A DECISION SUPPORT SYSTEM FOR EVALUATING INFORMATION TECHNOLOGY PROJECTS

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A DECISION SUPPORT SYSTEM FOR EVALUATING INFORMATION TECHNOLOGY PROJECTS

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DECLARATION OF ORIGINALITY

I, Şeyhmus Atlı, certify that

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ABSTRACT

A Decision Support System for Evaluating Information Technology Projects

The increasing pressures of global competition, the continuous stream of innovative technologies, and the introduction of new products to satisfy customer needs make Information Technology (IT) projects a key element of the business market. Due to the proactive nature of IT, its value is difficult to evaluate in advance, which means that organizations often select to implement IT projects that do not realize the intended benefits. A well-designed selection process for IT projects should decrease the failure rate of implemented solutions and increase the financial success of the companies. This study attempts to resolve the IT project selection problem in the companies by combining an ANP with fuzzy logic and strengthening the solution with a Monte Carlo simulation. While there have been previous attempts to combine any two of the three underlying methods, the combination of all three should lead to a method that gives optimal results for any given case. The study reviews existing literature on IT project selection. Every criteria that can be relevant to IT projects are obtained with literature review and currently significant ones are selected using feedback from experts. The most effective ones respectively finance, organizational goals, risk and technical are used for the study. Based on existing knowledge and analysis of problems facing the companies, a detailed theoretical model is developed and applied to a real-world case study. In this context, this study should be useful to IT project selection committee members and researchers in the field of decision making, but it should also be of interest to IT managers of companies.

ÖZET

Bilgi Teknolojileri Projelerinin Değerlendirilmesi için Karar Destek Sistemi

Küresel rekabette artan baskılar, sürekli yenilikçi teknolojiler, akışı ve müşteri ihtiyaçlarını karşılamak için yeni ürünlerin sunulması Bilgi Teknolojileri (BT) projelerini iş piyasasının önemli bir unsuru haline getirmektedir. BT'nin proaktif doğası nedeniyle, değerinin önceden belirlenmesi zordur; bu da, kuruluşların çoğu zaman amaçlanan faydaları gerçekleştirmeyen BT projelerini uygulamayı seçmelerine neden olmaktadır. BT projeleri için iyi tasarlanmış bir seçim süreci, uygulanan çözümlerin başarısızlık oranını düşürmeli ve şirketlerin maddi başarısını arttırmalıdır. Proje seçimi için birçok araç mevcuttur, ancak çoğunlukla niceliksel veya nitel ölçütleri içermektedir. Bu çalışma, Analitik Ağ Süreci'ni Bulanık Mantık ile birleştirerek ve çözümü Monte Carlo Simülasyonu ile optimize ederek şirketlerin BT proje seçim problemini çözmeye çalışmaktadır. Üç temel metottan herhangi ikisini birleştirerek çözüm üreten örnekler olsa da, üçünün kombinasyonu, herhangi bir vaka için en iyi sonuç veren bir metoda öncülük etmektedir. Çalışma, BT proje seçimi ile ilgili mevcut literatürü gözden geçirmektedir. Bilişim teknolojileri projeleri ile ilgili olabilecek her kriter literatür taraması ile elde edilmiş ve uzmanlardan gelen geribildirimleri kullanarak en etkili olanlar finans, risk, teknik faktörler ve örgütsel hedefler araştırma için kullanılmıştır. Mevcut bilgilerin ve şirketlerin karşı karşıya kaldığı sorunların analizine dayanarak, ayrıntılı bir teorik model geliştirilmiş ve gerçek dünya vaka analizine uygulanmıştır. Bu bağlamda, bu çalışma, karar alma alanında BT proje seçim komitesi üyeleri ve araştırmacıları için yararlı olmakla beraber şirketlerin BT yöneticileri için de ilgi çekici olmaya adaydır.

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ABBREVIATIONS

AI: Artificial Intelligence

AHP: Analytic Hierarchy Process

ANP: Analytic Network Process

CBA: Cost-Benefit Analysis

DCF: Discounted Cash Flow

EAM: Extent Analysis Method

FMCGDM: Fuzzy Multi Criteria Group Decision Making

FNIS: Fuzzy Negative Ideal Solution

FPIS: Fuzzy Positive Ideal Solution

FPP: Fuzzy Preference Programming

GUI: Graphical User Interface

IRR: Internal Rate of Return

IS: Information Systems

IT: Information Technology

MCDM: Multi-Criteria Decision Making

NPV: Net Present Value

R&D: Research and Development

ROI: Return-On-Investment

TOPSIS: Techniques for Order Preference by Similarity of Ideal Solutions

CHAPTER 1

INTRODUCTION

1.1. Research problem

Innovative Information Technology (IT) projects are crucial to building and sustaining competitive advantage (Porter, 1980). Due to their proactive nature, however, the value of IT projects can be difficult to evaluate. Research shows that companies spend over $50 billion each year on IT projects that are finished but never used in practice (Pinto, 2010). Well-designed selection process for IT projects decreases failure rate of projects, helps managers to work simultaneously on several opportunities, and as a consequence increases the financial success of the organization (Şen and Gürsoy, 2005). This means that companies need to define a method of data collection and processing that will ultimately result in an optimal investment decision within a limited set of resources.

A good method must take into account the fact that valuable information for the rating of a given IT project proposal is often revealed only after completion of the selection process. Practical experience in the realization of complex IT projects suggests that during the initial stages of the project development process there may be no cash flow estimates available. It would be difficult to either justify or invalidate a given project's approval without such data, but in practice, every company has a deadline in which it has to commit itself to a positive or negative decision regarding the launch of a given project. If making a decision without adequate data is deemed too risky, the company could decide to wait and see if new information would be revealed over time. At the same time, in the absence of quantitative data, management could rely on qualitative statements by technological experts to stimulate the decision making (Carlsson et al., 2007).

In the framework of IT project selection, the latter approach has substantial merit. Bowman and Hurry (1993) describe how strategic management can be represented in the light of option theory. According to their approach, the strategic management process can be viewed as a chain of so-called “shadow” options, where no specific options have been clearly identified or made known from the beginning. Shadow options seem to become real options only when real assets or the expectations of real assets get connected to the options of starting an IT project. Real options give the company management a tangible strategic alternative, an investment possibility that can be realized at a given point in time. Thus, detecting such shadow options or including such options in the decision making process may significantly affect the overall strategy of the company.

In other terms, given that there are no unlimited funds and resources in any organization, appropriate selection and prioritization of IT projects are necessary (Meade and Presley, 2002). IT project selection can be considered difficult and complex because of the variety of variables that can influence the decision. Objectives that are usually taken into consideration during analysis of IT projects are economic desirability, technical issues, environmental and social factors (Nowak, 2005).

Selection criteria for an IT project is the key point for success. Although there are lots of criteria on literature, IT projects and their criteria are changing rapidly. Since the technology is evolving exponentially, user needs, criteria that satisfying the needs and effects of the criteria is growing accordingly. For example hardware costs are decreasing and computational power is increasing. These changes effect selection of IT project directly. Communication tools for projects were relatively important for the last decade. However, changes in technology and minimization of communication costs removed the communication cost from IT project selection criteria as expected. Another example of change in criteria is patentability of a project. Patentability was relatively important for IT project selection. Customization of IT projects for every environment, tendency to in-house implemented solutions and rapid changes in IT trends pushed the importance of patentability criteria back and made lose its significance. In this research decision making committee for criteria selection involves relatively young and dynamic IT professionals. This leads the study to eliminate older criteria which are either lost their significance or not as effective as for the previous studies.

IT project selection criteria can be categorized as qualitative and quantitative. Qualitative criteria include potential risks, feasibility, suitability and productivity improvements, while quantitative criteria are Return-On-Investment (ROI), total investment, pay back and Discounted Cash Flow (DCF) (Chen, 2002). How the two types of criteria are combined depends on the specific needs of the company, which is why there is continued research devoted to optimization of IT project selection methods.

For this research, decision of the related criteria is completed as follows. First, literature review is completed and every single criteria that can be relevant to IT projects are noted (Table 1). Then, using feedback from experienced field experts (decision making committee), the control criteria and subcriteria are determined (Table 2). Detailed information will be discussed on CHAPTER 4.

Table 1. IT Related Criteria Eliminated by Field Experts

Criteria	Definition	Elimination Reason
Service Level	Measures the performance of a system	Performance is not a concern for all projects
Training Cost	Costs include course fees, books, equipment and materials, and personal costs such as transport	Training costs are similar for IT projects
Competitor Advantage	Identification of weaknesses and strengths that a company's competitors	Competitor Advantage is not a concern for internal project selections
References	Obtained information on related project by experienced users	Most of the projects are specific for a company
Communication Cost	Costs of timely and appropriate collection, storage, distribution and generation of project information	Communication cost is not a concern for contemporary IT projects
Suitability to Standards	Meeting the company standards	IT trends highly motivate the change in standards
Auditability	Process of verification of the extent to which the project realisation complied with the rules and principles of the company	Auditability is similar for IT projects
Flexibility of Project	adaptation to variances and changes happening within the environment	Flexibility is not a big concern for big projects
Employee Satisfaction	Fulfilling the employee desires and needs at project	Employee satisfaction is not on first row
User and Customer Satisfaction	How project meet or surpass a customer's expectation	Customers are usually employees for IT projects.
Political Dimension	Regulations or obligations enforced by the political members	Most of the projects are independent of politics
Project Life Cycle	Series of activities which are necessary to fulfil project goals or objectives	Project Life Cycle is similar for IT projects
Organizational Learning	Process of creating, retaining, and transferring knowledge within an organization	Organizational learning is similar for IT projects
Regulatory Clearance	State of having satisfied the official conditions or regulations	Regulations are similar for IT projects
Complexity	Interrelated parts between knowledge of the degree and nature of the relationship	Complexity is big picture of the all other criteria
Patentability	Eligibility for patent protection	Patentability is not a big concern for IT projects anymore
Organizational Learning	The process of creating, retaining, and transferring knowledge within an organization	Organizational Learning is not having priority for fast-paced IT projects

Table 2. Usage of Selected Subcriteria in Relevant Literature

Criteria	Subcriteria	Relevant literature
Finance	NPV/IRR	Carlson et al. (2007) Enea and Piazza (2004) Kim et al. (2009) Meade and Presley (2002) Pinto (2010) Rosacker and Olson (2008)
	ROI	Carlson et al. (2007) Enea and Piazza (2004) Kim et al. (2009) Pinto (2010)
	Payback period	Kim et al. (2009) Pinto (2010) Rosacker and Olson (2008)
Risk	Complexity	Asosheh et al. (2010) Carlson et al. (2007) Enea and Piazza (2004) Karami and Guo (2012) Kim et al. (2009)
	Probability of success	Kim et al. (2009) Meade and Presley (2002) Rosacker and Olson (2008)
	Time to complete / duration of project	Asosheh et al. (2010) Enea and Piazza (2004) Kim et al. (2009) Lee and Kim (2001) Meade and Presley (2002) Pinto (2010)
Technical	Personnel	Asosheh et al. (2010) Meade and Presley (2002)
	Hardware	Asosheh et al. (2010) Karami and Guo (2012) Kim et al. (2009) Lee and Kim (2001)
	Software	Asosheh et al. (2010) Karami and Guo (2012) Kim et al. (2009)
Organizational goals	Module reusability	Asosheh et al. (2010) Meade and Presley (2002)
	Strategic fit	Carlson et al. (2007) Meade and Presley (2002) Pinto (2010) Rosacker and Olson (2008),
	User need / Market demand	Asosheh et al. (2010) Meade and Presley (2002) Pinto (2010)

1.2. Research focus

This study attempts to resolve the IT project selection problem for qualitative and quantitative criteria in the context of the banking sector. To achieve this, a new framework is offered that addresses two research questions. First, how can the attributes of an IT project in the banking sector be incorporated in a project selection method? Second, how can existing IT project selection methods be optimized to provide the most effective solution for the banking sector?

By answering these questions, the study aims to contribute to existing knowledge concerning methods for project selection and evaluation. The objectives of the study can be described as follows. Firstly, to develop a simulation-based model for IT project selection method in the banking sector. Secondly, to analyse competing IT project alternatives on the basis of quantitative and qualitative metrics. Thirdly, to provide recommendations for bank project managers and researchers for future improvements in project selection and evaluation techniques.

It should be noted here that even though the research questions and the objectives focus on applications related to decision making in banks, the results of the study should be applicable to different types of financial institutions and other IT project selection situations.

1.3. Research methodology

To address the defined research questions, the study follows an inductive research method (Saunders et al., 2009). A new model for IT project selection in the banking sector is developed by combining an Analytic Network Process (ANP) with fuzzy logic and optimizing the solution with a Monte Carlo simulation. While there have been previous attempts to combine any two of the three underlying methods, the combination of all three should lead to a method that gives optimal results for any given case. An important element of the method is the application of fuzzy Techniques for Order Preference by Similarity of Ideal Solutions (TOPSIS) to analyse the gathered data and recommend a solution to the problem. The method has similarities to two previously established methodologies by Shyur (2006); Sari (2013) and Nguyen, Dawal, Nukman and Aoyama (2014). A real-world case study is used to test the developed model. The study case data is collected through a survey of professionals with IT project selection experience working in banks in Turkey.

1.4. Thesis outline

In order to achieve the objectives of the study, the thesis is presented in six chapters, with each chapter representing a separate stage in the research process. The study proceeds in chapter 2 by presenting a discussion of existing literature on R&D and IT project selection. The applied methodology is described in chapter 3, defining the research philosophy, as well as the data collection used to realize the aim of the study. In chapter 4, a detailed theoretical model including a decision making tree is developed and discussed from the aspect of its application in the banking sector. Chapter 5 details the findings of a case study based on the model developed in chapter 4, but other possible applications of the proposed approach are also presented. A conclusion discussing the strengths and weaknesses of the model, as well as opportunities for further research, are offered in chapter 6.

CHAPTER 2

LITERATURE REVIEW

There is a large body of literature on the issue of project selection, especially in the context of R&D and product development. The topic is rather broad, covering different types of investment and a range of methods. Some methods are less effective because they take into account either quantitative or qualitative measures, but there are also methods that overcome this issue, and are therefore readily applicable in practice for IT project selection. It is argued that existing methods can be further optimized. This chapter provides an overview of the relevant project selection methods explored in theoretical and empirical studies, and discusses the benefits and practical limitations of each method. Approaches that integrate ANP, fuzzy logic, and Monte Carlo simulation are presented in separate chapters. Methods that are used specifically in the banking sector are also reviewed.

