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THE USE OF RESOURCE ALLOCATION TOOLS IN PROJECT PORTFOLIO MANAGAMENT: LITHUANIAN CASE

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Abstract. A wide variety of resource allocation models have been introduced over the years, including linear programming, scoring models, group decision techniques and so on. Some of these techniques are not widely used because they are too complex and require too much input data or they are too complicated for decision making. This paper presents the results of research carried out in Lithuanian enterprises on the use of resource allocation tools in making decisions concerning project portfolio management. Firstly, the background information on resource allocation models is given. This is followed by a review of advantages and disadvantages of existing models. Finally, the results of research into the situation in Lithuanian enterprises are presented.

Keywords: resource allocation models, resource allocation tools, project portfolio management, advantages, disadvantages.

JEL classification: 022, G11, M21, L21.

1. Introduction

Project portfolio management (PPM) is a fairly new field. It may be applied to all types of organisations, for all kinds of projects in economics or other unrelated areas. Over the last fifteen to twenty years, quite some enterprises have adopted a project portfolio management framework. The number of publications on project portfolio management has also increased. Not only has project portfolio management become a particularly significant element of the project management theory, but its economic importance has also been recognised. Moreover, the issues of project selection and prioritisation, resource allocation have been extensively examined. Philips and Bana e Costa (2007) and Kleinmunz (2007) pointed out several challenges faced by managers in charge of allocating resources, which can be summarised as follows: 1) there is usually a large number of potential projects and scarce resources; 2) benefits are typically characterised by multiple and sometimes conflicting objectives; 3) no manager has a complete understanding of all consequences of every project as such information is spread across different organisational levels; 4) the allocation of resources to organisational units considered individually will not necessarily result in a total allocation that is collectively efficient; 5) if the resource allocation is not properly managed, it may lead managers to invest in projects that might be not in line with the organisation's strategic objectives (Montibeller *et al.* 2009; Wahl, Prause 2013).

In order to help decision makers properly allocate resources, project portfolio management specialists (Elahi, Najafizadeh 2012; Murray *et al.* 2010; Rafiee *et al.* 2013; Bhattacharyya *et al.* 2011; Rebiasz 2013 and others) developed different resource allocation models. However, some authors (Liberator, Titus 1983; Schmidt, Freeland 1992; Eilat *et al.* 2006; Solak *et al.* 2010) concluded that the use of quantitative and computer-aided project selection and resource allocation methods, due to their complexity, is rather limited. We carried out an analysis of the use of resource allocation tools in Lithuanian construction companies to assess the situation in Lithuania. The construction sector was chosen because it is one of the main production sectors in the European Union and one of the key drivers of economic development.

The objectives of this article are as follows: 1) to review the literature on quantitative modelling approach for resource allocation in the project portfolio; 2) to describe advantages and disadvantages of existing resource allocation models; 3) to present the results of research on the use of resource allocation tools in Lithuanian companies.

The research methods: analysis of scientific literature and other information sources, survey and statistical analysis (IBM SPSS Statistics 22).

2. Overview of resource allocation models

Current literature on project portfolio management covers a large number of resource allocation methods and techniques. There are also several classifications of resource allocation and project selection methods and models (e.g. Baker 1974; Hall, Nauda 1990; Martino 1995; Heidenberger, Stummer 1999; Iamratanakul *et al.* 2008). We updated previous classifications and divided resource allocation methods and models into 8 groups, namely benefit measurement methods, mathematical programming models, decision and game theory, simulation, heuristics, cognitive emulation, real options and ad hoc models (see Table 1). In some cases, models may be placed in more than one group.

