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Staff Assignment to Multiple Projects Based on DEA Efficiency

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An adequate staff assignment plan is recognized as one of the most important factor for fulfilling the foreseeable delivery of multiple projects with restrictions on available budget, time and quality. This problem is very complex and becomes more complicated as the number of projects, tasks and staff members increases. Decision makers need to find a single unique performance measure as the primary criterion for making a balanced and efficient staff assignment plan. The efficiency of an assignment plan depends on different input and output criteria related to staff member performances which can be economic, qualitative or quantitative by nature. Therefore, the main question is how to make the most efficient assignment plan in multi-project, multi-task environment if several staff members can carry out different tasks at the different level of performance. This paper proposes an integration of all input-output criteria, regardless of their type through a DEA-based mixed-integer programming model. It evaluates the efficiency of staff members as a unique criterion, based on their past performances, together with making an assignment plan. Practical examples with different restrictions empirically demonstrate the possibilities of the decision model. The results show that the fulfilling of maximum efficiency criteria of all staff members in implementing the required tasks provides balanced efficiency in the implementation of all on-going projects, which makes this model a useful tool for decision makers.

Keywords: *Staff Assignment Plan; Multi Project Management; Efficiency Evaluation; Data Envelopment Analysis (DEA); Mixed-integer Programming.*

Introduction

In a multi-project framework, optimal allocation of the available consultants and the formation of an adequate project team for each on-going project becomes one of the most important tasks. The goal is to allocate available consultants to project and ensure the maximum value in terms of time, cost and quality (Razavi Hajiagha *et al.*, 2015). The selection and allocation problem is complex, given that business process principal consultants (the most experienced consultants) may be engaged on several different tasks on projects and may form teams of different structure and efficiency. Therefore, it is necessary to take into consideration several different criteria related to the skills and experience of staff. On the other hand, the decision maker could have made an easier decision based on a single unique performance measure or the rank of the candidates.

This paper proposes a methodology for solving multi-criteria assignment problem (Pentico, 2007) based on Data envelopment analysis (DEA) and mixed-integer programming (MIP). We determine an assignment plan which provides the highest possible overall efficiency in the implementation of all tasks on all on-going projects. Another method commonly used to solve this problem is a two-phase approach (DEA efficiency evaluation in the first phase and MIP assignment model in the second phase), as it is stated by Tavana *et al.*, 2015. The proposed combined DEA and MIP model provides simultaneous efficiency evaluation of each consultant on each task and their assignment to the most appropriate tasks on the on-going project.

The assignment plan balances the tasks required for projects and the set of skills of business process principal consultants, such as years of experience, extent of knowledge, current reputation and other professional performance. We are considering the situation of several simultaneous projects which must be implemented in a quality manner, within specific timeframes and budgets. Each project is significant, but they still have specific priorities in implementation. Also, consultants need to be optimally deployed in a defined period on each of the agreed projects. The allocation of fixed costs and common resources depends on the achieved level of consultants' efficiency.

The paper starts with a literature review, defines the problem and specifies the characteristics essential for the efficiency evaluation process. The following sections describe the proposed DEA mixed-integer programming model and its application for optimal allocation of the available consultants to projects based on DEA efficiency, followed by a survey and its results. The conclusions and bibliography are found in the final sections.

Literature Review

Recently, new performance evaluation systems have been proposed and presented in the scientific literature. For example, Cao & Hoffman (2011) designed a new project performance evaluation system that would enable managers to audit a project and determine where improvements could be made. Xu & Yeh (2014) presented a new performance-based approach for integrating project assignment and project performance evaluation, two important and separate research issues in project management, by using the expected contribution value of the projects and the expected performance score specified by project managers.