2.1. Project selection methods

2.1.1. General characteristics

There are several classifications of the basic project selection methods. According to one classification, there are two main approaches. The first is influenced by the conclusions of Baker (1974) and Baker and Freeland (1975), which explore quantitative methods and focus on the behavioural aspects of the decision process. Following this approach, the research field can be divided into benefit measurement and resource allocation methods, and identification of patterns based on a series of empirical investigations. The second approach involves the research of Souder and

Mandakovic (1986) and follow-up studies such as Zanakis, Mandakovic, Gupta, Sahay and Hong (1995), which evaluate qualitative criteria and entail different psychometric approaches to maximizing organizational involvement in the project selection process.

One of the used project selection methodologies is benefit measurements methods, which include a variety of comparative models. That model evaluate projects by cross-relating the characteristics of each individual proposal to all other project proposals within a group (Zanakis et al., 1995; Iamratanakul et al., 2008). Scoring approaches using checklists, multiple criteria, multi-attribute utility analysis, or Analytic Hierarchy Process (AHP), are also forms of benefit measurement methods. Economic models such as DCF fall into a third group of benefit measurement methods.

Similarly, the popular method for project selection based on a Monte Carlo simulation is recognized in the group of simulation and heuristics models. This method uses probability distributions of all stochastic elements in a given R&D program to determine the overall probability distribution of objective values and means. Versapalainen and Lauro (1988) present such an application of the Monte Carlo simulation for the assessment of portfolio balance and competitor strategies, and their impact on the company's win probability and expected return on R&D investment. As with all other methods, the Monte Carlo simulation is applicable in a specific set of circumstances, and has several strengths and weaknesses, discussed in more detail in chapter 2.3. System dynamics simulations, which provide feedback loops to improve analysis of different project selection scenarios, and heuristics models, which are looking for acceptable rather than optimal solutions, follow similar basic principles as Monte Carlo simulation models (Iamratanakul et al., 2008).

Pinto (2010) lists six problems that decision-makers need to address when evaluating projects selection methods:

- Realism – the method should reflect the organizational objectives and strategic goals, while the criteria should correspond to the availability of resources;
- Capability – the method should be applicable to a variety of projects, but also robust enough to include additional criteria and information according to the organization's needs;
- Flexibility – the method should be easy to adjust in case there are legal or other type of changes that affect the basic project selection process;
- Ease of use – the method should be simple and comparatively fast, while the inputs and outputs must be clear and understandable for organizational representatives at different levels;
- Cost – the project selection method should be relatively cheap in order for managers to use it on regular basis; and
- Comparability – the method should be broad enough to include a number of different project alternatives.

Many theoretical methods do not satisfy these criteria, and are therefore applied in limited context or not at all. Some methods address few of the issues relevant to the problem, while others are too complex, require too much input data, or are too difficult to understand. A method that uses only quantitative data cannot be employed when there are qualitative factors (e.g. corporate strategy goals) that influence the project process (Meade and Presley, 2002). Many methods also require data with a high degree of certainty, which is difficult to achieve in practice (Novaresh et al., 2006).

Furthermore, there is a number of different factors that can be used to evaluate projects. A project can have several types of risk involved, including technical risk related to how tested the technology is, financial risk related to the company's financial exposure due to a given project, and safety risk related to the project's effects on its users (Pinto, 2010). Similarly, a project can be evaluated based on commercial factors or internal operating issues. In practice, the different factors are usually weighted, which means that some issues will carry higher importance for one project than they will for others. In either case, because project selection methods take into account a limited number of factors, which may be based on both objective and subjective data, no project selection method can perfectly correspond to the complexities concerning a single choice.

This study uses concepts from three previously established methodologies by Shyur (2006), Sari (2013) and Nguyen, Dawal, Nukman and Aoyama (2014). Shyur (2006) combines ANP and TOPSIS to evaluate commercial-off-the-shelf products. Since the identification of the relationships between criteria for this paper is subjective as expected, power of the fuzziness seems to be missing. Sari (2013) integrates fuzzy AHP and a fuzzy TOPSIS technique with Monte Carlo simulation for the evaluation of radio frequency identification providers. Although the methodology applied by Sari in this paper is strong enough for decision problem of a radio frequency identification providers, criteria is not interdependent as much as an IT project bucket criteria. Therefore AHP usage for the research will not cover the strong inter relations between the criteria. Nguyen, Daawal, Nukman and Aoyama (2014) develop a hybrid approach using fuzzy ANP and complex proportional assessment of alternatives with grey relations (COPRAS-G) for fuzzy multi-attribute decision making in the context of evaluating machine tools. On most studies TOPSIS and COPRAS are used interchangeably because of their similarities. Lack of strength coming from a simulation tool is the only missing part for this paper. One could add an appropriate simulation technique to this methodology and use it for further studies, however manipulation of a methodology is not easier than the creation of a new one. Other hybrid methods combining any two of the ANP, fuzzy logic and Monte Carlo simulation models previously discussed are also used as a reference (e.g. Mahmoodzadeh et al., 2007).

2.1.2. Characteristics of IT project selection methods

Any of the methods discussed above could be applied in the context of management Information Systems (IS) and IT, according to the specific needs of the organization. Project selection in this environment is considered to be a Multi-Criteria Decision Making (MCDM) problem, but in practice it could be approached from a number of different perspectives. The role of the IS manager in choosing or prioritizing projects based on predefined constraints could be seen as an optimization problem. To solve optimization problems of this type, researches tend to use mathematical models such as linear programming, goal programming, or dynamic programming.

A number of methodologies designed specifically for the selection of IS projects have been explored in academic literature (Lee and Kim, 2000, 2001; Chen, 2002; Liberatore and Pollack-Johnson, 2003; Lawson et al., 2006; Asosheh et al., 2010). Some of these methodologies focus on the interdependencies among criteria and candidate projects, while other research discusses the qualitative and quantitative factors of projects. One methodology integrates the techniques balanced scorecard and data envelopment analysis into an approach for ranking project that focuses on IT project selection criteria (Asosheh et al., 2010). While some methodologies take into account the actual success probability of the selected projects, many do not.

A survey-based study by Rosacker and Olson (2008) analyses the utilization of IT project selection by the State Government from the aspect of quantitative and qualitative evaluation methodologies, and links the process to measures of perceived project success. In essence, public-sector project selection methods are assumed to include CBA, Net Present Value (NPV) or Internal Rate of Return (IRR), budget constraints, probability of successful completion, legal requirements, or subjective assessment. As Bozeman and Bretschneider (1986) point out, project selection in the public sector is quite different from similar processes implemented by private entities, mostly because public organizations are risk-averse, have complex relationship with authority and regulation, and function in the context of short-term goals and budgets. For this reason, project selection methods used by private entities tend to be more efficient.

Overall, most of the studies focus on the following project selection methods:

- Unstructured peer review – a popular and practical method due to its relative simplicity, typically used in combination with other methods such as scoring tables;
- Scoring methods – starting with checklists, which are fairly easy to implement but are highly subjective, the complexity of scoring methods varies significantly and are continuously improved to eliminate subjectivity and reflect reality as closely as possible;

- Mathematical programming algorithms – included here are methods such as integer programming, linear programming, nonlinear programming, goal programming, and dynamic programming, all of which are rather complex and difficult to understand without specific training;
- Economic models – popular metrics for a project proposal such as CBA, IRR, NPV, ROI, and option pricing theory, which are commonly used among managers, but often require additional qualitative assessment to reach an investment decision;
- Decision analysis methods – using quantitative and qualitative criteria, methods included here are the multi attribute utility theory, decision trees, risk analysis, and AHP;
- Interactive methods – more complex methods such as Delphi, -sort, behavioural decision aids, and decentralized hierarchical modelling;
- Artificial Intelligence (AI) methods – these methods include expert systems and fuzzy sets, which are highly sophisticated but are increasingly used for general management decisions; and
- Portfolio optimization methods – typically involving simulation and heuristic processes.

2.1.3. IT project selection methods in the banking sector

The discussed IT project selection methods can be used in various industries and for various needs, including investments in new IT projects for a given bank. All banking operations are set strategically in an IS environment based on a crucial alignment of business and information strategies. In this context, banks and other financial institutions are highly information-sensitive and critically dependent on continuous investment in IS and IT projects (Broadbent and Weill, 1993). This dependence is greater for the major banks that operate in a particularly competitive environment – research has shown that most IT projects are developed primarily with the aim of responding to the existing market expectations (Prasad and Harker, 1997). For this reason, banks were among the first groups to implement interorganizational IS linking institutions at national and international level.

IT project implementation in banks is a long and complex process, in large part because of inefficient decision making processes, and extensions related to changes in scope during the project's implementation. The procurement of IT projects in the World Bank takes 2.2 years on average, and the approval of any decision is slowed down by bureaucracy (Dener et al., 2011). The implemented projects are quite costly, which is why the decision makers require extensive analysis before the final approval. The World Bank insists on a project selection process based on the design of the available alternatives as well as a realistic cost/benefit analysis, taking into account the total cost of project ownership.

Even though IS/IT is important for the banking sector, it is surprising that there are relatively few studies on project selection methods that explore applications in the banking sector. Benaroch and Kauffman (2000) is a rare example, using real options analysis in order to assess projects that deploy point-of-sale debit services in an electronic banking network. In this model, the potential investment is defined as a call option that pays dividend, and the asset's value for a given time period is calculated by subtracting the present value of the cash flows foregone. By doing so, this model improves on the commonly used DCF analysis, which does not recognize the influence of managerial flexibility in the cash flow, and decision tree analysis, which evaluates a number of clearly irrelevant decision possibilities.

Building on these findings, Schwartz and Zozaya-Gorostiza (2003) present two models for IT project acquisition and IT project development using the real options approach. Both models account for uncertainty in the costs and benefits of each investment opportunity. In the case of IT project acquisition model, the concept of stochastic cash flows is used to track the changes in the value of the underlying asset. Notable variables here are the amount of money, the point of time, the interval and the cash flows. Similarly, for the IT project development model, an extension of the model for technical and input cost uncertainty first developed by Pindyck (1993) is applied to account for the decrease in costs for certain IT assets. Additional variables here are the duration, the investment that is less than or equal to the maximum investment rate, and the underlying asset.

Finally, Pinto (2010) briefly discusses the implementation of a scoring model to rate the project opportunities in the Royal Bank of Canada. This scoring model combines criteria such as project importance (e.g. magnitude of impact and economic benefits) and ease of doing (e.g. cost of development and project complexity) with the expectations for annual expenditure and total project spending to prioritize the alternatives.

2.2. Analytic Network Process (ANP)

The ANP was originally proposed by Saaty (2008b) as an extension of his own quite popular AHP (1990, 2008a). The AHP is one of the better known methodologies for project selection and decision making in general, enabling the manager to break down a problem based on the perceptions, feelings and previous knowledge related to the critical issues, and then aggregate the solution of all sub-problems into a solution. The AHP is creative in the sense that it relies on experts to structure the problem as a hierarchy and derive appropriate priority scales by decomposing the problem into the most general and easy-to-control factors. In effect, the AHP reduces a distinctly multidimensional problem to a one-dimensional problem (Saaty, 2008b).

Thus, the first step in a project selection process based on AHP is the construction of a hierarchy of criteria and sub-criteria through extensive communication with relevant professionals and the end users (Pinto, 2010).

The AHP then proceeds as a comparison of pairs, using scales of absolute judgments that represent to what extent one element dominates over another with respect to a predefined attribute (Saaty, 1990). In this context, a judgment or comparison is a numerical representation presented in a square matrix where each element is compared to all other elements. The comparison can be assigned a value on a 1-9 scale based on the importance of the elements with respect to a higher level criterion (Table 3). Reciprocal numbers are also included to express the relationship value from aspect of the criteria. If criterion A has "strong importance" compared to criterion B, then the numerical representation of the relationship A-B is 5 while the relationship B-A has a reciprocal number of 1/5 or 5^{-1}.The priority scales are synthesised by multiplying them by the priority of their parent nodes. The priority is typically presented as a proportion of the value that a given criterion has compared to the values of the other criteria. Effectively, this is the point at which a qualitative value (the judgment element in a given comparison of attributes) has been transformed into a quantitative value (the assigned numerical value, which is a subject of further processing).

The AHP focuses on measuring and improving the consistency of judgments and optimizing the weights given to each criterion. This process resolves the issue of double counting present in standard scoring models where criteria such as Service and Quality would be treated as separate or overlapping (Pinto, 2010).

Table 3. The Fundamental Scale

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong or demonstrated importance
9	Extreme importance
2, 4, 6, 8	For compromise between the above values
Reciprocals of above	Reciprocal number of one activity to another activity
Rationals	Ratios arising from the scale
1.1-1.9	For tied activities

Source: Saaty, 1990.

The AHP method is widely adopted in decision making, mostly because it is intuitive, easily adaptable, and rather simple as a construct. It has been applied to a range of different issues, including: bid evaluations in the US public administration; partial production requirements in the private sector; and proposals related to management of natural resources and environmental decision making, developed by non-governmental bodies. Among the more interesting applications, IBM used the AHP method for decision making in designing the successful mid-range AS 400 computer in 1991, while the carrier airline British Airways used the AHP method in

1998 to choose the entertainment system vendor for its entire fleet of airplanes (Saaty, 2008a).

The AHP method also has an important limitation: problems that have constraints on resource feasibility, optimization requirements, or project independence cannot apply AHP (Saaty, 2008b). In practice, there are many projects with such problems, and they have to be taken into account to ensure effective financial management. Because of the inter-dependence between different elements in the hierarchy, the problem can be best represented by a network, instead of a hierarchy. In the context of IT projects, sharing of hardware and software resources among projects is a regular occurrence. Programming code originally written for a specific project or any basic generic code could be reused for several other projects, providing significant savings. In such cases, the ANP approach is more applicable method than AHP (Meade and Sarkis, 1999; Meade and Presley, 2002; Agarwal et al., 2006; Gencer and Gürpinar, 2007; Jharkharia and Shankar, 2007).

The ANP takes into consideration the interrelationships between the different decision levels and attributes, and uses ratio scale measurements based on pair wise comparisons (Saaty, 2008b). To a certain extent, the ANP is a generalization of the AHP, but it acknowledges that just as the importance of the criteria determines the importance of the alternatives, the importance of the alternatives themselves affects the importance of the criteria. Decision problems often involve the interaction and dependence of higher-level elements in a hierarchy on lower-level elements, which is why the problem can be better represented as a network of clusters and nodes, rather than a hierarchy. This means that in ANP the criteria at the lower levels may provide feedback to the criteria at the higher levels, but also, that the interdependence between the criteria at the same level is possible. Another crucial difference between

AHP and ANP is that the concept of “super matrix” is involved in the calculation process for ANP.