Table 1. Resource allocation methods and models (source: compiled by authors)

Benefit measurement methods	***Mathematical programming models***	***Decision and game theory***	***Simulation models***	***Heuristics models***	***Cognitive emulation***	***Real options***	***Ad hoc models***
Comparative models (e.g. Kuei *et al.* 1994; Elahi and Najafizadeh 2012) ***Scoring models*** (e.g. Ulvila and Chinnis 1992; Coldrick *et al.* 2005; Murray *et al.* 2010) ***Traditional economic models*** (e.g. Ramsey 1981) ***Group decision techniques*** (e.g. Khorramshahgol *et al.* 1988)	***Linear programming models*** (e.g. Rinquest and Graves 1990; Rabbani *et al.* 2006) ***Non-linear programming models*** (e.g. Souder 1973; Santhanam and Kyparisis 1996) ***Integer programming models*** (e.g. Schmidt 1993; Carlsson *et al.* 2007) ***Goal programming models*** (e.g. Mukherjee and Bera 1995; Lee and Kim 2000) ***Dynamic programming models*** (e.g. Choi *et al.* 2007; Silva and Costa 2013). ***Stochastic programming models*** (Solak *et al.* 2010; Rafiee *et al.* 2013) ***Fuzzy mathematical programming models*** (e.g. Huang 2007; Bhattacharyya *et al.* 2011; Rebiasz 2013)	***Decision tree methods*** (e.g. Hess 1993; Stonebraker and Kirkwood 1997) **Game-theorethical models** (e.g. Ali *et al.* 1993; Gruver 1991)	Versapalainen and Lauro 1988; Choi *et al.* 2007; Gabriel *et al.* 2006.	Mandakovic and Sounder 1985; Oral *et al.* 1991; Coffin and Taylor 1996; Carazo *et al.* 2010; Choi *et al.* 2004; Dorner *et al.* 2004; Fitzpatrick and Askin 2005; Narasimhan *et al.* 2006.	***Statistical methods*** (e.g. Martino 1995; Cooper 1981) ***Expert systems*** (e.g. Liberatore and Stylianou 1993; Pearson *et al.* 1996) ***Decision process analysis*** (e.g. Winkofsky *et al.* 1981)	Roger *et al.* 2002	Cooper 1978

Benefit measurement methods are most frequently referred to in the literature and typically use one or multiple relative or absolute measures for economic return (e.g. ROI, NPV) or benefit-cost ratios. Benefit measures constitute metrics rather than methods and techniques and are used as inputs for ranking and scoring. As an example for comparative models, Q-Sort stands out as the most intuitive approach and can be used for large portfolios. The Analytical Hierarchy Process (AHP) provides advancements in scoring to improve decision making and gives a robust mathematical support to the human ability to make comparison. The AHP enables the decision makers to build a hierarchical model of goals and criteria, identifying an overarching goal (top level of hierarchy) and structure of objectives (second level), sub-objectives (third level), and so on. The lowest level of the hierarchy is represented by alternatives, a set of potential decisions (see Figure 1). After the hierarchical decision model is designed, the AHP provides a framework for setting priorities. The AHP uses pair-wise comparison between elements at a given level of hierarchical model, in terms of relative importance of the pair of elements with respect to the parent node in the hierarchy.

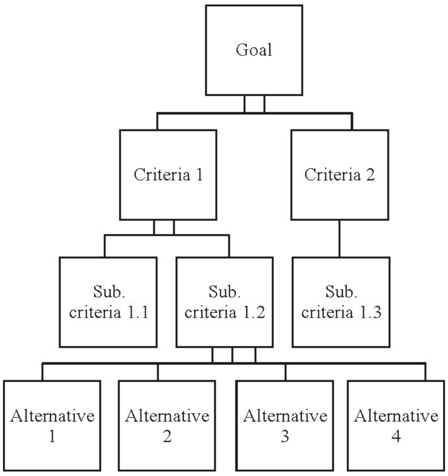

Fig. 1. Example of AHP Decision Model (source: compiled by authors)

Scoring models are used by many practitioners and constitute the core of most project portfolio management solutions (Arlt 2010). The popularity of scoring models primarily depends on their ease of use based on standardized weighting of priorities and objectives, and the potential to include both qualitative and quantitative criteria. In addition, risk can be incorporated in the scoring criteria. Lastly, users of scoring models can adjust weights and other parameters, which allows performing "what-if" analysis and simulations (Meredith, Mantel 1999).