DEA is also used in different aspects of project performance evaluation. Fu & Ou (2013) proposed a new method, combining PCA (Principal Component Analysis) and DEA to enhance the efficiency of decision-making units substantially. Sudhaman & Thangavel (2015) identified efficient ERP projects for project managers, practitioners and consultants based on projects quality measures (defect counts) using the DEA model, thus enabling them to adopt software processes and quality models of these projects for their future ERP projects. Jahantighi *et al.* (2015) proposed a method for selecting high performance projects to solve a problem with limited resources for producing finite projects, in order to obtain the desired level of efficiency. Spalek (2014) determined specific roadmaps for three industries to increase project management efficiency in terms of time reduction.

Another important aspect of project management is resource allocation. Lombardi & Milano (2012) gave a review of optimal methods for resource allocation and scheduling. Fatemi *et al.* (2002) considered the problem of multi-project resource allocation (MPRA) as a multi-channel queuing system and the ways to determine the optimal timing of projects in case of simultaneous multi-projects with shared resources. Van den Bergh *et al.* (2013) reviewed the literature, identified trends in the research on personnel scheduling problems and indicates areas which should be the subject of future research.

Wu & An (2012) presented a new approach for resource allocation via DEA models which transforms the multiple objective linear programming (MOLP) problem into a single objective linear programming model. Hassan *et al.* (2010) considered a multi-objective resource allocation problem (MORAP) in which decision-making units were controlled by a central unit and use a method based on DEA model to evaluate centralized-MORAP.

There have been many approaches based on DEA method (Liu *et al.*, 2013; Liu *et al.*, 2016; Emrouznejad *et al.*, 2016) which attempted to solve the problems of cost allocation and resource scheduling. Athanassopoulos (1995, 1998) used goal programming formulations integrated in the interactive planning framework to develop a DEA model for resource allocation. On the other hand, Cook & Kress (1999) made the first attempt of fixed costs allocation, based on two theoretical principles - invariance and Pareto minimum. This approach was further expanded in a paper published 2005 (Cook & Zhu, 2005), where the authors used the DEA approach to achieve uniform allocation of shared costs among decision making units (DMUs). Lin (2011) extended the approach given in Cook & Zhu (2005) to obtain the permissible fixed costs or resources allocation when they were subject to special restrictions. Li *et al.* (2009) observed fixed costs as a complement to other inputs and combine them with other measures of costs to form a single input measure in assessing the performance.

Amirteimoori & Tabar (2010) presented a DEA-based approach for allocating fixed resources or costs across a set of DMUs at the same time, with output targets setting allocating input resources. Keke *et al.* (2015) suggested the way how resources allocation mechanism of manufacturing enterprises based on multilevel programming can improve efficiency of resources allocation.

Fang (2013) introduced a new generalized centralized resource allocation and extended the Lozano & Villa's (2004), and Asmild *et al.* (2009) models, which assumed that a centralized decision maker could rearrange inputs and outputs across all decision-making units. An alternative model based on the so-called centralized DEA was proposed by Lopez-Torres & Prior (2016) in order to adapt resources to the allocated budget without losing outputs. Centralized decision making aims to minimize total amount of input or maximize the total amount of produced outputs by all decision making units, rather than considering the consumption of each individual DMU (Korhonen & Syrjanen, 2004; Fang & Zhang, 2008; Du *et al.*, 2010). Wu *et al.* (2013) developed new DEA models based resource allocation considering both economic and environmental factors.

Du *et al.* (2014) used the cross-efficiency concept in DEA to approach cost and resource allocation problems. In a different manner, Hatami-Marbini *et al.* (2015) proposed an alternative common-weights DEA model for centrally imposed resource or output reduction across the reference set.

Obviously, DEA has become a leading approach to efficiency analysis in many fields. It is used to assess efficiency based on empirical boundaries of efficiency, but can also be used for resource allocation and setting goals for future predictions. DEA models use continual data but there are many problems in real life in which data must be treated as integer, such as the number of workers, machines, experts and other (Beasley, 2003; Lozano & Villa, 2006; Lozano & Villa, 2007; Kuosmanen & Kazemi Matin, 2009; Kazemi Matin & Kuosmanen, 2009; Wu & Zhou, 2015; Foroughi, 2011; Gholami & Beigi, 2013; Bernini *et al.*, 2013; Lotfi *et al.*, 2013).