As with the AHP, the main benefits of using an ANP-based approach is that it provides a relatively simple and intuitive approach to analysis based on transforming the qualitative value of a group judgment into quantitative values, which can be processed (Meade and Sarkis, 1999; Meade and Presley, 2002). Furthermore, because ANP allows for more complex relationships than unidirectional hierarchical links and interdependency among criteria, enablers and sub-criteria, the ANP model can find a more widespread use. The ANP model can be easily adapted to evaluate alternative projects in the context of different environments, such as an agile manufacturing process (Meade and Sarkis, 1999; Agarwal et al., 2006).

One of the more distinctive aspects of the ANP approach is that it allows for a feedback loop that makes it possible to reach better informed decisions (Saaty, 2008b). This feedback loop does not have a clear top-to-bottom sequence that reflects a hierarchy, but looks more like a network, with a number of cycles that connect its components to other elements. The ANP also has source nodes or origins of a path of influence, as well as sinks or destinations of a path of influence. A full network can include source nodes; intermediate nodes that fall on paths from source nodes, lie on cycles, or fall on paths to sink nodes; and finally sink nodes. Any dual combination of cycles, sources, and sinks is possible (Figure 1).

The priorities in a pairwise comparison matrix can also be entered in a form of supermatrix, which represents the influence priority of an element on the left of the matrix on an element at the top of the matrix with respect to a given criterion. The component C1 in the supermatrix presented in Figure 2 includes all the priorities for nodes that are “parent” nodes in the C1 cluster. Because ANP combines across several levels, the supermatrix essentially has one layer more than a matrix in an AHP model. Using different forms of the supermatrix it is possible to show the connections between AHP and ANP solutions to a process (Saaty, 2008b).

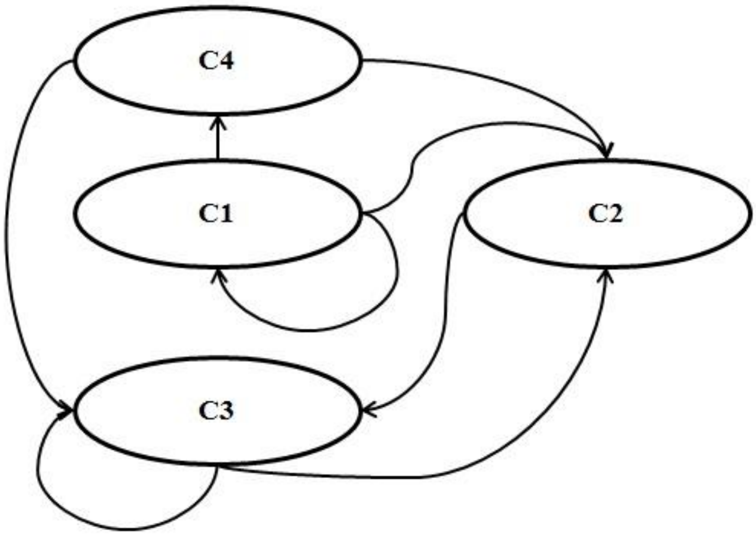


Figure 1. A network with inner and outer dependence among components
Source: Saaty, 2008b.

The ANP numerical values are based on the fundamental scale used for AHP-based solutions (Table 3). Each judgment is first defined in a verbal manner as indicated in the scale, and then it is associated with a given number. The method involved in this study also relies on the fundamental scale of the questionnaire (APPENDIX A). The vector of priorities is the principal eigenvector of the matrix, giving the relative priority of the criteria measured on a ratio scale. A consistency index (C.I.) is also associated with the matrix, with a consistency ratio (C.R.) obtained based on each order value (Table 4). The randomly generated reciprocal matrices use the scale 1/9, 1/8,…,1/2, 1, 2,…, 8, 9, and calculate the average of their eigenvalues, which is used to form the Random Consistency Index R.I (Saaty, 2008b).

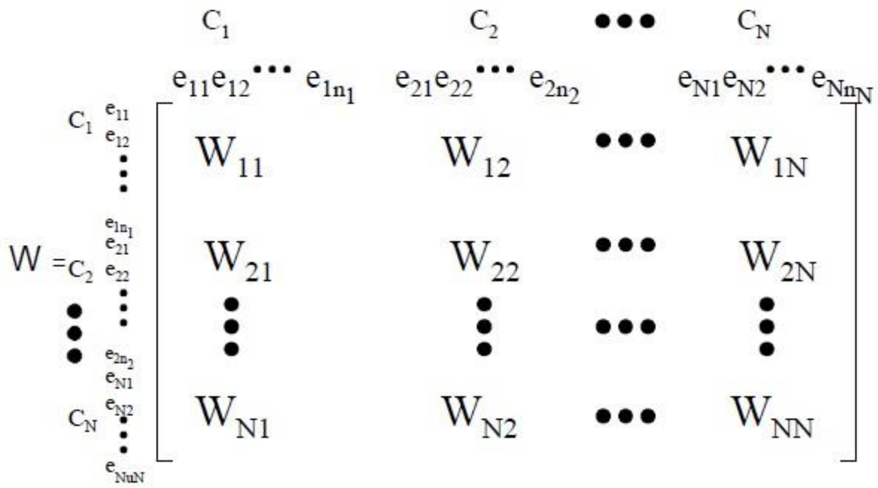


Figure 2. The supermatrix of a network
Source: Saaty, 2008b.

Table 4. Random Index

Order	1	2	3	4	5	6	7	8	9	10
R.I.	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

Source: Saaty, 2008b.

Saaty (2008b) and Meade and Presley (2002) propose a series of steps in the basic ANP decision process that would lead to selection of the best alternative project:

- Describe the decision problem including its objectives, criteria and subcriteria, actors and their objectives, as well as the possible outcomes of that decision;

- Determine the control criteria and subcriteria in the four control hierarchies for the benefits, opportunities, costs and risks of a decision, and obtain their priorities from paired comparisons matrices;
- Determine the most general network of clusters/components and their influence on all control criteria;
- Determine the clusters of the feedback system and connect them according to their outer and inner dependence influences;
- Determine the approach followed in the analysis of each cluster or element;
- Construct the supermatrix by crossing the clusters in the order they are numbered and all the elements in each cluster both vertically on the left and horizontally at the top;
- Perform paired comparisons on the elements within the clusters themselves according their inner and outer dependence;
- Perform paired comparisons on the clusters as they influence each cluster to which they are connected;
- Compute the limit priorities of the stochastic supermatrix according to whether it is irreducible or it is reducible and whether the system is cyclic or not;
- Synthesize the limiting priorities for each of the four merits: Benefits (B), Opportunities (O), Costs (C) and Risks (R);
- Determine strategic criteria and their priorities to rate the four merits one at a time, and calculate the overall synthesis of the four merits; and
- Perform sensitivity analysis on the final outcome and interpret the results.

One limitation of the ANP method is its dependency on the subjective opinion of the decision maker, which is explicitly expressed in the weightings of the criteria. For the ANP approach to be effective, the decision maker should understand all aspects of the project selection process and its impact on the company. Possible enhancements to the model that overcome this limitation include using weightings based on company-wide consensus of relevant expert information, or the inclusion of a feedback loop for regret factor or a disappointment factor (Meade and Presley, 2002).

Another important limitation of the ANP model is that despite its elementary simplicity, a high number of pairwise comparisons can make the evaluation and calculation process prohibitively time-consuming (Shyur, 2006). If the number of criteria/subcriteria is too high, full implementation of ANP can become too complex to implement, which is why the simpler AHP is often preferred or ANP is adapted and combined with other methodologies. In this direction, Saaty and Takizawa (1986) have proposed a solution which maintains the basic logic of ANP but includes a simplified method for “supermatrix” formation. While this version of the ANP method is rarely used in its pure form, it is often combined with other methods such as TOPSIS (e.g. Shyur, 2006).

Several methods have expanded the basic ANP approach in the context of IT project selection by combining it with other techniques. Lee and Kim (2000, 2001) have combined ANP with goal programming and the Delphi method. Goal programming can be a useful tool when incorporating multiple objectives to reach an optimal solution, but it requires decision makers to specify goals and priorities to avoid conflicts. The ANP and the Delphi method, which is used as a systematic procedure for evoking expert group opinion, are added to zero-one goal programming to formulate an integrated approach to IT project selection (Lee and Kim, 2011). This approach, however, does not reflect the influence of quantitative and qualitative factors such as investment cost, return of investment, and probability of success. Furthermore, this approach does not cover for the issue of subjectivity in deciding the criteria weightings.

2.3. Fuzzy logic

To compensate for the flaws of the ANP process, fuzzy logic has been introduced to IT project selection (Buckley, 1987; Kim et al., 2009; Mohanty et al., 2005; Khalili-Damghani et al., 2013). Fuzzy logic is generally used to model systems that are difficult to define or for which there is imprecise data. Fuzzy logic is attractive because it incorporates imprecision and subjectivity typical of human decision making into formulation of a model or solution.

Fuzzy logic was first developed in the context of the fuzzy set theory by Zadeh (1965), which defines fuzzy sets as “a class of objects without a precisely defined criterion of membership” (p.338). Fuzzy sets are characterized by membership functions, which link the objects to membership grades in the range from zero to one (corresponding to the area between a “yes” and “no” answer in a given problem), and clearly established properties related to inclusion, union, intersection, etc. Fuzzy logic became popular during the 1980s when a variety of solutions in different fields, such as industrial process control, medical diagnosis and securities trading, were proposed (Lin and Lee, 1991). Because fuzzy logic deals with approximate, rather than fixed data, it is used in various fuzzy logic systems or fuzzy rule-based (FRB) systems, which are applied to engineering problems or risk and impact assessments dealing with nonlinear, time-varying or ill-defined factors (Lin and Lee, 1991; Karami and Guo, 2012).

Fuzzy logic systems depend on inputs expressed as linguistic variables derived from formulas that determine the fuzzy set to which a value belongs, as well as the degree of membership in that set (Lin and Lee, 1991). By definition, a linguistic variable is any variable whose value can be expressed in linguistic terms. “Weight” can be treated as a linguistic variable where the values can include “very low”, “low”, “medium”, “high”, “very high”, etc. The variables are matched with the preconditions of linguistic IF-THEN rules, also known as fuzzy logic rules, and the response of each rule is weighted according to the degree of membership of its inputs, with the centroid being calculated to generate the appropriate output. In practice, the easiest approach to design a fuzzy logic system is to define the membership function and rules by studying an existing human-operated system, and then test and adjust for the proper output. The resulting fuzzy logic system consists of: a fuzzifier, which maps from a given observational input to a fuzzy set; an inference engine based on determined fuzzy logic rules; deffuzifier, which results in a single solution; a plant to which the resulting value is assigned; and a capacity for learning or adapting from each performance.

All of these components of a fuzzy logic system are typically included in a software solution that is used for decision making, along with a number of optional components meant to speed up the process or increase the system’s capacity. Furthermore, research concerning fuzzy logic systems in the past two decades has largely evolved over the possibility of making this process automatic i.e. enabling the fuzzy logic systems to overcome the necessity for external expertise and learn from their own past activities or processes. This means that fuzzy logic systems are becoming increasingly human in how they approach subjectivity in decision making, and in this context present an important link in the formation of AI (Zadeh, 1997).

However, as with AHP/ANP models, how fuzzy logic rules will be defined and applied to a given problem still depends on inputs from experts in the field.

One of the earliest studies to apply fuzzy mathematics in financial decision making was conducted by Buckley (1987), demonstrating how a model could use fuzzy sets to formulate the concepts of future value, present value and IRR over *n* periods, but also how to rank fuzzy investment alternatives according to these outcome values. Today, fuzzy logic is often integrated in decision making models of high complexity, connecting several layers of input and output nodes that form the final solution. The model designed by Lin and Lee (1991) consists of five mode layers including: input linguistic nodes, input term nodes, rule nodes, output term nodes, and output linguistic nodes. Another example involves a fuzzy multi-objective R&D portfolio selection model based on a programming approach, which maximizes the outcome while minimizing costs given a set of resource constraints (Bhattacharyya et al., 2011). On the other hand, Chang and Lee (2012) propose the use of fuzzy logic in context of Data Envelopment Analysis (DEA) model that also uses knapsack formulation for problems of project selection in engineering and construction. In practice, fuzzy logic is most useful when assessing vendor characteristics due to the high number of linguistic variables that are not included in other models.

Fuzzy logic is often used as an extension of AHP or ANP to efficiently handle the fuzziness of the data involved in the decision making, but also because it can effectively work with both qualitative and quantitative data in MCDM problems. A combination of fuzzy logic and the ANP has been used to support decision making related to environmental impact assessment (Liu and Lai, 2009). In the work of Liu and Lai (2009), fuzzy set theory and fuzzy logic are introduced to the model and manipulate the impact of subjectivity of the decision making process, which results in fuzzy ANP that manages the dependences between different environmental factors. The work of Liu and Lai (2009) is an extension of Mikhailov (2003) and Mikhailov and Singh (2003), which originally proposed the use of fuzzy ANP, allowing for fuzzy weights when dealing with imprecise human comparison judgments. Fuzzy ANP has also been used for shipyard location selection (Guneri et al., 2009), prioritizing Six Sigma projects (Boran et al., 2011), and machine tool selection (Nguyen et al., 2014).

A similar fuzzy AHP has been applied for selection of drilling equipment for offshore oil and gas operations, and it incorporates the decision maker's risk attitude and associated confidence in the estimates of pairwise comparisons (Tesfamariam and Sadiq, 2006). Other models based on fuzzy AHP/ANP include the proposal by Ayağ and Özdemir (2009), which evaluates conceptual design alternatives related to new product development, and the approach of Pires, Chang and Martihno (2011), which uses a combination of AHP and fuzzy TOPSIS to assess the sustainability of solid waste management systems in Portugal. In essence, the use of fuzzy AHP/ANP reflects real-life situations where the decision makers are not certain of their own preferences and exact goals, due to a combination of factors such as incomplete information, project complexity, or uncertainty within the decision environment.

Interestingly, Saaty (2008b) argues against the use of fuzzy sets in combination with AHP/ANP for decision making purposes. The main point is that the fundamental scale used to quantify the judgments of experts regarding a set of criteria is technically fuzzy. In this sense, further fuzzyfying the outcomes of the AHP/ANP process might not actually improve the final decision. At the same time, the range of possible solutions that fuzzy models provide does go beyond the single solution typically provided by the standard AHP/ANP model.

2.4. Monte Carlo simulation

The uncertainty of future events poses a number of difficulties when performing IT project selection. A Monte Carlo simulation should reveal the nature of that uncertainty, but only if its application and limitations are well understood (Rubinstein and Kroese, 2011). Underlying the Monte Carlo simulation approach is the idea of a random experiment in probability theory, meaning an experiment with outcome that cannot be determined in advance. This approach has been used for several decades in the context of mathematical and scientific situations, but its usage in the business environment is a relatively recent trend (Kwak and Ingall, 2007).