Traditional economic models are designed to perform cost-benefit analysis and/or assess the financial risk of a project. They are based on cash-handling methods and are closely interrelated or related to extensions of traditional methods used in capital budgeting.

The use of *group decision techniques* allows for a systematic collection and collation of knowledge and evaluations of specialists in specific areas of expertise. Therefore, this method is regarded as appropriate in the performance of practical operations or at least as a means of verification for the purpose of receipt of data necessary for the development of a more complex model (Khorramshahgol *et al.* 1988). The Delphi method is a widely used group decision technique. Other group decision techniques include the nominal interaction process and the impact and ordinal intersection methods.

Mathematical programming describes the optimization of one or multiple objective functions, subject to specific constrains. Numerous PPM software solutions provide the functionality for constrained optimization, which is complex to perform without computational aid, especially for large portfolios. Mathematical programming models are divided into linear programming, non-linear programming, integer programming, goal programming, dynamic programming, stochastic programming and fuzzy mathematical programming models. A mathematical programming model developed by Wang *et al.* (2002) is expressed as follows:

Maximize

$$maxY = 1/T$$

subject to

$$Y \le \sum_{r=1}^{R} \frac{\beta_{\alpha,r} \cdot \mu_{\alpha,r}}{\omega_{\alpha}} \; for \, \alpha = 1,2,\ldots,A \qquad (1)$$

and

$$\sum_{\propto=1}^{A} \beta_{\alpha,r} \le 1 \; for \, r = 1,2,\ldots,R,$$

where A is the number of activities, and R is the number of resources.

Both *decision and game theory* methods clearly emphasize possible future events or reactions of the company environment that are undefined in their scope. The difference between these methods is that decision-making theory states that environmental changes do not depend on the company's actions, whereas game theory clearly emphasizes rational competitors (Heidenberger, Stummer 1999). Decision-making and game theory models are divided into decision tree methods and game-theoretical models. Decision tree analysis can deal with individual decision problems. It allows analysing the expected values of a project at each event node to choose the case with the maximum value (Sato, Hirao 2012). In general terms, a decision tree is made up of two types of nodes, namely nodes of classical probabilistic events and decision nodes. Heidenberger (1996) introduced the third type of node, the "computed chance".

Simulation models allow for a much more detailed expression of real systems as compared to optimization models, while during modelling only "what-if" type of questions have to be answered. They are used in cases where experiments in reality are inappropriate, too expensive or take too long, and the performance of complex analytical procedures is impossible or they cannot be applied without exceeding permissible costs or taking too long (Heidenberger, Stummer 1999). In Monte Carlo simulation, probability distributions of all probabilistic elements are used in the programme in order to calculate the overall distribution of the target values and probability of the used values. Systemic dynamics simulation creates feedback cycles so that analyses could be expanded based on a certain scenario, for example, considering consequences and reactions in certain markets after the presentation of a certain new product (Milling 1996).

Cognitive emulation methods are designed for the development of a model of actual decision-making process within an organization (Hall, Nauda 1990). They are based on the previous experience acquired under similar circumstances where, given the possible data, drawing conclusions seems reasonable. Cognitive emulation models can be divided into statistical methods, expert systems and decision process analyses. There are models employing statistical methods in order to determine factors affecting project implementation in a programme. Those factors can be ensured by statistical methods, such as discriminant, regression and cluster analysis (Iamratanakul *et al.* 2008). An expert system is aimed at repeating the manager's decision-making process when decision-making projects are analysed to a certain degree (Hall, Nauda 1990). An expert system is a computer programme designed to replicate conclusion-drawing process used by specialists (Heidenberger, Stummer 1999). The aim of decision process analysis is to improve the understanding of general managerial principles and reflect a hierarchical organization where manifold groups operate, including the selection process. The work of Schmidt and Freeland (1992) introduces essential changes when decision-making cases lead to decision-making processes. Winkofsky *et al.* (1981) describe the resource allocation process covering various units at three hierarchical levels.