Problem Description

As stated above, the focus of this paper is the assignment of consultants in a multi-project environment, taking into consideration several different criteria.

Most commonly, projects are contracted at the end of year, with implementation due in the following fiscal year. Consultants to be involved in the project implementation should be allocated so that all projects could be successfully implemented. Allocation plan in its entirety should be as efficient as possible.

In practice, the decision maker, has a list of consultants which can be chosen as appropriate project team members on the required tasks, taking into consideration the size of project, consultants' skills, costs, project timeline and consultants' availability in the designated period. Obviously, the decision maker often faces a multi-criteria problem and the necessity to find the best solution without

using an exact optimization method. The problem is combinatorial and it is employed in the deployment of consultants to positions on the project based on the assessment of their performance. This is the reason for choosing efficiency as the criterion of suitability of consultants in this study.

Efficiency evaluation is based on the following criteria:

- Consultancy Cost (CC): Represents the Consultancy Services Price per person per day.
- Trainings (TR): Lists the number of courses (trainings) or certifications which a consultant has past, e.g. trainings related to the functional modules that are necessary for project implementation.
- References (RE): Defines the number of consultant references from previous projects.
- Performance & Reward (PR): An internal process for setting objectives and assessing performance. The actual efficiency will be determined based on the consultant's performance, evaluated as employee self-assessment, manager and customer assessment and peers' assessment as additional appraisers. The PR range is 1 to 4 (1–progressing, 2–successful, 3–outstanding, 4–extraordinary). Candidates with PR equal to 1 are excluded as unsuitable.
- Customer Recommendation (CR): Score of customer satisfaction with the consultant, obtained by survey after the implementation is completed in the required areas. The scores are given on a 1 to 5 scale; however, candidates with CR less than 2.5 are excluded as unsuitable.
- Awareness of Responsibility (AR): Refers to the liability of consultants in terms of their work. The scores are based on the feedback given by team members and their experience from the previously implemented projects.
- Ability to Persuade (AP): Indicates the ability of the consultant to present best practices and convince the client to opt for a proposed solution. Communication abilities are assessed by the decision maker based on an interview with the potential candidate. Only consultants with AR and AP between 3 and 9 are taken into consideration (candidates with a score less than 3 are unsuitable).

These criteria are selected based on practical experience of ERP project implementation. Also, they are defined as the most suitable criteria for consultant selection problem in Vayvay *et al.* (2012).

Business processes principal consultant can be engaged as a consultant (team lead for implementation module – task_1), solution architect (task_2) or project manager (task_3). However, it is not possible for the same person perform two tasks on the same project. Annual key performance indicator (KPI) defined for each staff member (which must be achieved during the year) is approximately 190 days +20% which results in a maximum of 228 days per project team member. In this study KPIs are predefined even thought their selection can be the subject of research (Xie *et all.,* 2017; Jahangirian *et all.,* 2017; Fuentes *et all.,* 2016; Collins *et all.,* 2016). Tao (2012) proposed a methodology for the selection of KPIs, their aggregation into four dimensions of Workforce Scorecard (WS) and the employees' performance evaluation using DEA.

Martinovic & Delibasic (2013) used Analytic Hierarchy Process (AHP) method combined with Interpolative realization of Boolean algebra to generate new criteria that include the relationship between the initial criteria. They adopted the model given in Vayvay *et al.* (2012), where AHP, Fuzzy AHP and Analytic Network Process (ANP) are used, for the specific case of selecting the most suitable consultant to be engaged in ERP implementation. For efficiency evaluations on a small sample with a number of criteria, another model was applied in research of Martinovic & Savic (2015). They modified DEA model by reducing the number of criteria with implying 'Exclusive OR' rules.