The practical approach to creating the forecasted part of any type of future projection has evolved over time. Estimates of future market returns are based primarily on different approaches to time value of money calculations. These approaches fall into the category of deterministic modelling where there is no randomness in the future outcome of a given problem. An alternative to deterministic modelling is presented by stochastic models, which incorporate randomness into the modelling process, and thus enable optimization of the final results (Vepsalainen and Lauro, 1988; Cheah and Liu, 2006; Rubinstein and Kroese, 2011, 2013; Sari, 2013). Stochastic models estimate the probability distribution of potential outcomes to a problem by including random variation of the input variables based on similar situations recorded in historical data. The probability distribution is derived through a series of simulations using different values for the inputs. Stochastic models are used extensively in the insurance industry and different investment models focusing on the returns and prices of assets or asset classes. The Monte Carlo simulation is one of the most popular stochastic models currently used.

The Monte Carlo simulation involves different techniques of statistical sampling within a given model or a real-life situation used to calculate solutions to quantitative problems (Metropolis and Ulam, 1949; Caflisch, 1998; Kwak and Ingall, 2007). In essence, the Monte Carlo simulation operates with the variables contained in the model. Each variable has a variety of possible values within the limits of a probability distribution function, and they can be triangular, rectangular or trapezoidal in nature. As with other stochastic models, the Monte Carlo techniques simulate the model, reaching many different solutions with a randomly chosen value within the probability distribution. Ultimately, the simulation produces a probability distribution of all calculated values for the model (Figure 3). This method is attributed to Stanislaw Ulam and Nicholas Metropolis (1949), which introduced it to solve problems with differential equations in mathematical physics, and named it after the casinos in Monte Carlo.

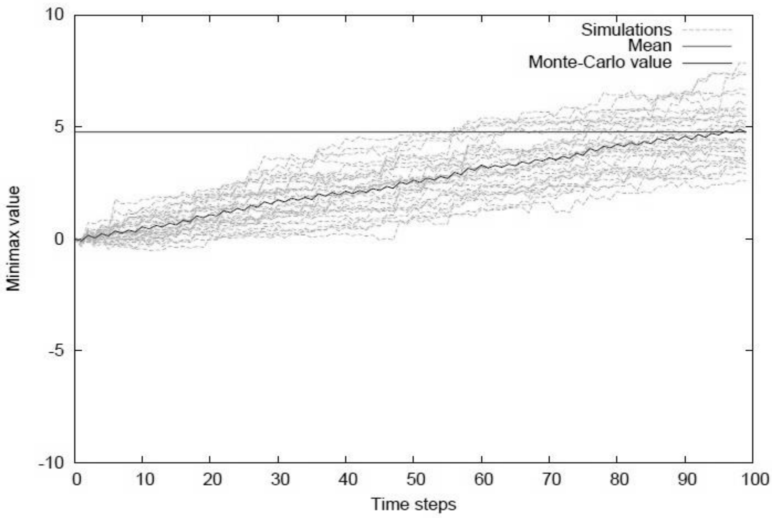


Figure 3. Results from a Monte Carlo simulation

Source: Silver and Tesauro, 2009.

Today, the Monte Carlo simulation is increasingly used in risk management, scheduling and budgeting (Kwak and Ingall, 2007). This trend is mostly due to the lowered computing costs, the increased recognition by managers that real returns are random, and the need for more robust results in treating a given problem. In terms of risk management, the Monte Carlo simulation is often used to quantify the risk of going over the projected budget. Similarly, the method can be employed to calculate the confidence level in a targeted day or duration for project completion. For any of these operations to succeed, the project manager and experts define the probability distribution of the cost or duration for each relevant task, including the most-likely, worst-case, and best-case scenarios. Based on the results of the simulation, project managers set aside a project budget reserve or additional resources, which can be used as contingency. A simple version of this method is available in any standard project management software. In principle, this is how the Monte Carlo simulation can be used in portfolio management or project selection: a probability distribution is used for each factor that affects the net cash flow. Managers benefit from the information about the levels of variance in NPV distribution that the simulation offers, which is useful in case two investments have a similar mean NPV (Kwak and Ingall, 2007).

In most cases using the Monte Carlo simulation, the returns of any given project are treated as random, fluctuating according to the assumed mean, standard deviation and correlation factor (Rubinstein and Kroese, 2011, 2013). These inputs are typically defined by the user, which can have a significant effect on the final results of the simulation. If the standard deviation in a given model is set to zero, the simulation would effectively be deterministic, since each return would be assumed to be known with absolute certainty and there would be no assumed variability in the forecast. Another approach to the Monte Carlo simulation could define the value by establishing a range of possible values from which an input can be randomly used. In this direction, a common criticism of the Monte Carlo simulation is that it ignores such phenomena as similar returns and autocorrelation, but in practice, the constraints are set entirely by the user and therefore, any negative effect of such phenomena cannot be attributed to the tool itself. A much stronger criticism of the method is that it does not take into account the possibility of a managerial action in the results that it provides for a given time period (Kwak and Ingall, 2007). In practice, if a certain activity gives negative results at a certain point in time, the company management would most likely react to eliminate the causes, thus changing the basic formula for calculation of the outcome. Having that said, the management can actually use the Monte Carlo simulation to test a number of different outcomes by adapting the variables before an actual change is performed. Then, once the first set of feedback results is received, the management could run new simulations to test the original conclusions.

There are several variations of the Monte Carlo simulation created with the aim of eliminating its weaknesses and improving the results that it provides (Marinari, 1998; Kwak and Ingall, 2007; Silver and Tesauro, 2009). A number of optimization methods focusing on the weights used have been introduced, such as the Lee-Yang zeroes, Simulated Tempering and Parallel Tempering methods (Marinari, 1998). It has also been proposed that the simulation uses open-ended or lognormal distributions in place of the standard close-ended distribution (Kwak and Ingall, 2007). Typically, the Monte Carlo simulation uses a distribution with clearly defined minimum and maximum beyond which calculations are impossible. In practice, though, deadlines and budget figures often cross over the most pessimistic assumptions for a given problem. Including open-ended distributions based on a base estimate, a contingency amount, and an overrun probability estimate should make the results of the Monte Carlo simulation more realistic. The method can also be simplified by excluding the influence of trends, cycles and correlation, and simply defining the "likely bounds" for the relevant variables at the beginning and end of the project within a given correlation matrix (Kwak and Ingall, 2007).

Because it can be used to optimize the results of a given model, the Monte Carlo simulation is often used in combination with other methods for project selection. Sari (2013) presents the selection of an RFID solution provider based on integration of Monte Carlo simulation with fuzzy AHP and fuzzy TOPSIS methods. Similarly, Monte Carlo simulation of a DCF is used to evaluate the real options of governmental support in infrastructure projects (Cheah and Liu, 2006). The Monte Carlo simulation has also been combined with fuzzy logic. Buckly and Jowers (2008) have developed a fuzzy Monte Carlo method for multivariate fuzzy nonlinear regression, which uses a quasi-random number generator to make random fuzzy/crisp vectors in order to uniformly fill the search space.

CHAPTER 3

METHODOLOGY

While the previous section focuses on defining the relevant gaps in the literature for IT project selection, this chapter describes the research method applied to develop a general framework for addressing the identified gaps. The chapter is followed by establishing the research philosophy in which the study is framed, and discussing the manner in which quantitative and qualitative measures are incorporated in the new model. The chapter also presents in detail the survey questionnaire on which the study is based, along with relevant details regarding sampling, data collection, data analysis, and ethical considerations.

3.1. Research philosophy

A research needs to follow a distinct research philosophy in developing and applying the knowledge on the given subject. The research philosophy which has a significant influence on the choice of research strategy and method is crucial for obtaining relevant results from the study.

There are four dominant research philosophies from which a researcher can choose: positivism, realism, interpretivism, and pragmatism (Sullivan, 2001; Saunders et al., 2009).

On the first philosophy, positivism, the research should probably adopt the philosophical stance of the natural scientist. The researcher prefer ‘working with an observable social reality and that the end product of such research can be law-like generalisations similar to those produced by the physical and natural scientists' (Remenyi et al., 1998).

On the second philosophy, realism, what the senses show us as reality is the truth: that objects have an existence independent of the human mind. Realist perspectives are grounded in a theoretical belief that our knowledge of reality is imperfect and that we can only know reality from our perspective of it.

On the third philosophy, interpretivism, involves researchers to interpret elements of the study, thus interpretivism integrates human interest into a study (Myers, 2008). Because of the subjective nature of this approach and great room for bias on behalf of researcher it is not suitable for this study.

On the last philosophy where this study follows, the pragmatist research philosophy, according to which the most important determinant when evaluating scientific methods is the research question. This means that the pragmatist research philosophy focuses on the research problem, and applies all available approaches to solving it (Creswell, 2003). From this aspect, the methods for data collection and data analysis are chosen based on how useful they are in obtaining insight into the problem, not on their association with a particular research philosophy.

To address a given research problem, the researcher can apply inductive method, deductive method or a combination of both. This study uses the inductive approach, as it explores the problem from the bottom up in order to define a new theoretical model (Saunders et al., 2009). This means that the theory of the study is developed after the data is collected. Most studies on project selection methods (e.g. Saaty, 2008a, 2008b) apply the inductive approach in building the general argument.

The inductive approach is generally linked to qualitative research methods, but it can be applied to quantitative research as well. In principle, both quantitative and qualitative research methods aim at gaining comprehension of how society participants – individuals, groups, systems and institutions – behave or interact with each other (Sogurno, 2001). The qualitative method generally relies on interviews, surveys or case studies, while the quantitative method is based on surveys that require processing of numerical data. This study appropriates both quantitative and qualitative techniques towards building a new theoretical model, as well as a research questionnaire and a study case for presenting and testing the developed model. The qualitative method is necessary for evaluating the available literature on IT projects in the banking sector and identifying a list of possible criteria for project selection. The quantitative method is needed for measuring the relative importance of the different criteria, and demonstrating how the proposed model functions.

3.2. Research design

This study presents a hybrid approach to IT project selection in the banking sector, based on three methods with different theoretical background: ANP (an extension of AHP), fuzzy logic with TOPSIS and a Monte Carlo simulation.

In this study the following methodology is applied by using the formerly described theoretical background.

Fuzzy AHP/ANP models use triangular fuzzy numbers (TFNs) for the preferences of one criterion over another, after which the synthetic extent value of the pairwise comparison is calculated (Mahmoodzadeh et al., 2007). A triangular fuzzy number M is usually denoted as (m_1, m_2, m_3), where m_1, m_2, and m_3 respectively represent the smallest possible value, the most promising value, and the largest possible value of a fuzzy event (Figure 4). Many more values are possible apart from the three stated, and they should be located with differing frequencies in the range between m_1 and m_3. This means that the linear representation of a triangular fuzzy number can be such that the membership function of the depicted situation is calculated as:

$$\mu_M(x) = \begin{cases} (x - m_1)/(m_2 - m_1) & m_1 < x < m_2 \\ (m_3 - x)/(m_3 - m_2) & m_2 < x < m_3. \\ 0 & otherwise \end{cases}$$

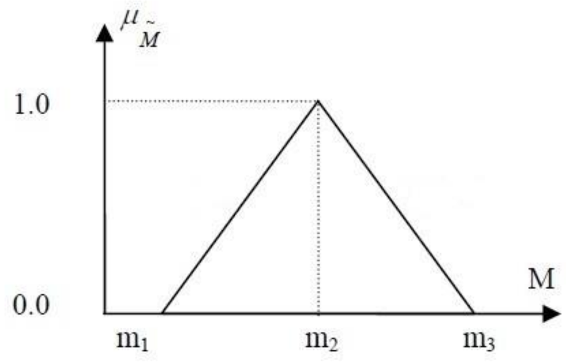


Figure 4. A triangular fuzzy number
Source: Mahmoodzadeh et al., 2007.

A fuzzy set M on the universe of discourse x is defined as $\mu_M(x) \rightarrow [0,1]$, where each element of x is mapped to a value between 0 and 1. This value, called membership value or degree of membership, quantifies the grade of membership of the element x in to the fuzzy set M. Membership functions allow us to graphically represent a fuzzy set. The x axis represents the universe of discourse, whereas the y axis represents the degrees of membership in the [0,1] interval.

The value of x at m_2 gives the maximum grade of $\mu_M(x) = 1$, which is typically the most probable value of the evaluation data. Furthermore, the values of x at m_1 and m_3 give the minimum grade of $\mu_M(x) = 0$, which is typically the least probable value of the evaluation data.

The results from mathematical operations between two triangular fuzzy numbers can be quite different:

- addition or subtraction results in triangular fuzzy numbers;
- multiplication or division may not result in triangular fuzzy numbers; and
- max or min operations do not result in triangular fuzzy numbers.

Relevant mathematical operations related to two triangular fuzzy numbers $\tilde{A}$ $(l_1, m_1, u_1)$and $\tilde{B}$ (l_2, m_2, u_2)can be expressed as follows:

$\tilde{A} \oplus \tilde{B} = (l_1 + l_2\,, m_1 + m_2\,, u_1 + u_2)$

$\tilde{A} \otimes \tilde{B} = (l_1 \times l_2\,, m_1 \times m_2\,, u_1 \times u_2)$

$k \otimes \tilde{A} = (k \times l_1, k \times m_1, k \times u_1) \quad k > 0, \;\; k \in R$

$\tilde{A}^{-1} = (1/u_1, 1/m_1, 1/l_1).$

The distance between two triangular fuzzy numbers $\tilde{A}$ and $\tilde{B}$ can be calculated as:

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]}.$$

Fuzzy numbers can be used to represent linguistic values like “very low”, “low”, “medium”, “high” and “very high”. A fuzzy linguistic variable can be expressed quantitatively through a pertinence function (Ganga et al., 2011). This means that the membership function of a triangular fuzzy number for a linguistic value can be described by a composition of pertinence functions with the points (x_i;y_i), where x_i represents the possible discourse of the variable and y_i represents the pertinence level for each given measure level. In Figure 5 the highlighted points describe the limits of the triangular functions. The points (0,1) and (50,0) define the relevance of the crisp variable to the linguistic term “low”, while the points (0,0), (50,1) and (100,0) describe the relevance of the crisp variable to the linguistic term “medium”. Following from this, for the pertinence related to the linguistic term “high”, one should consider the points (50,0) and (100,1).

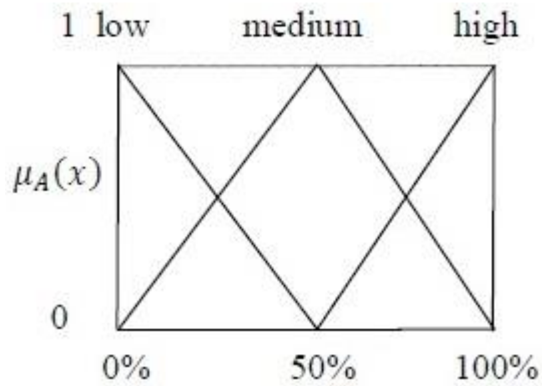


Figure 5. Fuzzy linguistic numbers and membership values
Source: Ganga et al., 2011.