Heuristic modelling is designed for finding acceptable although not necessarily optimal decisions. This is because companies would "<…> need for particularly realistic approaches, which consider lots of interactions between the various elements of the models" (Mandakovic, Souder 1985). Heuristics procedures can be divided into four groups: PR-based X-pass heuristics, classical meta-heuristics, non-standard meta-heuristics, and miscellaneous heuristics (Browning, Yassine 2010).

For the strategy to be successful, *real options* are necessary when applying evaluation methods in relation to projects combining uncertainties in business and active decision-making. Real options start with drawing an investment opportunity, taking into account an option. To make this possible, variables have to be determined that allow defining project characteristics and the value of a simple option.

Ad hoc models are models of a different type, they are unstructured and developed for specific purposes (Iamrantanakul *et al.* 2008). These methods include "top-down" approach to project selection and resource allocation. One usually successful method is a technique which is referred to as a "genius award" method (Cooper 1978) that simply provides funding to proven researchers to work on any project of their choice. This technique is often as successful as complex analytical approaches (Hall, Nauda 1990).

3. Advantages and disadvantages of resource allocation models

Each model or method has its own advantages and disadvantages. For instance, the advantages of comparative models include ease of understanding, ease of use, and possibility of integrating quantitative and qualitative analysis. As far as their disadvantages are concerned, these models are characterised by lack of explicit consideration of risks, repetition of the entire process when new projects are added or deleted, difficulty in use in the case of a large number of projects to be compared and incapability to identify really good projects.

The scoring method aims at ranking the project set, after which resources are distributed on the basis of the priorities established in the ranking. However, this approach assumes that candidate projects are independent which is not always true; consequently, the best individual projects do not necessarily make the best portfolio (Carazo *et al.* 2010). Scoring is often arbitrary (Iamratanakul *et al.* 2008).

The AHP is relatively simple in terms of its procedure. It can present a complex decision problem as graphical hierarchical structures. However, the AHP is subjective in nature. Different decision makers can attribute different levels of importance to the same criteria. As the number of criteria increases, the tabulation and calculations become too complex (Iamratanakul *et al.* 2008).

All these limitations have resulted in an increasing interest in mathematical programming models. However, mathematical programming models also have some limitations. Ordinary linear and integer programming models are limited in that they can account for only a single objective. For example, one of the objectives, profit or market share, is maximized, subject to applicable constraints on capital, personnel, etc. A modification of ordinary linear programming, i.e. goal programming, was first used to address more than one objective. This technique sets certain aspiration levels or goals for each objective, then minimizes deviations from these goals. However, there are also some difficulties with goal programming. Aspiration levels for goals may be difficult to choose. And when the chosen aspiration levels are not ambitious enough, the solutions that result may not be the best available. When goals are prioritized, the formulation implies that there is absolutely no permissible tradeoff between goals. Another difficulty in tradeoff between goals arises in that they are usually not measured in the same units. Despite these problems, goal programming has obvious advantages: 1) standard single-objective linear programming procedures can be used to solve the problem at each priority level, and 2) for integer problems, standard integer programming algorithms may be applied at each priority level (Graves, Rinquest 2003).

For example, game-theoretical models are useful in evaluating resource allocation strategies, taking into consideration rationally operating competitors. Most game-theoretical methods are limited in that they emphasize duopoly competition in two-stage race for patents, where the second stage starts only after the successful completion of the first one.

Decision tree analysis can deal with individual decision problems. It allows analysing the expected values of a project at each event node to choose the case with the maximum value. However, it cannot address decision problems of a continuous type. If we try to apply it to a large number of activities, the tree branches would rapidly grow to an impractical degree of complexity (Sato, Hirao 2012).

For example, simulation is very appropriate for a portfolio in a dynamic organization. However, its limitation is prohibited of its practice when an organization does not have a well established standard and flow of information (Iamratanakul *et al.* 2008).

Real options approach helps translate project options into visualized effects. It can reduce both downside and upside risk associated with project investment. It can quantify the value of postponing the investment decision. Despite the benefits, real option requires extensive data and analysis (Iamratanakul *et al.* 2008).