Research Methodology

The problem of interest is to allocate consultants in a multi-project, multi-task environment. Assumptions of the decision problem are as follows:

- At the beginning of the fiscal year, a set of P projects are to be started and implemented until the end of observed period.
- Each project $p \in P$ involves set of L tasks.
- A set of consultants C is given (known) and each consultant can perform one or more tasks $l \in L$.
- A consultant $c \in C$ would perform an assigned task l $(l \in L)$ at the same level as it was in the past. Historical data on consultants' KPIs are known.
- The efficiency of one project is calculated as the addition of efficiencies of all assign consultants.

Staff allocation means selecting and assigning consultant c $(c \in C)$ to perform task l $(l \in L)$ on project p $(p \in P)$. The goal is to realize all projects in the most efficient way. The decision is based on historical data of consultants' KPIs, and time resources requirements for all projects $p \in P$.

The problem belongs to a group of complex, combinatorial problems. The maximal number of possible combinations for full coverage of all tasks on all projects by all consultants is $|P| \times |L| \times |C|$. In order to easily solve the defined problem, the approximate approach is employed. Having the assumptions given above, the possible set of covering (Crhistofides & Korman, 1975) schemes *S* is made in advanced. One scheme $s \in S$ corresponds to the combination project-task-consultant and represents a triplet $(p, l, c), (p \in P, l \in L, c \in C)$. Therefore, the number of feasible schemes $|S|$ is less than or equal to the number of combinations in case of full coverage $\left(|P| \times |L| \times |C|\right)$, and depends on the capability of consultants to perform tasks required by the on-going projects.

The aim is to select the subset of schemes *S* so that all projects are performed with maximal relative efficiency. This means that relative efficiency of project $p \in P$ is equal to the sum of efficiencies of all selected corresponding schemes Sp $(Sp \subset S,\ p \in P)$. On the top level, the overall relative efficiency would be the sum of efficiencies of all selected schemes for all projects.

A mixed-integer (binary) program, as a modification of DEA prioritization model (Cook & Green, 2000) is proposed for modelling the efficiency assessment and staff

assignment simultaneously. The schemes are considered as DMU$_s$ ($s \in S$) and characterized with a set of inputs I and outputs O. The values of inputs x_{is} $(i \in I,\ s \in S)$ and outputs y_{rs} $(r \in O,\ s \in S)$ are given as historical data of KPIs for the corresponding consultant $(c \in C)$ performing a task $(l \in L)$.

Preliminary, DEA-based model (Charnes *et al.,* 1978) can be used to evaluate the efficiency e_s of each scheme $(s \in S)$ by choosing input weights $u_i (i \in I)$ and output weights $v_r (r \in O)$ with a restriction that efficiency score should be less than or equal to 1.

As an extension, a DEA prioritization model (Cook & Green, 2000) provides a selection of project portfolio and additionally imposes a binary variable to indicate if a project is selected or not. In this paper, we impose binary variable q_s to indicate if scheme s $(s \in S)$ is selected or not. If $q_s = 1$, schemes s is selected – corresponding consultant $c \in C$ is allocated to perform task $l \in L$ on project $p \in P$. Additionally, time consumption for each task $l \in L$ on the project $p \in P$, means that time consumption t_s ($s \in S$) is given in advance and imposed as restriction into the model. The assigned consultant is obligated to finalize the task on time and fulfil the required number of working days on the project, but s/he can organize working day dynamics on their own. The maximum number of working days T allowed for each consultant in the observed period is also given in advance. The required number of consultants U_{lp} on the concrete task $l \in L$ on the project $p \in P$ is also imposed as a constraint. This paper proposes a modified DEA-based mixed-integer programming model (1-7) for schemes selection, i.e. choosing a concrete consultant to perform a concrete task on a concrete project.