The popular model of Mikhailov (2003) and Mikhailov and Singh (2003) is used here to demonstrate how fuzzy ANP is used in the context of project selection. It is assumed that a prioritization problem with n elements needs to be solved. The pairwise comparison judgments for this problem are represented as either normal fuzzy sets or fuzzy numbers. Assuming that the decision-maker is able to provide a set $\mathrm{F} = \{\tilde{\mathrm{a}}_{\mathrm{ij}}\}$ of $\mathrm{m} \le \mathrm{n}(\mathrm{n}-1)/2$ fuzzy comparison judgments, $\mathrm{i} = 1, 2, \dots, \mathrm{n} - 1;\ \mathrm{j} = 2, 3, \dots, \mathrm{n};\ \mathrm{j} > i$, can be represented as triangular fuzzy numbers $\tilde{\mathrm{a}}_{\mathrm{ij}} = (\mathrm{l}_{\mathrm{ij}}, \mathrm{m}_{\mathrm{ij}}, \mathrm{u}_{\mathrm{ij}})$. The problem is to derive a crisp priority vector characterized as $\mathrm{w} = (\mathrm{w1}, \mathrm{w2}, \dots, \mathrm{w}_{\mathrm{n}})^{\mathrm{T}}$, such that the priority ratios $\mathrm{w}_{\mathrm{i}}/\mathrm{w}_{\mathrm{j}}$ are within the scope of the initial fuzzy judgments,

$$l_{ij} \gtrapprox \frac{w_i}{w_j} \lesseqqgtr u_{ij}.$$

where the symbol $\lesseqqgtr$ is used to denote the statement “fuzzy less or equal to”.

In this case, each crisp priority vector w satisfies the double-side inequality of equation which can be measured by a membership function, linear with respect to the unknown ratio w_i/w_j:

$$u_{ij}\left(\frac{w_i}{w_j}\right) = \begin{cases} \frac{(w_i/w_j)-l_{ij}}{m_{ij}-l_{ij}}, \frac{w_i}{w_j} \leq m_{ij}, \\ \frac{u_{ij}-(w_i/w_j)}{u_{ij}-m_{ij}}, \frac{w_i}{w_j} \geq m_{ij}. \end{cases}$$

The membership function in formula is expected to be linearly increasing in the interval $(-\infty, m_{ij})$ or to be linearly decreasing in the interval $(m_{ij,}\infty)$. The function $u_{ij}\left(\frac{w_i}{w_j}\right)$results in negative values in cases when $w_i/w_j < l_{ij}$ or $w_i/w_j >$ u_{ij}, and achieves a maximum value $u_{ij} = 1$ at $w_i/w_j = m_{ij}$. Over the range (l_{ij}, u_{ij}), the membership function seems to coincide with the fuzzy triangular expression (l_{ij}, m_{ij}, u_{ij}) of the judgment.

The benefit of this model is that instead of a prioritization using eigenvectors, a Fuzzy Preference Programming (FPP) method is applied, thus acquiring the consistency ratios of fuzzy pairwise comparison matrices. Two key assumptions are made here. First, this method requires the existence of non-empty fuzzy feasible area P on the *(n-1)* dimensional simplex Q^{n-1} calculated as

$$Q^{n-1} = \{(w_1, w_2, \dots w_n) | w_i > 0, \sum_{i=1}^{n} w_i = 1\},$$

which represents an intersection of the membership functions. In this case, the membership function of the fuzzy feasible area is given by:

$$u_p(w) = min\{u_{ij}(w) \big| i = 1,2, \dots, n-1; j = 2,3, \dots, n; j > 1\}.$$

Secondly, there is a selection rule for determining a priority vector with the highest degree of membership $w^* \in Q^{n-1}$ where

$$\lambda^* = u_p(w^*) = max\, min\, \{u_{ij}(w)\}.$$

Thus, the maximum prioritization problem of the fuzzy ANP can be represented as $Max\lambda$ where:

$\lambda \leq u_{ij}(w), i = 1,2, \dots, n-1; j = 2,3, \dots, n; j > 1,$

$\sum_{k=1}^{n} w_k = 1, w_k > 0, k = 1,2, \dots, n.$

The solution for this problem (λ^*, w^*) can be obtained using numerical methods for non-linear optimization such as the Monte Carlo method. The resulting optimal value λ^* is then used for measuring the consistency of the initial fuzzy judgments.

A similar version of fuzzy ANP can be found in Chang (1996), which uses the Extent Analysis Method (EAM) for fuzzy comparison matrices. To show how EAM works, one assumes an object set $X = \{x_1, x_2, \dots, x_n\}$ and a goal set $G = \{g_1, g, \dots, g_m\}$. If extent analysis for each goal $g_i$is performed, the extent analysis for each object can be obtained as:

$\tilde{M}_{gi}^{1}, \tilde{M}_{gi}^{2}, \dots, \tilde{M}_{gi}^{m} \qquad i=1,2,\dots,n$

where $\tilde{M}_{gi}^{j} (j = 1,2 \dots, m)$ is a triangular fuzzy number.

In this context, the value of fuzzy synthetic extent with respect to the *i*th object is

$$S_i = \sum_{j=1}^{m} \tilde{M}_{gi}^{j} * \left[\sum_{i=1}^{n} \sum_{j=1}^{m} \tilde{M}_{gi}^{j}\right]^{-1}$$

To calculate the result for $\sum_{j=1}^{m} \tilde{M}_{gi}^{j}$ it is sufficient to perform fuzzy addition operation of *m* extent analysis values using formula where

$$\sum_{j=1}^{m} \tilde{M}_{gi}^{j} = \left[\sum_{i=1}^{n} lj, \sum_{j=1}^{m} mj, \sum_{j=1}^{m} uj\right],$$

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} \tilde{M}_{gi}^{j}\right]^{-1} = \left[\sum_{i=1}^{n} li, \sum_{i=1}^{m} mi, \sum_{i=1}^{m} ui\right]$$

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m}\widetilde{M}_{gi}^{j}\right]^{-1} = \left[\frac{1}{\sum_{i=1}^{n} li}, \quad \frac{1}{\sum_{i=1}^{m} mi}, \quad \frac{1}{\sum_{i=1}^{m} ui}\right].$$

In addition to devising a standard matrix using the definitions in Table 3, it is also possible to summarize the answers using a fuzzy version of the fundamental scale, which represents a linguistic scale for relative importance (Table 5). Such summary consists of triangular fuzzy numbers, and functions as an integral step in the development of a fuzzy ANP. In case of the example where “NPV/IRR” is rated with 5 compared to “ROI”, this would translate to a triangular fuzzy number of (4, 5, 6), which stands for “important”, as well as a reciprocal value of (1/6, 1/5, 1/4). On the other hand, in case “strategic fit” receives an average score of -9 in relation to “module reusability”, the triangular fuzzy reciprocal number would be (1/9, 1/9, 1/8), which correspond to “module reusability” being “absolutely important” to “strategic fit”. All the fuzzy evaluation matrices are produced in the same manner.

This study uses EAM for calculating fuzzy comparison matrices, combined with fuzzy TOPSIS. The use of TOPSIS in this case is warranted because it is an effective tool for solving MCDM problems with a finite set of alternatives (Shyur, 2006; Sodhi and Prabhakar, 2012). Typically, MCDM problems are divided into two types: classical MCDM problems where the metrics are measured using crisp numbers, and Fuzzy Multi Criteria Group Decision Making (FMCGDM) problems where linguistic terms and fuzzy numbers are used (Kannan et al., 2009). TOPSIS is often applied for solving the latter.

Originally designed by Hwang and Yoon (1981), TOPSIS functions by defining the Fuzzy Positive Ideal Solution (FPIS), as well as the Fuzzy Negative Ideal Solution (FNIS). In practice, the positive ideal solution will be the problem solution that maximizes the benefit metrics and minimizes the cost metrics. The negative ideal solution will be the problem solution that maximizes the cost metrics and minimizes the benefit metrics.

Table 5. Linguistic Scales for Relative Importance

Definition	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Equal importance	(1, 1, 2)	(1/2, 1, 1)
Intermediate 1	(1, 2, 3)	(1/3, 1/2, 1)
Moderately important	(2, 3, 4)	(1/4, 1/3, 1/2)
Intermediate 2	(3, 4, 5)	(1/5, 1/4, 1/3)
Important	(4, 5, 6)	(1/6, 1/5, 1/4)
Intermediate 3	(5, 6, 7)	(1/7, 1/6, 1/5)
Very important	(6, 7, 8)	(1/8, 1/7, 1/6)
Immediate 4	(7, 8, 9)	(1/9, 1/8, 1/7)
Absolutely important	(8, 9, 9)	(1/9, 1/9, 1/8)

Source: Zhou, 2012.

Given that no alternative is 100% equivalent with the ideal positive solution, in order to choose the best alternative, one looks at the alternative with the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The difficulty here is that the decision maker should assign a precise rating to an alternative for the criteria under consideration. A fuzzy TOPSIS approach solves this problem by assigning fuzzy numbers. The distance of the fuzzy numbers equation provides the calculation of the distance between two triangular fuzzy number with the characteristics $\tilde{A}\ (l_1, m_1, u_1)$and $\tilde{B}\ (l_2, m_2, u_2)$.

Since ANP is a powerful method for MCDM, it is used for the research as basis. To support the inputs gathered for ANP, fuzziness is added. Fuzzy decreases the noise of qualitative inputs by giving a range of suitable numbers. TOPSIS, as a popular mean of decision algorithm finds the optimal solution for a set of alternatives by maximizing the benefits - opportunities and minimizing the cost - risks. TOPSIS ranks a number of possible alternatives according to closeness to the ideal solution which is the maximum value of the criteria used for the study. Finally, Monte Carlo simulates the fuzzy numbers in order to show the most accurate and the most possible solution for the given methodology by randomizing the each criteria values.

In order to set up a functional model, the research requires analysis of collected data and relevant case studies. The biggest challenge from this aspect is to define a logical process where the evidence from different studies is examined in the context of the proposed theoretical model. The decision on how certain data is collected and processed can significantly influence the final shape of the model.

3.3. Data collection

In order to present a hybrid project selection model based on ANP, fuzzy logic with TOPSIS and Monte Carlo simulation, three steps are undertaken.

Firstly, a set of criteria are selected from literature review. In order to identify the specific needs of professionals in the banking sector, interviews are conducted with 16 experts from a specific bank project management office. Their opinions together with the information gained from the literature review are then transferred into evaluation criteria i.e. four clusters and three nodes for each cluster. Analysis of the required inputs and outputs for these criteria is performed for each step of the process. A set of formulas used in fuzzy ANP, fuzzy TOPSIS and Monte Carlo simulation are combined to create the basis of the proposed project selection method.

Secondly, to decide weights and network relations of the criteria a questionnaire is conducted to project management experts. In addition to the 16 project management office experts from former step, 32 more project management experts are involved to this data collection phase in order to strengthen the accuracy of the data collected. Total of 48 participants are requested to give scores to previously decided clusters which are financial, risk, technical and organizational goals and nodes which are NPV/IRR, ROI, payback period, complexity, probability of success, project duration, personnel, hardware, software, module reusability, strategic fit, market demand. These inputs are used for ANP calculations and show the interrelations between clusters and nodes

Thirdly, to present the validity of the model, a data set of a real-world scenario is constructed by applying a survey. The survey is developed and distributed to 16 project management office experts from the first step with project selection experience in context of the banking sector. The responses to the survey is expected to provide data for conducting a case study of a real-world scenario. The details of the data set and the related findings are discussed in chapter 5, where they are used to clarify and improve the general framework.

Case studies are an effective method for conducting and presenting quantitative research with related surveys. A case study represents an empirical investigation into a contemporary phenomenon in its real-life context in which a number of different sources of evidence can be used (Yin, 1994; Saunders et al., 2009). By focusing the research on a specific context, the case study method can be a valuable tool in combination with a survey. As a research method, case studies are often used in research areas such as psychology, sociology, economics, management, and information systems (IS), and are particularly useful for complex social phenomena, such as decision making (Benbasat et al., 1987; Yin, 1994).A case study of an IS can be valuable because it evaluates the subject matter in a natural setting, making it possible to generate a theory from practice (Benbasat et al., 1987).

The combination of the survey and case study methods is allowed in the pragmatist research philosophy. By using both tools, the researcher should be able to adequately respond to the basic research problem. In the case of this study, the use of a survey questionnaire and case studies is justified by the research objectives defined in chapter 1.2. It is only questionable how many study cases are sufficient to justify the given theoretical proposition. According to Benbasat, Goldstein and Mead (1987), IS problems should be optimally resolved with multiple-case analysis, but a single case study can also be used in situations where: the case is revelatory i.e. refers to previously inaccessible knowledge; it tests a new theory; or it represents an extreme or unique case. Given that this study proposes a new theoretical model for a familiar problem, a single case study is an acceptable solution.

3.4. Data analysis

There are several available options for processing the data obtained in the questionnaire. For simple AHP/ANP models, the results of the questionnaire can be easily computed using the Super Decisions software, which is developed to specifically accommodate the principles outlined in Saaty (2008a; 2008b). However, because of the fuzzy extension and the use of fuzzy TOPSIS, which add an additional layer of weights for quantitative and qualitative factors Super Decisions, used by most of the ANP solutions, is not used here. Technically, Super Decisions could be used to calculate the results of a fuzzy AHP/ANP (e.g. Zhang, 2013), adaptation of the input data is required, which could significantly dilute the results. Instead, the relevant calculations are conducted by designing relevant tables and formula in Microsoft Excel, using add-ins that enable calculations based on Monte Carlo simulation. Excel is generally avoided in literature for decision making problems at this level of complexity, because the potential difficulty of defining inputs, and Matlab is preferred (Buckley and Jowers, 2008; Zhou, 2012). However, Excel provides better overview of the data, it is easier to understand, as well to manipulate and adapt based on the researcher’s needs. Ultimately, the processing of the data should result in relevant tables for completing IT project selection, including pairwise comparison matrices, fuzzy decision matrices, including a normalized fuzzy decision matrix and a weighted fuzzy decision matrix, as well as tables towards the calculation of the final solution.

For the complete analysis and calculations of the research, after use of Microsoft Excel, a GUI (Graphical User Interface) is developed from scratch for the internet browsers. GUI is designed to get inputs of number of the participants (*n*) and number of the projects to be compared (*m*). Then produces *n* matrix of *m* x *number of criteria* to be scored. After scoring is completed and number of iteration for Monte Carlo simulation is given, the calculations take place in background and output is printed as a bar chart to the browser screen. Details of the GUI will be given in CHAPTER 5.

