_{cb}) + (10x^B_{bh} + 5y^B_{Bh} + 5y^B_{Ch}) \\
& + (10x^B_{ed} + 10x^B_{fd} + 10z^B_d) + (10x^B_{de} + 10x^B_{fe} + 5y^B_{Ce}) \\
& + (10x^B_{eg} + 10x^B_{eg} + 10x^B_{fg} + 20z^B_g) \\
& + (10x^B_{ef} + 10x^B_{gf} + 10x^B_{df} + 5y^B_{Bf})) \\
& + ((10x^C_{na} + 10x^C_{ma} + 15z^C_a) \\
& + (7y^C_{Bn} + 7y^C_{An} + 7y^C_{Bm} + 7y^C_{Am}) \\
& + (10x^C_{cb} + 10x^C_{hb} + 20z^C_b) \\
& + (10x^C_{bc} + 10x^C_{hc} + 20z^C_c + 8y^C_{Bc}) \\
& + (10x^C_{bh} + 10x^C_{ch} + 18z^C_h + 8y^C_{Ch}) \\
& + (10x^C_{ed} + 10x^C_{fd} + 18z^C_d + 5y^C_{Bd} + 5y^C_{Cd}) \\
& + (10x^C_{de}10 + 10x^C_{fe} + 18z^C_e + 5y^C_{Be}) \\
& + (10x^C_{eg} + 10x^C_{eg} + 10x^C_{fg} + 18z^C_g)
\end{aligned}
$$

$$+(10x_{ef}^{C}+10x_{df}^{C}+20z_{f}^{C}+5y_{Cf}^{C}))$$

s.t.

Constraints for department A :

$$3+z_a^A+x_{na}^A+x_{ma}^A \geq 4$$
$$z_b^A+x_{cb}^A+x_{hb}^A+y_{Cb}^A \geq 2$$
$$1+x_{bc}^A+x_{hc}^A+y_{Bc}^A \geq 4$$
$$4+x_{bh}^A+x_{ch}^A+y_{Ch}^A \geq 3$$
$$4+x_{ed}^A+x_{fd}^A-y_{Ad}^C-y_{Ad}^B \geq 3$$
$$z_e^A+x_{de}^A+x_{fe}^A+y_{Be}^A+y_{Ce}^A \geq 3$$
$$1+z_g^A+x_{eg}^A+x_{eg}^A+x_{fg}^A \geq 2$$
$$2+x_{ef}^A+x_{df}^A-y_{Af}^C-y_{Af}^B \geq 1$$
$$y_{Ah}^C+y_{Ah}^B \leq 1$$
$$y_{Ad}^C+y_{Ad}^B \leq 1$$
$$y_{Am}^C+y_{Am}^B \leq 2$$
$$y_{An}^C+y_{An}^B \leq 1$$
$$y_{Af}^C+y_{Af}^B \leq 1$$
$$x_{na}^A+x_{ma}^A \leq 3$$
$$x_{cb}^A+x_{hb}^A+\leq y_{Cb}^A$$
$$x_{bc}^A+x_{hc}^A+\leq y_{Bc}^A+1$$
$$x_{bh}^A+x_{ch}^A \leq y_{Ch}^A+4$$
$$x_{ed}^A+x_{fd}^A \leq -y_{Ad}^C-y_{Ad}^B+4$$
$$x_{de}^A+x_{fe}^A \leq y_{Be}^A+y_{Ce}^A$$
$$x_{eg}^A+x_{eg}^A+x_{fg}^A \leq 1$$
$$x_{ef}^A+x_{df}^A \leq -y_{Af}^C-y_{Af}^B+2$$