$$\max e = \sum_{s \in S} e_s = \sum_{s \in S} q_s \left(\sum_{r \in O} v_r y_{rs} \right) \tag{1}$$

s.t

$$\sum_{s \in Sp \subset S} q_s \left(\sum_{i \in I} u_i x_{is} \right) = 1, \forall p \in P \tag{2}$$

$$\sum_{r \in O} v_r y_{rs} - \sum_{i \in I} u_i x_{is} \le 0, \quad s \in S \tag{3}$$

$$\sum_{s \in S_{lp} \subset S} q_s = U_{lp}, \ \forall l \in L, \ \forall p \in P \tag{4}$$

$$\sum_{s \in S_c \subset S} q_s t_s \le T, \ \forall c \in C \tag{5}$$

$$q_s \in \{0,1\}, \ s \in S \tag{6}$$

$$v_r \ge 0, u_i \ge 0, \ r \in O, \ i \in I \tag{7}$$

The objective function (eq. 1) maximizes the overall efficiency of all selected schemes. The upper limit of overall efficiency per each project $\forall p \in P$ is set to 1 by constraint (eq. 2). This constraint summarises virtual input of schemes in subset $Sp \subset S$ which correspond to concrete project $p \in P$. Eq. (3) limits other schemes to be evaluated with rate less than or equal to 1. The required number of consultants U_{lp} is emulated as a sum of schemes selected from the corresponding subset $S_{lp} \subset S$, ($l \in L,\ p \in P$) by eq. (4). The limitation on the maximum number of working days given in the eq. (5) is calculated as sum of time consumption t_s for the selected schemes from subset of schemes S_c related to consultant c.

The proposed model (1-7) is non-linear. Even though, the software capable of solving it is available, it might be time consuming. In order to overcome this problem, the model can be linearized by imposing new variables $g_{is} = q_s u_i$ and $f_{rs} = q_s v_r$, and new constraints (13-18) to connect those new variables with the original ones u_i, v_r and q_s. Now, DEA-based mixed-integer linear programming model is given by eqs. (8-19):

$$\max e = \sum_{s \in S} \sum_{r \in O} f_{rs} y_{rs} \tag{8}$$

s.t

$$\sum_{s \in Sp \subset S} \sum_{i \in I} g_{is} x_{is} = 1, \ p \in P \tag{9}$$

$$\sum_{r \in O} v_r y_{rs} - \sum_{i \in I} u_i x_{is} \le 0, \quad s \in S \tag{10}$$

$$\sum_{s \in S_{lp} \subset S} q_s = U_{lp}, \ \forall l \in L, \ \forall p \in P \tag{11}$$

$$\sum_{s \in S_c \subset S} q_s t_s \le T, \ \forall c \in C \tag{12}$$

$$f_{rs} \le q_s M, \ r \in R, s \in S \tag{13}$$

$$v_r - (1 - q_s) M \le f_{rs} \le v_r, \ r \in R, s \in S \tag{14}$$

$$g_{is} \le q_s M, \ i \in I, s \in S \tag{15}$$

$$u_i - (1 - q_s) M \le g_{is} \le u_i, \ i \in I, s \in S \tag{16}$$

$$q_s \in \{0,1\}, \ s \in S \tag{17}$$

$$f_{rs} \ge 0, g_{is} \ge 0, \ r \in O, \ i \in I, s \in S \tag{18}$$

$$v_r \ge 0, u_i \ge 0, \ r \in O, \ i \in I \tag{19}$$

where M represents a big positive multiplier. The model solution denotes the overall efficiency of all selected schemes in the term of weights of input ($u_i \ge 0, \ i \in I$), weights of outputs ($v_r \ge 0, r \in O$), selection variable $q_s \in \{0,1\}, \ s \in S$ and composite multipliers f_{rs} and g_{is}. Consequently, triplet project-task-consultant (p, l, c) selection is provided together with its efficiency evaluation.