3.5. Ethical considerations

Following the guidelines for ethical conduct, each respondent is informed of the purpose of the research and his or hers rights in relation to the questionnaire, which includes the freedom to withhold any data or to submit an incomplete questionnaire. This is achieved by including an information and consent form at the beginning of the questionnaire. Furthermore, all answers are given anonymously and are combined or aggregated to be observed and evaluated as a group.

CHAPTER 4

SIMULATION-BASED PROJECT SELECTION METHOD

This chapter provides a detailed explanation of the proposed simulation-based project selection method, including description of the inputs and outputs for the relevant criteria, as well as a step-by-step guide for completing the evaluation of different alternatives. The proposed method presented here attempts to provide the optimal solution in a process of evaluating potential investments in IT for the needs of the banking sector. To this end, a generic process is developed, one which should address the six problems that decision-makers typically face: realism, capability, flexibility, ease of use, cost, and compatibility (Pinto, 2010).

The proposed project selection method operates in three phases corresponding to the three underlying processes and a step of preliminary work. The preliminary step consists of the forming the decision making experts committee who will be a team of 16 people of a bank’s project management office and will decide the suitable criteria as well as the case study inputs. The first phase is focused on the extraction and the design of an ANP network for the IT investment possibilities or offers received from alternative solution providers. The second phase continues with weighting of the projects by combining the ANP and fuzzy methods, including the forming of an unweighted supermatrix and a normalized unweighted supermatrix. The third phase combines the fuzzy TOPSIS approach with a Monte Carlo simulation, which optimizes the final results.

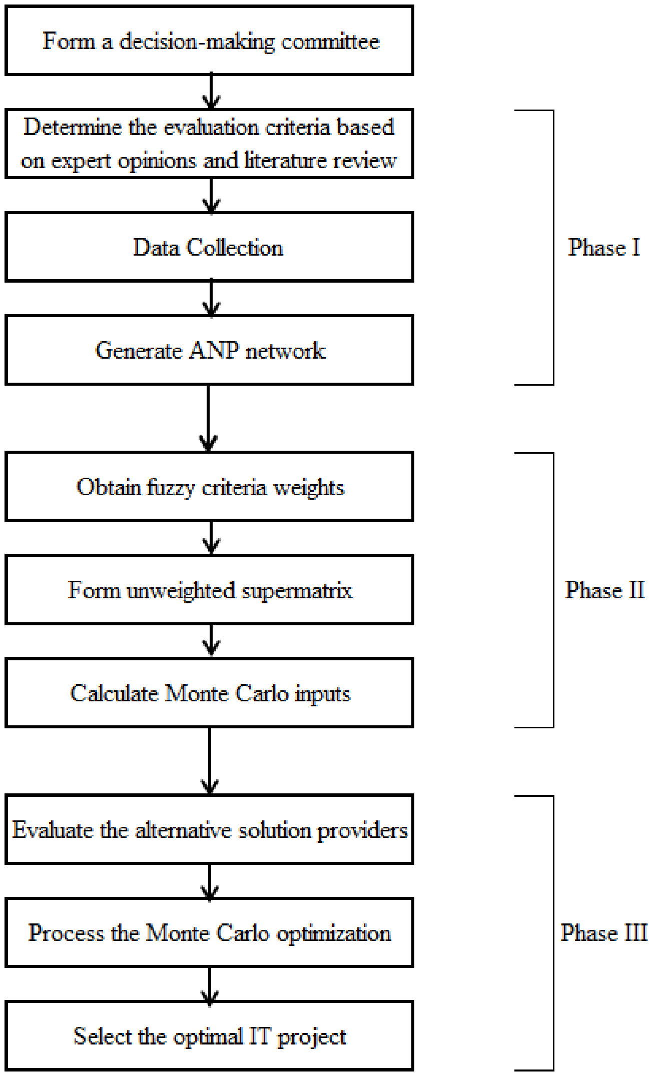


Figure 6. Proposed hybrid methodology

Building on the literature review for ANP, fuzzy logic, and Monte Carlo simulation discussed in Chapter 2, and the theoretical background presented in 3.2. Research design, a general framework for a simulation-based approach to IT project selection is developed.

The steps of this method generally follow the simplified version of the ANP decision process proposed by Saaty and Takizawa (1986). ANP is a powerful tool when the research involves many interdependent criteria. Then ANP is combined with TOPSIS likewise by Shyur (2006). TOPSIS gives the research a rational and understandable straightforward process flow. The concept permits the pursuit of the best alternatives for each criterion depicted in a simple mathematical form. Triangular fuzzy numbers are added at step 5 instead of crisp numbers in order to describe the range of possible values that the criteria/subcriteria can have. There are two benefits of use of fuzzy numbers. First, fuzzy numbers reduce the noise of subjectivity when it comes to scoring the criteria. Second, fuzzy numbers are giving the ease of use to following Monte Carlo simulation inputs. Integration with Monte Carlo simulation is performed at step 8 in order to generate results which will reflect a full spectrum of possible values between the lowest and highest possible values described by the calculated triangular fuzzy numbers. The proposed hybrid approach consists of the following steps in details.

4.1. Phase I - Definition of Criteria, Data Collection, ANP Network

*Step 1.*Before phase I (Figure 7) actually starts, the process requires creation of a decision making committee or a decision making team, which will be responsible for the evaluation of the criteria / subcriteria. In this direction, the main task of the committee is to establish the boundaries of the decision problem, including the definition of the project's objectives, criteria, and subcriteria. There are no specific limitations for the size of the committee, but the chosen members need to possess an adequate mix of expertise in order to perform their duties. For this step to be effective, the decision making committee has to clearly identify the relevant experts in an eventual IT project investment decision and subsequent development.

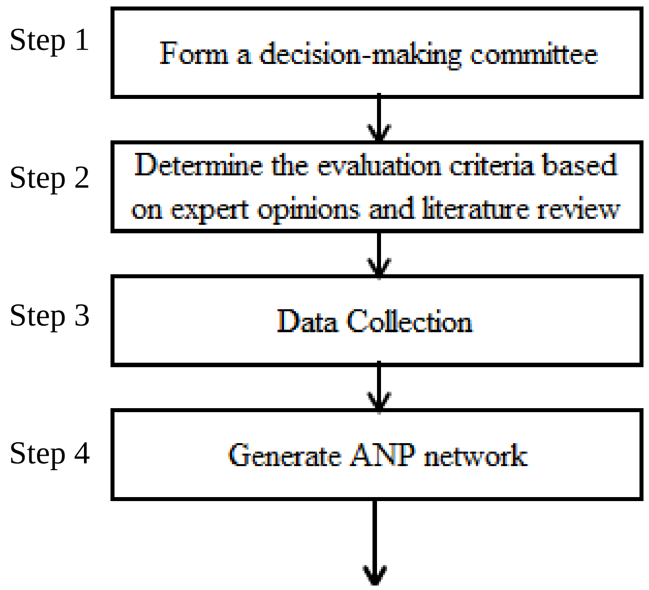


Figure 7. Phase I of the proposed hybrid methodology

Step 2. To understand which criteria should be used during the evaluation of bank-related IT projects and how they are correlated internally, it is necessary to understand how IT and IS are used in the context of the banking sector. This is difficult, given that there is little research devoted to the subject compared to the variety of IT and IS projects implemented continuously among both private and public organizations (Dener et al., 2011). In general, banks need IS for sales and marketing, finance and accounting, human resources and customer relationship management. In addition, banks need to satisfy a number of legal requirements in relation to monitoring, inter-branch reconciliation of accounts, and submission of balance sheet and profit and loss accounts. To achieve this, the banking sector relies on core banking systems, but it also enables services such as ATMs, online banking and payment services, including mobile payments and online ticket booking. Even if portions of these processes are outsourced, banks still need a rather complex underlying IS structure, which requires detailed analysis before implementation. The principle of electronic banking and the use of debit and credit cards ask for special consideration, and have been the subject of several studies (e.g. Benaroch and Kauffman, 2000).

As the result of the conducted interview with bank IT project managers, a list with four criteria/nodes is defined, including “finance”, “risk”, “technical” and “organizational goals”, as well as 12 subcriteria that represent the basis of the proposed hybrid model (Table 6). Fuzzy logic is typically applied to project selection methods in order to find the weights for quantitative and qualitative factors. In context of the proposed attribute details, the financial criteria are treated as quantitative factors, while the risk, technical and organizational goal criteria are considered to be qualitative factors (Kim et al., 2009).

Technically, the number of criteria/nodes could be expanded to include several additional layers. For example, “Risk” criteria are extended to include the subcriteria “complexity”, “probability of success”, and “time to complete / duration of project”, which have additional qualifiers that can be turned into evaluation nodes. Given that the model is meant to be applicable to a number of different projects, a simple hierarchy of criteria and subcriteria is preferred.

The questionnaire contributes to the forming of the model. The respondents evaluate the importance and direction of dependency in each pairwise comparison of criteria and subcriteria, using a 9-point scale with answers ranging from 1 (Equal importance) to 9 (Extreme importance). The scale extends both in positive and negative direction, relative to the dominant item (APPENDIX B). The evaluation scores are aggregated and compared across all criteria and subcriteria in line with the fundamental scale (Table 3). The ultimate goal is to create a pairwise comparison matrix from which priorities for each item are calculated. According to the fundamental scale, any criteria has stronger importance to the other receive higher integer score n. On the other hand, any criteria has weaker importance to the other receive a reciprocal score of 1/n. Based on these scores, two types of priorities are calculated, and the relevant matrices are developed.

The theoretical basis for the chosen subcriteria is provided by a number of studies focusing on project selection methods in general or IS and IT project selection methods in particular (Table 6). The subcriteria related to finance and risk are well-known, as they form the basics of a Cost-Benefit Analysis (CBA). On the other hand, the technical subcriteria are covered only by a specific set of studies, which may use different terminology to refer to the same constructs. Hardware and software are often combined to refer to a certain level of innovation of the proposed technology (Karami and Guo, 2012), but they can be used separately, too.

In order to keep all modelling options open, the questionnaire respondents are given the opportunity to define and rate other criteria or subcriteria that might have been omitted from the list. It is proposed that for each additional item a series of pairwise comparisons should be provided with all the existing items. If subcriteria for example “organizational learning” or “synergy/compatibility with other projects” are added as important, their level of importance on a scale from 1 to 9 should also be provided, as well as a single direction comparison between these items and each of the dimensions defined in Table 6. In principle, no additional subcriteria have been obtained through the questionnaire.

Table 6. Criteria and Subcriteria Details

Criteria	Subcriteria	Definition	Application
Finance	NPV/IRR	NPV is a performance measure for the difference between the present value of cash inflows and the present value of cash outflows. IRR is the discount rate at which NPV is zero. Price, maintenance costs, consultant expenses, and infrastructure costs factor here.	Projects with positive NPV and high IRR are financially sustainable.
	ROI	ROI is a performance measure for the amount returned on a given investment relative to the investment's cost.	Projects with positive and high ROI are preferable.
	Payback period	Expected time period for recovering the investment.	Projects with shorter payback periods are preferable.
Risk	Complexity	Project complexity introduces risk because it is difficult to understand and adapt to across the business.	More complex projects are riskier and less preferable.
	Probability of success	Probability of success is negatively proportional to risk.	Projects with higher probability of success are preferable.
	Time to complete / duration of project	During the project's development, the bank's human and financial resources are engaged. Long developments or sliding deadlines place pressure on banks.	Projects with shorter (but realistic) completion schedules are preferable.
Technical	Personnel	The vendor's personnel demonstrate through customer references R&D or innovation capability, technical support capability and experience with similar implementation.	Companies with better customer references or more skilled personnel are preferable.
	Hardware	Hardware components are of high quality, easy to integrate or replace, and have adequate warranty.	Projects with better hardware features are preferable.
	Software	Software modules conform to specification, items are fully functional, parameter setting is flexible, scalability – possibility of extending to multiple users in multiple formats – is ensured, permission management and database protection are defined, common programming language is applied, platform independence is achieved, etc.	Projects with better software features are preferable.
Organizational goals	Module reusability	The modules can be integrated across an organization or incorporated in other solutions to achieve uniformity and save resources.	Projects that demonstrate module reusability are preferable.
	Strategic fit	The project is in line with the bank's strategy and long-term investment plan.	Projects that demonstrate strategic are strategic fit are preferable.
	User need / Market demand	The project is needed for the benefit of the employees' performance and the service provider. User friendliness and easy of learning are achieved.	Projects for which there is current need or demand are preferable.

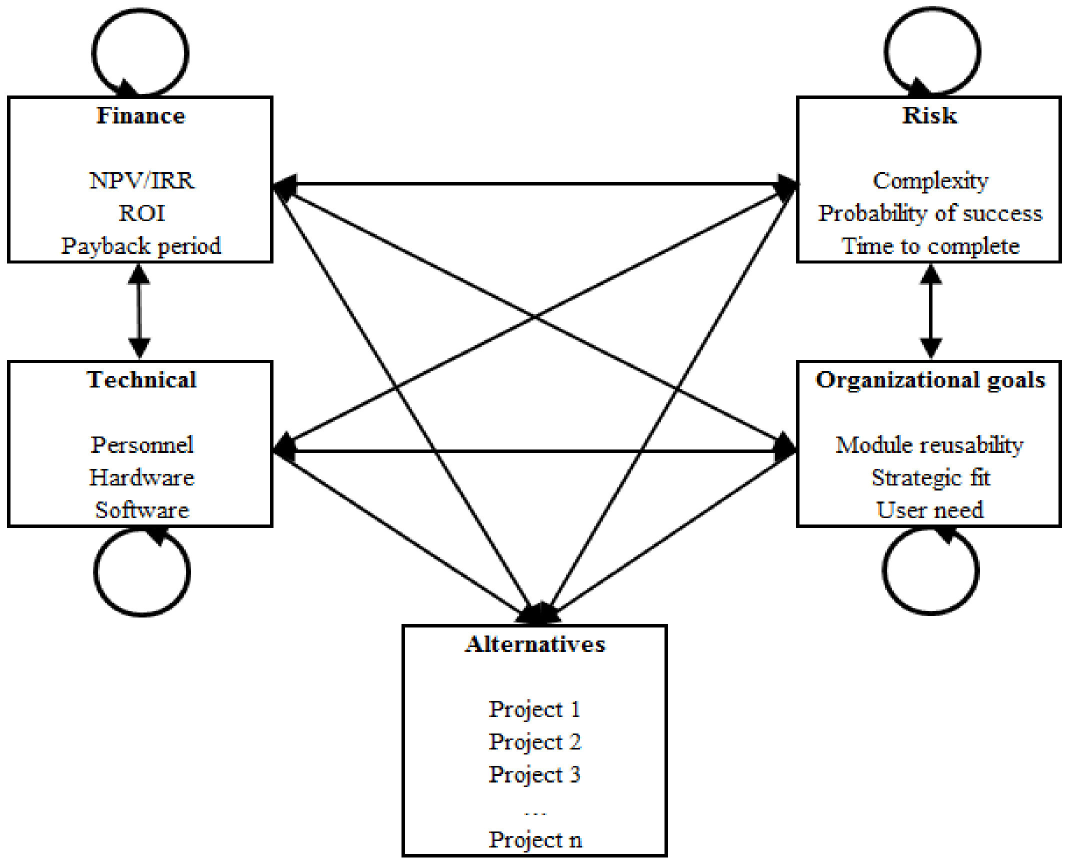


Figure 8. The ANP structure for IT project selection in the banking sector

Step 3. The four control hierarchies for the benefits, opportunities, costs and risks (BOCR) are related to each criterion, and subcriteria are combined to reach the ideal form from the aspects of BOCR. Priority ratings for BOCR are also developed and normalized. For this step, findings from 48 professionals are used (Table 7).