Constraints for department B :

$$z_a^B+x_{na}^B+x_{ma}^B \geq 2$$
$$3+z_b^B+x_{hb}^B+y_{Cb}^B \geq 3$$
$$1-y_{Ac}^C-y_{Ac}^A \geq 1$$
$$2+x_{bh}^B+y_{Ah}^B+y_{Ch}^B \geq 2$$
$$1+z_d^B+x_{ed}^B+x_{fd}^B+y_{Bd}^B \geq 2$$
$$3+x_{de}^B+x_{fe}^B+y_{Ce}^B-y_{Ae}^C-y_{Ae}^A \geq 2$$
$$z_g^B+x_{eg}^B+x_{eg}^B+x_{fg}^B \geq 1$$
$$2+x_{ef}^B+x_{df}^B+y_{Bf}^B \geq 2$$
$$y_{Bn}^C+y_{Bn}^A \leq 1$$
$$y_{Bm}^C+y_{Bm}^A \leq 2$$
$$y_{Be}^C+y_{Be}^A \leq 1$$
$$x_{na}^B+x_{ma}^B \leq 0$$
$$x_{hb}^B \leq y_{Cb}^B+3$$
$$0 \leq -y_{Bc}^C-y_{Bc}^A+1$$
$$x_{bh}^B \leq y_{Ah}^B+y_{Ch}^B+2$$
$$x_{ed}^B+x_{fd}^B \leq y_{Ad}^B+1$$
$$x_{ed}^B+x_{fe}^B \leq y_{Ce}^B-y_{Be}^C-y_{Be}^A+3$$
$$x_{eg}^B+x_{eg}^B+x_{fg}^B \leq 0$$
$$x_{ef}^B+x_{df}^B \leq y_{Af}^B+2$$

Constraints for department C :

$$1+z_a^C+x_{na}^C+x_{ma}^C \geq 3$$
$$4+x_{cb}^C+x_{hb}^C-y_{Cb}^A-y_{Cb}^B \geq 1$$
$$1+z_c^C+x_{bc}^C+x_{hc}^C+y_{Bc}^C \geq 5$$
$$3+x_{bh}^C+x_{ch}^C+y_{Ch}^C-y_{Ch}^A-y_{Ch}^B \geq 1$$
$$z_d^C+x_{ed}^C+x_{fd}^C+y_{Cd}^C \geq 3$$
$$2+x_{de}^C+x_{fe}^C+y_{Be}^C+y_{Ae}^C-y_{Ce}^B \geq 1$$
$$z_g^C+x_{eg}^C+x_{eg}^C+x_{fg}^C \geq 3$$
$$z_f^C+x_{ef}^C+x_{df}^C+y_{Af}^C \geq 1$$
$$y_{Cb}^A+y_{Cb}^B \leq 3$$
$$y_{Cm}^A+y_{Cm}^B \leq 1$$
$$y_{Cn}^A+y_{Cn}^B \leq 1$$
$$y_{Ch}^A+y_{Ch}^B \leq 2$$
$$y_{Ce}^A+y_{Ce}^B \leq 1$$
$$x_{na}^C+x_{ma}^C \leq 1$$
$$x_{cb}^C+x_{hb}^C+\leq -y_{Cb}^A-y_{Cb}^B+4$$