Results and Discussion

Case Study Background

The real-world problem considered in this paper assumes the implementation of three IT projects (P1-P3) simultaneously. These projects are only limited by size (one big, one medium and one small size), but not by the scope and the type of tasks to be performed. Successful implementation of each project assumes engaging two project consultants (T1), one solution architect (T2) and one

project manager (T3), which means four consultants in total on each project. On the other hand, there are eight candidates capable of performing the required task as given in the graph (Figure 1). The maximal possible number of schemes project–tasks-consultants is $|P| \times |L| \times |C| = 3 \times 3 \times 8 = 72$. But feasible set S consists of 45 schemes (15 for each project) which are defined in accordance with projects, tasks and consultants capable to perform them, as given in Figure 1. Each consultant can perform task T1, but only 3 consultants (C3, C6 and C7) can perform task T2 and only four of them (C3, C6, C7 and C8) are capable of fulfil task T3 successfully. Finally, the data set consists of 45 schemes (DMUs). Efficiency evaluation is based on seven KPIs defined in section 3. This KPI set is divided into sets of inputs and outputs, according to the characteristics, the cost of the consultant and her/his results. In addition to the consultancy cost (CC) criterion, the following criteria - performance & reward (PR), number of references (RE) and completed trainings (TR) as measures of experience and education of the consultant - are taken as inputs. The criterion of customer recommendation (CR) and two criteria of communication ability (AR and AP) are taken as outputs. The criteria values for consultants are given based on the author's experience in project implementations, interviews with other senior delivery managers and experience of implementation in companies in the past. The given values are a simulation of the real market values, due to data confidentiality. Initial values for inputs and outputs, in accordance with the assessment of the decision maker, are given in Table 2.

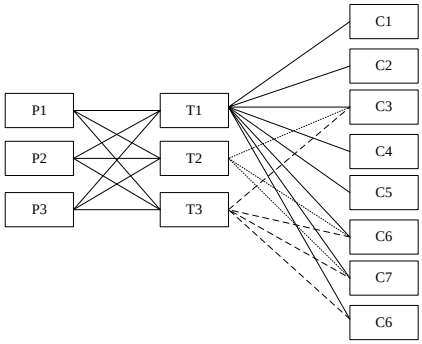

Figure 1. Project-Task-Consultant Relationships

The model (8-19) is extended with the constraint that one consultant can perform only one task on one project (eq. 20).

$$\sum_{s \in S_{lc} \subset S} q_s \leq 1,\ l = 1,\ c \in C \qquad (20)$$

where $S_{lc} \subset S$ represents the corresponding subset of schemes $(l \in L,\ p \in P)$.

Table 1

Data on Required Days

Project	Task	Required days per task	Required number of consultants per task	Total
P1	T1	144	1	
P1	T2	72	1	504
P1	T3	144	2	
P2	T1	120	1	
P2	T2	60	1	420
P2	T3	120	2	
P3	T1	96	1	
P3	T2	48	1	336
P3	T3	96	2	

In addition, maximum time limit for each consultant is defined at level of 228 days annually (1824 days in total) and the required time for performing each task on each project is also given in advance (Table 1). The total time needed for performing all tasks is 1260 days. This way, a feasible solution is provided: it is expected that an optimal assignment plan can be found since there are more available work days than required.

Results

Efficiency scores for all schemes are calculated using model (8-20) and are shown in Table 2. According to the model, the efficiency scores of schemes depend on the input and output values with the constraint that the virtual input of any project must be equal to 1. The expected efficiency index value for each DMU (scheme) is 0.25. Accordingly, efficiency scores differ for each combination of task-consultant, regardless of the project being implemented. The most efficient consultants, with the score of 0.2938, are C3 in performing any task (T1, T2 or T3) and C6 in performing task T1.

Binary variables q_s, $s \in S$, which indicate if scheme s is selected or not, are given in the Table 3. A detailed analysis of the assignment plan shows that the assignment of consultants is fair, taking into consideration the overall efficiency of the projects. Consultants implementing projects P2 and P3 are expected to be the most efficient, but with a small difference of 0.0167 in comparison to project P1. All projects are implemented with an efficiency score over 0.93.