Step 4. Before prioritization is performed, it is necessary to confirm the general network of nodes/clusters that applies to the selected criteria and subcriteria. The nodes/clusters are connected according to the direction of influence and apply to all the criteria and subcriteria included in the four control hierarchies for the decision problem. The problem decision network has to be finalized and tested at this stage. Then, the first phase of the process is completed and the evaluation process continues forward.

Table 7. Survey Questionnaire Data

SAMPLE DATA (N=48)			
	Category	Frequency	Percent
Bank	Bank #1	2	4.17
	Bank #2	1	2.08
	Bank #3	1	2.08
	Bank #4	1	2.08
	Bank #5	2	4.17
	Bank #6	4	8.33
	Bank #7	1	2.08
	Bank #8	4	8.33
	Bank #9	2	4.17
	Bank #10	2	4.17
	Bank #11	2	4.17
	Bank #12	6	12.50
	Bank #13	20	41.67
Professional experience	1-5 years	20	41.67
	6-10 years	19	39.58
	11-15 years	4	8.33
	16-20 years	1	2.08
	21 years or above	4	8.33
Project evaluation	1-5 times	35	72.92
	6-10 times	7	14.58
	11-15 times	1	2.08
	16-20 times	2	4.17
	21 or above	3	6.25

4.2. Phase II – Calculations and Analysis

The proposed hybrid approach continues with phase II as follows (Figure 9).

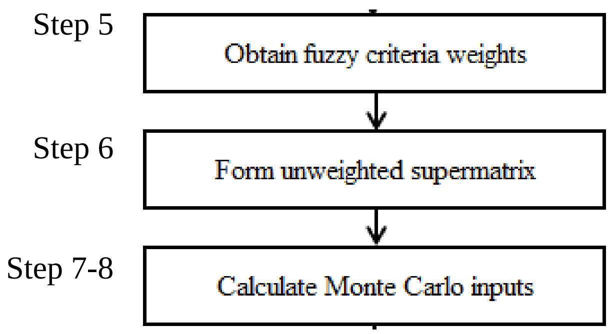


Figure 9. Phase II of the proposed hybrid methodology

Step 5. A pairwise comparison matrix is developed with data for each control criterion. The matrix combines the clusters and their elements following a given order. In context of the proposed hybrid model, the matrix uses triangular fuzzy numbers in line with Table 5. The formula used for *k* decision makers is:

$$\tilde{A}^k = \begin{bmatrix} 1 & \cdots & \tilde{a}_{1n}^k \\ \vdots & \ddots & \vdots \\ \tilde{a}_{n1}^k & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \cdots & \tilde{a}_{1n}^k \\ \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1n}^k & \cdots & 1 \end{bmatrix}, \; k = 1,2,\ldots,K$$

Step 6. The pairwise comparison matrix is computed using geometric mean:

$$\tilde{a}_{ij} = (\tilde{a}_{ij}^1 \otimes \tilde{a}_{ij}^2 \otimes \ldots \otimes \tilde{a}_{ij}^K)^{1/K}$$

where $\tilde{a}_{ij}$ is the aggregated fuzzy comparison value of dimension *i* to criterion *j*, while *K* represents the total number of experts engaged in the process (Table 8).

Table 8. Unweighted Supermatrix

		Finance			Risk			Technical			Organizational goals		
		C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
Finance	C_{11}	1,00	1,27	2,42	3,10	3,10	3,10	4,25	4,25	4,25	1,83	1,83	1,83
	C_{12}	0,79	1,00	1,66	3,10	3,10	3,10	4,25	4,25	4,25	1,83	1,83	1,83
	C_{13}	0,41	0,60	1,00	3,10	3,10	3,10	4,25	4,25	4,25	1,83	1,83	1,83
Risk	C_{21}	0,32	0,32	0,32	1,00	0,65	0,61	1,53	1,53	1,53	0,93	0,93	0,93
	C_{22}	0,32	0,32	0,32	1,54	1,00	1,45	1,53	1,53	1,53	0,93	0,93	0,93
	C_{23}	0,32	0,32	0,32	1,64	0,69	1,00	1,53	1,53	1,53	0,93	0,93	0,93
Technical	C_{31}	0,24	0,24	0,24	0,65	0,65	0,65	1,00	0,80	0,72	0,59	0,59	0,59
	C_{32}	0,24	0,24	0,24	0,65	0,65	0,65	1,25	1,00	1,85	0,59	0,59	0,59
	C_{33}	0,24	0,24	0,24	0,65	0,65	0,65	1,39	0,54	1,00	0,59	0,59	0,59
Org. goals	C_{41}	0,55	0,55	0,55	1,08	1,08	1,08	1,69	1,69	1,69	1,00	0,54	0,48
	C_{42}	0,55	0,55	0,55	1,08	1,08	1,08	1,69	1,69	1,69	1,85	1,00	1,26
	C_{43}	0,55	0,55	0,55	1,08	1,08	1,08	1,69	1,69	1,69	2,08	0,79	1,00

Step 7. The local weights of the criteria and subcriteria included in the second and third level of the ANP model are calculated. A geometric mean method originally proposed by Buckley (1987) and used in Sari (2013) is employed for this purpose:

$$\tilde{r}_i = (\tilde{a}_{i1} \otimes \ldots \otimes \tilde{a}_{ij} \otimes \ldots \otimes \tilde{a}_{in})^{1/n}$$

where $\tilde{r}_i$ stands for the geometric mean of fuzzy comparison value for each criterion i. In this case, the fuzzy weight for criterion i is indicated by a triangular fuzzy number with specification, $\widetilde{w}_i = (m_1 w_i, m_2 w_i, m_3 w_i)$. To calculate for the fuzzy weight, the following formula is used:

$$\widetilde{w}_i = \tilde{r}_i * (\tilde{r}_1 \oplus \ldots \oplus \tilde{r}_i \oplus \ldots \oplus \tilde{r}_n)^{-1}$$

Step 8. The calculated fuzzy weight in step 7 represents only the hierarchical influences, and needs to be adapted to include data from the influences within the ANP network. This is performed using a normalized version of an ANP unweighted matrix (Table 9), which is synthesised with the weights. The calculation of the ANP unweighted matrix follows the same basic math as for the construction of the pairwise comparison matrices. The unweighted matrix is based on a series of comparisons between all subcriteria in the model, regardless of their node membership. Unlike the pairwise comparison matrices, the data in the unweighted matrix is presented as a series of real numbers. Per equation, the product of the multiplication of a real number and a triangular fuzzy number is still a triangular fuzzy number, which means that it can be used further in the process. The output is calculated as: $\widetilde{w}_{ic} = B\widetilde{w}_{i_2}^{T}$

Table 9. Unweighted Normalized Matrix

		Finance			Risk			Technical			Organizational goals		
		C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
Finance	C_{11}	0,18	0,21	0,29	0,17	0,18	0,18	0,16	0,17	0,16	0,12	0,15	0,14
	C_{12}	0,14	0,16	0,20	0,17	0,18	0,18	0,16	0,17	0,16	0,12	0,15	0,14
	C_{13}	0,07	0,10	0,12	0,17	0,18	0,18	0,16	0,17	0,16	0,12	0,15	0,14
Risk	C_{21}	0,06	0,05	0,04	0,05	0,04	0,03	0,06	0,06	0,06	0,06	0,08	0,07
	C_{22}	0,06	0,05	0,04	0,08	0,06	0,08	0,06	0,06	0,06	0,06	0,08	0,07
	C_{23}	0,06	0,05	0,04	0,09	0,04	0,06	0,06	0,06	0,06	0,06	0,08	0,07
Technical	C_{31}	0,04	0,04	0,03	0,04	0,04	0,04	0,04	0,03	0,03	0,04	0,05	0,05
	C_{32}	0,04	0,04	0,03	0,04	0,04	0,04	0,05	0,04	0,07	0,04	0,05	0,05
	C_{33}	0,04	0,04	0,03	0,04	0,04	0,04	0,05	0,02	0,04	0,04	0,05	0,05
Org. goals	C_{41}	0,10	0,09	0,07	0,06	0,06	0,06	0,07	0,07	0,07	0,07	0,04	0,04
	C_{42}	0,10	0,09	0,07	0,06	0,06	0,06	0,07	0,07	0,07	0,12	0,08	0,10
	C_{43}	0,10	0,09	0,07	0,06	0,06	0,06	0,07	0,07	0,07	0,14	0,06	0,08

4.3. Phase III – Simulation & Optimal Solution

The proposed hybrid approach continues with phase III as follows (Figure 10). Because the step "evaluate the alternative solution providers" involves several sub-operations, the explanation is broken down into steps 10 to 17.

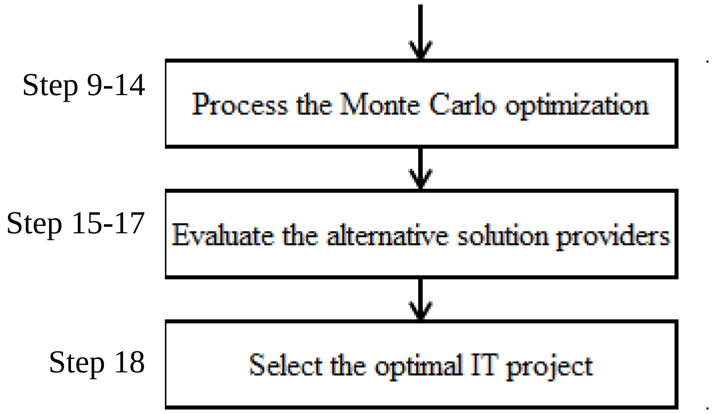


Figure 10. Phase III of the proposed hybrid methodology

Step 9. At this stage, the Monte Carlo simulation analysis is integrated into the model to optimize the results from the fuzzy ANP. The basic assumption used in this case is that the best alternative solution is the one that is the closest to the positive ideal solution of the project selection process. At the same time, the best alternative solution would also be the one is the farthest away from the negative ideal solution. What this means is that the positive ideal solution represents a result that maximizes the benefit criteria and minimizes the cost criteria while the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Sari, 2013). Thus, in selecting the most suitable alternative, the method considers simultaneously the distances to both positive and negative ideal solutions.

The key purpose of the Monte Carlo simulation analysis here is to better investigate the expert opinions. Assuming that there are *m* alternatives available

$(A_1, A_2, \ldots, A_m)$ and *n* decision criteria/attributes $(C_{1,} C_2, \ldots, C_n)$, it is necessary to determine the weightings of the evaluation criteria. As suggested above, the fuzzy preference weights can be expressed by a triangular fuzzy number, $\widetilde{w}_i = (m_1 w_i, m_2 w_i, m_3 w_i)$, or given the outcome of step 8, $\widetilde{w}_{ci} = (m_1 w_{ic}, m_2 w_{ic}, m_3 w_{ic})$. Each triangular fuzzy number can also be converted to random numbers $(\tilde{t}_i)$, which are derived from a triangular probability distribution function with parameters $(m_1 w_{ic}, m_2 w_{ic}, m_3 w_{ic})$ where $(m_1 w_{ic}, m_3 w_{ic})$ is the range and $(m_2 w_{ic})$represents the most likely value. These random numbers are used to conduct a Monte Carlo simulation analysis in order to better understand the impact of variability or uncertainty in the weights of evaluation criteria on the model results.

Step 10. The appropriate linguistic variable is chosen for each alternative in relation to the criteria, and described using triangular fuzzy numbers (Table 10). This means that an individual expert in the committee could argue that an alternative projects has very low (VL), low (L), medium (M), high (H), or very high (VH) performance values for a given criterion. For instance, if the expert rates the project's performance for the criterion with H, the assigned rating can be turned into the triangular fuzzy number (5,7,9) based on the scale. This triangular fuzzy number can be then used for further calculations and comparisons between the projects, especially towards the creation of a fuzzy decision matrix.

*Step 11.*A fuzzy decision matrix is constructed by aggregating the expert ratings for each alternative with respect to each criterion and the formula:

$$\widetilde{D} = \begin{matrix} \\ A_1 \\ \vdots \\ A_n \end{matrix} \begin{matrix} \begin{matrix} C_1 & \ldots & C_n \end{matrix} \\ \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{matrix} \; i = 1,2, \ldots m; j = 1,2, \ldots n$$

$\tilde{x}_{ij} = \frac{1}{K(\tilde{x}_{ij}^1 \oplus \tilde{x}_{ij}^2 \oplus \ldots \tilde{x}_{ij}^k)}$

where $\tilde{x}_{ij}$ is the performance rating of alternative A_i with respect to criterion C_j evaluated by the *k*th expert, and $\tilde{x}_{ij}$ is a triangular fuzzy number.

Table 10. Linguistic Scales for Evaluating the Performance of Alternatives

Definition	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Very low (VL)	(0, 1, 3)	(1/3, 1, 0)
Low (L)	(1, 3, 5)	(1/5, 1/3, 1)
Medium (M)	(3, 5, 7)	(1/7, 1/5, 1/3)
High (H)	(5, 7, 9)	(1/9, 1/7, 1/5)
Very high (VH)	(7, 9, 10)	(1/10, 1/9, 1/7)

Source: S. Boran et al.