$$x^C_{bc}+x^C_{hc} \le y^A_{Bc}+1$$

$$x^C_{bh}+x^C_{ch} \le y^C_{Ah}-y^A_{ch}-y^B_{Ch}+3$$

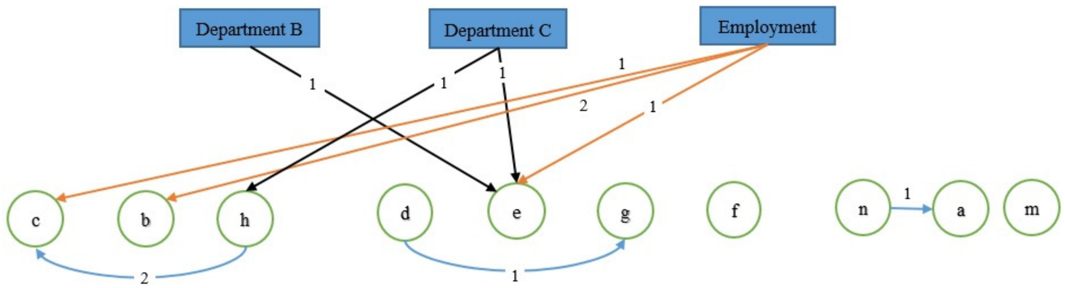
$$x^C_{ed}+x^C_{fd} \le y^C_{Ad}$$

$$x^C_{de}+x^C_{fe} \le y^C_{Be}-y^A_{Ce}-y^B_{Ce}+2$$

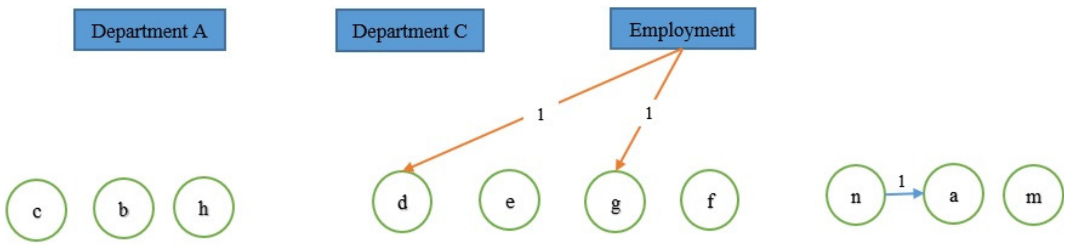
$$x^C_{eg}+x^C_{eg}+x^C_{fg} \le 0$$

$$x^C_{ef}+x^C_{df} \le y^C_{Af}.$$

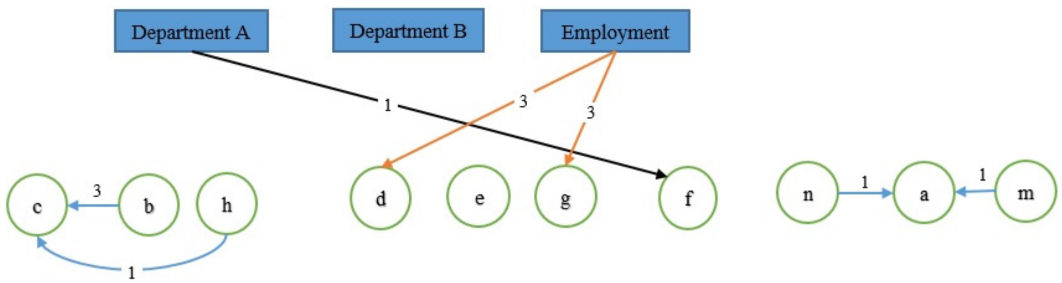
The model discussed above is linear and could be solved efficiently using linear solvers. The LINGO software is employed here to obtain the optimal solution yielding the following solution : $x^A_{hc}=2$, $x^A_{dg}=1$, $x^A_{na}=1$, $z^A_b=2$, $z^A_c=1$, $z^A_e=1$, $y^A_{Be}=1$, $y^A_{Ce}=1$, $x^B_{na}=1$, $z^B_d=1$, $z^B_g=1$, $x^C_{bc}=3$, $x^C_{hc}=1$, $x^C_{na}=1$, $x^C_{ma}=1$, $y^C_{Af}=1$, $z^C_g=3$, $z^C_d=3$ and other decision variables which are not listed here are equal to zero. Using the optimal variables, the final optimal cost gained is equal to \$314. Moreover, there are 2 experts with skill m in department A and 2 experts in department B who should leave the company. The results are shown graphically as follows :



〈Figure 5〉 Deduction Graph for Department A



〈Figure 6〉 Deduction Graph for Department B



〈Figure 7〉 Deduction Graph for Department C

4. Conclusion

A new model was developed for the implementation of new processes using the output of big data analysis and knowledge management system. The aim was to help managers to decide about the company's experts and skill requirements in a cost effective way in accordance with the new processes identified through the big data analysis. Training and transferring experts to other departments or employing new experts were the policies considered in the proposed model to satisfy the company's future expert requirements. The performance of the model was examined through a numerical example and an optimal solution was gained using LINGO. The optimal solution can help the management to decide upon employee training, transferring or hiring.

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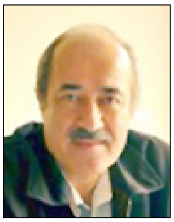

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