Table 2

Input and Output Values and Efficiency Score

Task L	Consultant C	Inputs				Outputs			Efficiency scores
		CC x_{1s}	TR x_{2s}	RE x_{3s}	PR x_{4s}	CR y_{1s}	AR y_{2s}	AP y_{3s}	
T1	C1	400	2	4	2	3	5	3	0.1734
T1	C2	450	3	5	2	3.25	5	7	0.1849
T1	C3	500	5	6	4	5	9	9	0.2938
T2	C3	500	4	3	4	5	9	9	0.2938
T3	C3	500	3	3	4	5	9	9	0.2938
T1	C4	470	3	2	2	3.5	5	5	0.1963
T1	C5	490	3	4	3	4.3	7	7	0.2474
T1	C6	550	5	7	4	5	9	9	0.2938
T2	C6	550	4	4	3	4.8	9	9	0.2847
T3	C6	550	3	2	2	4.5	7	7	0.2565
T1	C7	520	4	2	2	3.65	5	3	0.2032
T2	C7	520	3	2	2	2.9	3	4	0.1545
T3	C7	520	1	1	2	2.6	5	2	0.1551
T1	C8	510	5	4	3	5	6	6	0.2723
T3	C8	510	2	2	2	4	7	5	0.2336

Only four consultants (C3, C6, C7 and C8) can perform tasks T2 and T3. The main problem is how to deploy them to 6 positions (T2 and T3 on P1, P2 and P3) without overloading the limited number of annual working days. This problem is solved by excluding consultant C7 as a candidate for these tasks because s/he has the lowest relative efficiency (0.15-0.20) caused by the lowest levels of output performance (CR, AR and AP) and high labour costs (CC). The consultant C3 will act as a solution architect on all ongoing projects, and the consultant C8 will be employed as project manager on two projects (P2 and P3). Consultant C6 is assigned as project manager on project P1. The T3 tasks on all projects are assigned to the available consultants C1, C2, C4 and C5 considering the remaining working days and efficiency scores. The most burdened consultants in terms of time are C1, C5 and C8 while consultant C7 is not employed at all, since s/he has the lowest efficiency score (last column in Table 3).

Another possible extension of the model could be achieved by imposing constraint to the maximal number of projects (N) where a consultant can be assigned to the same task (eq. 21).

$$\sum_{s \in S_{lc} \subset S} q_s \leq N,\ l \in L,\ c \in C \tag{21}$$

Model (8-21) is solved in the two following practical cases:

1. business processes principal consultant can be assigned as project manager to only one project (21–1);
2. business processes principal consultant can be assigned as project manager to only one project and as a solution architect to only one project (21–2).

Additional restrictions caused decrease in the overall efficiency of project implementation in comparison to the efficiency presented in Table 3, but the rank of task-consultants is the same. In this case, the most inefficient consultant C7 cannot be excluded. S/he takes task T1 (consultant) on project P2 and task T2 (solution architect) on project P3, which causes a decrease in overall efficiency score (0.9426/0.9329/0.9092). The consultant's time burden also varies in comparison to the assignment shown in Table 3. The most burdened candidates are C6, C8 and C3.

Table 3

Consultant Assignment

Task (L)	Consultant (C)	Consultant efficiency score	Selected q_s			Efficiency score			Time consumption (days)
			P1	P2	P3	P1	P2	P3	
T1	C1	0.1734	0	1	1		0.1734	0.1734	216
T1	C2	0.1849	1	0	0	0.1849			144
T1	C3	0.2938	0	0	0				
T2	C3	0.2938	1	1	1	0.2938	0.2938	0.2938	180
T3	C3	0.2938	0	0	0				
T1	C4	0.1963	1	0	0	0.1963			144
T1	C5	0.2474	0	1	1		0.2474	0.2474	216
T1	C6	0.2938	0	0	0				
T2	C6	0.2847	0	0	0				144
T3	C6	0.2565	1	0	0	0.2565			
T1	C7	0.2032	0	0	0				
T2	C7	0.1545	0	0	0				0
T3	C7	0.1551	0	0	0				
T1	C8	0.2723	0	0	0				216
T3	C8	0.2336	0	1	1		0.2336	0.2336	
Efficiency per project						0.9315	0.9482	0.9482	**Max=228**