Ad hoc models are a simplified version of scoring, where projects that do not meet certain criteria are eliminated from choice set (Arlt 2010). Although this can be efficient, the applicability of such techniques is limited. Because of the interdependent nature of projects in a portfolio, particular care is needed, as profiling may exclude projects that do not meet a pre-defined threshold, but may be required as a prerequisite for a crucial other project (Arlt 2010).

4. Use of resource allocation tools in Lithuanian enterprises

Research was carried out in Lithuanian construction enterprises. The questionnaire was sent out to 500 construction enterprises selected on the basis of their turnover (at least 5 million LTL) and number of employees (at least 100). The questionnaire was completed by managers of 159 enterprises. The average number of years of experience of managers in project implementation was 12 years (minimum – 4 years, maximum – 25 years). Managers of 56% of the respondent organisations had over 10 years of experience in project management. The average maturity of project management in organisations was 2.69 scores (standard deviation – 0.85) (possible maximum value – 5 scores). The highest and lowest levels of project management maturity were respectively 3.7 scores and 1.31 scores.

Table 2. Correlation between the use of resource allocation tools and experience in project management (source: compiled by authors)

		Tool	Experience
Tool	Pearson Correlation	1	,515**
	Sig. (2-tailed)		,000
	N	159	159
Experience	Pearson Correlation	,515**	1
	Sig. (2-tailed)	,000	
	N	159	159

**. Correlation is significant at the 0.01 level (2-tailed).

This research aimed at determining whether decision makers apply resource allocation tools within an organisation. Research showed that as much as 44% of the respondent enterprises did not use any resource allocation tools. 25% of them responded that they were not aware of such tools, while 75% of them indicated that they were difficult to apply.

Furthermore, research revealed that there is a statistically significant, moderate linear correlation between the use of resource allocation tools in an enterprise and the manager's experience in project management (see Table 2).

The average years of experience of managers in project management in enterprises that do not use resource allocation tools are 10 years, whereas the average years of experience of managers in project management in enterprises using resource allocation tools are 14 years.

Moreover, there is also a statistically significant, moderate linear correlation between the use of resource allocation tools and the maturity of project management in an organisation (see Table 3).

Table 3. Correlation between the use of resource allocation tools and project management maturity (source: compiled by authors)

		Tool	Maturity
Tool	Pearson Correlation	1	,519**
	Sig. (2-tailed)		,000
	N	159	159
Maturity	Pearson Correlation	,519**	1
	Sig. (2-tailed)	,000	
	N	159	159

**. Correlation is significant at the 0.01 level (2-tailed).

The average maturity of project management in enterprises that do not use resource allocation tools is 2.22 scores. Accordingly, the average maturity of project management in enterprises using resource allocation tools is 3.06 scores.

6. Conclusions

The overview of resource allocation models showed that there are numerous tools that may be used by decision makers to ensure efficient allocation of resources. There are also several classifications of resource allocation and project selection methods and models. We updated previous classifications and divided methods into 8 groups, namely benefit measurement methods, mathematical programming approaches, decision and game theory, simulation, heuristics, cognitive emulation, real options and ad hoc models

Each model or method has its own advantages and disadvantages. Therefore, a model or method should be chosen in view of the circumstances of its application. For example, comparative models have a lot of advantages: ease of understanding, ease of use, and possibility of integrating quantitative and qualitative analysis. However, there is a difficulty in use when a large number of projects is involved. Another example can be simulation which is well suited for a portfolio in a dynamic organization. However its limitation is prohibited of its practice when an organization does not have a well established standard and flow of information.

The conducted research revealed that as much as 44% of the Lithuanian enterprises which took part in this research did not use any resource allocation tools. 75% of them indicated that they did not use such tools because they were complicated to apply in practice. It is likely that the same situation could be observed in other Lithuanian sectors. The results of our research supported the results of previous scientific research that the use of resource allocation models, due to their complexity, is limited.

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