Overall efficiency	0.9426

Discussions

The success of the project implementation greatly depends on allocated resources. Therefore, resource mobilization is one of the inputs frequently used for project performance evaluation (Iyer *et al.,* 2016). Problems of project portfolio selection (Cook & Green, 2000; Tavana *et al.,* 2015; Perez & Gomez, 2016) and project manager selection (Hadad et al., 2013) are also frequently considered in the literature. A general problem of staff selection and assignment (Wu & Sun, 2006; Bassett, 2000) is more complicated in multi-criteria, multi-project, multi-task framework. The practical significance of solving this problem is evident since a company usually signs contracts for the simultaneous implementation of several same or similar projects. This is very common in the implementation of IT projects.

In this paper, staff selection and assignment is done based on DEA efficiency, which may be considered as a contribution of this paper. The first step in consultant assignment is to select key performance indicators (KPIs) to be used as inputs and outputs. This selection is very important since it has a crucial impact on efficiency evaluation. This paper proposes seven KPIs significant for IT project implementation together with annual working days. The second step is *a priori* defining a set of all schemes covering triples of project, task and consultants. The third step is to choose a proper optimization model. The proposed model (8–19) can be used as a basic model for staff assignment in different areas by introducing different KPIs. The advantage of this approach is that this model can easily be extended by imposing constraints significant for practical implementation (eqs. 20 and 21).

The existence of a feasible solution will be provided if the total number of working days for all available consultants is greater than or equal to the required number, and if there is a sufficient number of candidates capable of performing individual tasks on all projects. The solution of the proposed model can improve the process of decision making by simultaneous efficiency evaluation, staff selection and assignment.

The proposed model does not cover time dynamic and does not include projects that should start latter than beginning of the fiscal year. Time dimension can be included by introducing the available working days for each consultant as a difference between maximal and assigned days (Bassett, 2000; Greiner & Ennsfellner, 2010). Another potential limitation of proposed approach appears when solving a large dimension problem, since schemes definition and solving the problem with many binary variables can be time-consuming. This issue opens an area for further research and the development of constructive heuristics (Sapkota & Reilly, 2011).

Conclusions and Further Research

This paper proposes a methodology which aims to solve the problem of simultaneous consultant assignment and efficiency evaluation in multi-criteria, multi-project, multi-task framework. Usually, in the real world, the decision maker understands that the main cause of problems in the selection and assignment of consultants is the inability to choose the best consultants when there are several alternatives. The second cause lies in the selection of the most appropriate and measurable criteria from the list. The decision maker could have made an easier decision based on a unique performance measure or rank of candidates. This means that criteria should be aggregated into one measure such as efficiency.

The methodology for staff (consultant) assignment based on efficiency evaluation includes multiply input and output criteria is set out in this paper. Historical data on selected staff performance and working days' requirements are used as criteria. The proposed DEA-based mixed-integer programming model enables efficiency evaluation of each consultant in fulfilling any task within the peer-group of consultants based on past performances and cost. Therefore, their ranking and benchmarking is provided. Another important feature is that the model provides the most efficient assignment plan, together with the expected efficiency in the implementation of each individual project within the overall efficiency.

The results of the real-world case study with three projects have shown the applicability and usability of the proposed model. The ease of adaptation and modification of the model for the practical application is also one of the benefits of the presented approach.

The approach proposed in this paper can be generally applied to making an adequate staff assignment plan, especially in application and projects implementation in IT sector. In practice, to apply the proposed model, decision maker need to select efficiency evaluation criteria, group them into inputs and outputs, define project—task-consultant relationships.

Further research can be directed towards modifying model by included priorities for projects and/or tasks implementation and the partial allocation of human resources in terms of time. Another direction can be developing the heuristics for easier and faster-finding solutions for large-dimension problems.

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