Step 12. The fuzzy decision matrix denoted by $\tilde{R}$ should be normalized:

$\tilde{R} = [\tilde{r}_{ij}]_{mxn}, i = 1,2 \ldots, m; j = 1,2, \ldots, n$

Step 13. The normalization proceeds by calculating for *B* and *C* as a set of benefit criteria and cost criteria, respectively:

$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right), j \in B$

$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right), j \in C$

$u_j^+ = max_{i\{u_{ij}|i = 1,2, \ldots, n\}}, \; j \in B$

$l_j^- = min_{i\{l_{ij}|i = 1,2, \ldots, n\}}, \; j \in C$

Step 14. The weighted normalized fuzzy decision matrix denoted by *V* is calculated:

$\tilde{V} = [\tilde{v}_{ij}]mxn, i = 1,2, \ldots, m; j = 1,2, \ldots, n$

$\tilde{v}_{ij} = \tilde{r}_{ij} * \tilde{t}_i$

where $\tilde{t}_i$ represents the preference weights of criteria, random numbers generated using Monte Carlo simulation at Step 9. For each run of the simulation model, there should be a different weighted normalized fuzzy decision matrix. The final result presents the optimal solution reached after *n* simulations.

Step 15. At this point of the process, the fuzzy positive-ideal solution (A^+) and fuzzy negative-ideal solution (A^-) should be identified:

$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+)$ where $\tilde{v}_j^+ = (1,1,1)$

$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-)$ where $\tilde{v}_j^- = (0,0,0)$

Step 16. The distance of the fuzzy positive-ideal solution (A^+) and fuzzy negative-ideal solution (A^-) should be calculated. For this purpose, a variation of the following formula is used to calculate the distance for each aspect:

$d_i^+ = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, v_j^+\right), i = 1,2, \dots, m; j = 1,2, \dots, n$

$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), i = 1,2, \dots, m; j = 1,2, \dots, n$

Neither d_i^+ nor d_i^- are triangular fuzzy numbers, which means that they could be treated as defuzzifiers.

Step 17. Using the distance of the fuzzy positive-ideal solution and fuzzy negative-ideal solution, the closeness coefficient of each alternative should be calculated:

$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1,2, \dots, m$

Step 18. Based on these equations, a simulation output analysis should be made, and the different alternatives according to the closeness coefficient values CC_i should be ranked. The rank table indicates what the best alternative is, and should provide basis for completing the decision making process. Following chapter provides a case study to demonstrate how this model can be applied in practice.

CHAPTER 5

MODEL CALCULATIONS AND CASE STUDY

This section presents a case study, which demonstrates how the model proposed in chapter 4 can resolve problems related to IT project selection. The case uses the data collected from the 16 participants, from a specific bank project management office formerly mentioned in 3.3. Data collection, of the same 3 arbitrary IT projects (APPENDIX C). The study case follows the corresponding steps of the general framework, provides the appropriate data tables calculated using the relevant formulas, and includes a discussion of the results. Also details of the GUI application will be discussed in this chapter.

5.1. Findings

Walking through the General Framework mentioned in Section 4.3:

Step 1. To evaluate how several different alternatives would compare based on the criteria/subcriteria, 16 respondents in one of the banks evaluate three IT project alternatives chosen by the bank. The projects may have change in criteria with changing time or conditions, but for the purpose of this study it is assumed that they are stable for comparison. It is also believed that because the evaluations are ultimately subjective, the collected data would have a similar quality if a limited number of respondents evaluated in parallel a fixed set of projects chosen specifically for the purpose of the study. At the same time, because IT project offers can be substantial in volume and detail, proper comparison of projects may require several months, which would be difficult to obtain from the respondents, given the limited study resources.

Steps 2-3-4. For the general framework, decision making committee survey respondents are used to define the weights of the criteria and subcriteria. The criteria ($C_l, l = 1,2,3,4$) and subcriteria are taken from Table 6, and correspond to the ANP network in Figure 8. The subcriteria are denoted as follows: NPV/IRR (C_{11}), ROI (C_{12}), payback period (C_{13}), complexity (C_{21}), probability of success (C_{22}), time to complete (C_{23}), personnel (C_{31}), hardware (C_{32}), software (C_{33}), module reusability (C_{41}), strategic fit (C_{42}), and user need (C_{43}). Based on the data received for these criteria and subcriteria, it is possible to create four pairwise comparison matrices from the aspect of each criterion. Triangular fuzzy numbers can be used for all comparisons.

Steps 5-6. To demonstrate how the pairwise comparisons are calculated, the combination of the subcriteria NPV/IRR and ROI is used. Using equation described in Methodology, where *i* stand for NPV/IRR and *j* stands for ROI while *K* represents the number of involved experts, the result is:

$$\tilde{a}_{ij} = (\tilde{a}_{ij}^{1} \otimes \tilde{a}_{ij}^{2} \otimes \ldots \otimes \tilde{a}_{ij}^{K})^{1/K}$$

$$\tilde{a}_{NPV/IRR-ROI} = (102791.36)^{1/48}$$

$$\tilde{a}_{NPV/IRR-ROI} = 1.2718$$

If the number is rounded to zero decimal places, it can be presented as the triangular fuzzy number (1,1,1), which is the same as the reciprocal number. In case of reciprocal numbers with fractal components, the calculation rounds to two decimals.

Step 7. Once the pairwise comparison calculations are performed, the results of the comparisons are entered into a matrix. Based on the results of the pairwise comparisons, it is possible to calculate the fuzzy weight for all subcriteria. For this, the geometric mean method is applied in line with equation described in methodology i.e. the entries in each row of the matrix are multiplied and then the n^{th} root of the product is calculated. This process is similar to normalization in the context of ANP analysis using crisp numbers. For NPV/IRR, the result is calculated as:

$$\tilde{r}_{NPV/IRR} = (\tilde{a}_{NPV/IRR-NPV/IRR} \otimes \tilde{a}_{NPV/IRR-ROI} \otimes \tilde{a}_{NPV/IRR-PP})^{1/3}$$

$$\tilde{r}_{NPV/IRR} = ((1,1,1) \otimes (1,1.5,2) \otimes (2,2.5,3)^{1/3}$$

$$\tilde{r}_{NPV/IRR} = ((1 \times 1 \times 2)^{1/3}, (1 \times 1.5 \times 2.5)^{1/3}, (1 \times 2 \times 3)^{1/3})$$

$$\tilde{r}_{NPV/IRR} = (1.26,1.55,1.82)$$

For calculation of the fuzzy weights, equation in methodology is used. Continuing with the example for NPV/IRR, the result is calculated as:

$$\widetilde{w}_{NPV/IRR} = \tilde{r}_{NPV/IRR} \otimes (\tilde{r}_{NPV/IRR} \oplus \tilde{r}_{ROI} \oplus \tilde{r}_{PP})^{-1}$$

$$\widetilde{w}_{NPV/IRR} = (1.26,1.55,1.82) \otimes ((1.26,1.55,1.82) \oplus (.79,1,1.26) \oplus (.55,.64,.79))^{-1}$$

$$w_{NPV/IRR} = (1.26,1.55,1.82) / ((1.26 + .79 + .55), (1.55 + 1 + .64), (1.82 + 1.26 + .79))$$

$$w_{NPV/IRR} = (1.26,1.55,1.82)/(2.60,3.20,3.87) = ((1.26/3.87), (1.55/3.20), (1.82/2.60)) = (0.33,0.49,0.70)$$

Pairwise comparison matrices based on these formulae are established for each of the clusters (Table 11 - Table 14).

Table 11. Pairwise Comparison of Subcriteria with Respect to Finance

	NPV/IRR	ROI	Payback period	Root values (r_i)	Weight (w_i)
NPV/IRR	(1,1,1)	(1,1.5,2)	(2,2.5,3)	(1.26,1.55,1.82)	(.33,.49,.70)
ROI	(.5,.67,1)	(1,1,1)	(1,1.5,2)	(.79,1,1.26)	(.21,.31,.48)
Payback period	(.33,.4,.5)	(.5,.67,1)	(1,1,1)	(.55,.64,.79)	(.14,.20,.31)

Table 12. Pairwise Comparison of Subcriteria with Respect to Risk

	Complexity	Probability of success	Time to complete	Root values	Weight
Complexity	(1,1,1)	(.33,.5,1)	(.33,.5,1)	(.48,.63,1)	(.11,.20,.44)
Probability of success	(1,2,3)	(1,1,1)	(1,1.5,2)	(1,1.44,1.82)	(.23,.45,.80)
Time to complete	(1,2,3)	(.5,.67,1)	(1,1,1)	(.79,1.10,1.44)	(.19,.35,.64)

Table 13. Pairwise Comparison of Subcriteria with Respect to Technical

	Personnel	Hardware	Software	Root values	Weight
Personnel	(1,1,1)	(.33,.5,1)	(.33,.5,1)	(.48,.63,1)	(.11,.20,.46)
Hardware	(1,2,3)	(1,1,1)	(1,2,3)	(1,1.59,2.08)	(.22,.49,.96)
Software	(1,2,3)	(.33,.5,1)	(1,1,1)	(.69,1,1.44)	(.15,.31,.67)

Table 14. Pairwise Comparison of Subcriteria with Respect to Organizational Goals

	Module reusability	Strategic fit	User need	Root values	Weight
Module reusability	(1,1,1)	(.33,.5,1)	(.33,.5,1)	(.48,.63,1)	(.11,.20,.44)
Strategic fit	(1,2,3)	(1,1,1)	(1,1.5,2)	(1,1.44,1.82)	(.23,.45,.80)
User need	(1,2,3)	(.5,.67,1)	(1,1,1)	(.79,1.10,1.44)	(.19,.35,.64)

Based on the weights, it is evident that NPV/IRR, probability of success, hardware, and strategic fit are the most influential subcriteria in the respective clusters. Analysis of the consistency ratio for each pairwise comparison matrix can be performed by calculating the consistency index and comparing it to the random index ratio for the order of 3. For example, the consistency ratio for the finance criteria can is calculated in Table 15.

Because the consistency ratio is well below 0.1 in all four cases, the pairwise comparisons are acceptable (Table 16).

Table 15. Consistency Ratio for Finance Criteria

	NPV/IRR	ROI	Payback period	Total	Average	Consistency Measure
NPV/IRR	0,48	0,47	0,50	1,456278	0,485425969	3,005232865
ROI	0,32	0,32	0,30	0,939129	0,31304297	3,004619333
Payback period	0,19	0,21	0,20	0,604593	0,201531061	3,004203106
Total	1	1	1		Lambda max	3,004685102
					CI	0,002342551
					CR	0,52
					C. ratio < 0.1	0,004504905

Table 16. Consistency Analysis of Pairwise Comparison Matrices

	Λ max	Consistency index (C.I.)	Random index (R.I.)	Consistency ratio (C.R.)
Finance	3.0047	0.0023	0.52	0.0045
Risk	3.0198	0.0099	0.52	0.0190
Technical	3.0537	0.0269	0.52	0.0517
Organizational goals	3.0198	0.0099	0.52	0.0190

A series of fuzzy global weights can also be calculated for the subcriteria. To do so, a fuzzy comparison must be performed at the level of the criteria, with n=4 (Table 17). The financial criteria carry the highest weight, which suggests that they are the most influential during the project selection. Once the weights for the criteria are calculated, the fuzzy global weights are formed by multiplying the weights of the subcriteria with the weight of the corresponding criterion (Table 18).

Table 17. Pairwise Comparison of Criteria

	Finance	Risk	Technical	Org. goals	Root values	Weight
Finance	(1,1,1)	(2,3,4)	(4,4.5,5)	(1,2,3)	(1.68,2.28,2.78)	(.29,.49,.78)
Risk	(.25,.33,.5)	(1,1,1)	(1,1.5,2)	(1,1,1)	(.71,.84,1)	(.12,.18,.28)
Technical	(.2,.22,.25)	(.5,.67,1)	(1,1,1)	(.33,5,1)	(.43,.52,.71)	(.07,.11,.20)
Org. goals	(.33,.5,1)	(1,1,1)	(1,2,3)	(1,1,1)	(.76,1,1.32)	(.13,.22,.37)

Table 18. Fuzzy Global Weights for Criteria and Subcriteria

Criteria	Weights	Subcriteria	Fuzzy global weights
Finance	(.29,.49,.78)	NPV/IRR	(.09,.24,.54)
		ROI	(.06,.15,.38)
		Payback period	(.04,.10,.24)
Risk	(.12,.18,.28)	Complexity	(.01,.04,.12)
		Probability of success	(.03,.08,.22)
		Time to complete	(.02,.06,.18)
Technical	(.07,.11,.20)	Personnel	(.01,.02,.09)
		Hardware	(.02,.06,.19)
		Software	(.01,.03,.13)
Organizational goals	(.13,.22,.37)	Module reusability	(.01,.04,.16)
		Strategic fit	(.03,.10,.29)
		User need	(.02,.07,.23)

Step 8. The normalized unweighted supermatrix which contains the results of the expert opinions about the influences of the criteria (APPENDIX C) needs to be synthesised with the fuzzy global weights. Using related equation, the calculation is performed as follows:

$$\widetilde{w}_{ic} = \begin{bmatrix} c_{11} \\ c_{12} \\ c_{13} \\ c_{21} \\ c_{22} \\ c_{23} \\ c_{31} \\ c_{32} \\ c_{33} \\ c_{41} \\ c_{42} \\ c_{43} \end{bmatrix} = \begin{bmatrix} .18 & .21 & .29 & .17 & .18 & .18 & .16 & .17 & .16 & .12 & .15 & .14 \\ .14 & .16 & .20 & .17 & .18 & .18 & .16 & .17 & .16 & .12 & .15 & .14 \\ .07 & .10 & .12 & .17 & .18 & .18 & .16 & .17 & .16 & .12 & .15 & .14 \\ .06 & .05 & .04 & .05 & .04 & .03 & .06 & .06 & .06 & .06 & .08 & .07 \\ .06 & .05 & .04 & .08 & .06 & .08 & .06 & .06 & .06 & .06 & .08 & .07 \\ .06 & .05 & .04 & .09 & .04 & .06 & .06 & .06 & .06 & .06 & .08 & .07 \\ .04 & .04 & .03 & .04 & .04 & .04 & .04 & .03 & .03 & .04 & .05 & .05 \\ .04 & .04 & .03 & .04 & .04 & .04 & .05 & .04 & .07 & .04 & .05 & 05 \\ .04 & .04 & .03 & .04 & .04 & .04 & .05 & .02 & .04 & .04 & .05 & .05 \\ .10 & .09 & .07 & .06 & .06 & .06 & .07 & .07 & .07 & .07 & .04 & .04 \\ .10 & .09 & .07 & .06 & .06 & .06 & .07 & .07 & .07 & .12 & .08 & .10 \\ .10 & .09 & .07 & .06 & .06 & .06 & .07 & .07 & .07 & .14 & .06 & .08 \end{bmatrix}$$

$$\times \begin{bmatrix} (.09,.24,.54) \\ (.06,.15,.38) \\ (.04,.10,.24) \\ (.01,.04,.12) \\ (.03,.08,.22) \\ (.02,.06,.18) \\ (.01,.02,.09) \\ (.02,.06,.19) \\ (.01,.03,.13) \\ (.01,.04,.16) \\ (.03,.10,.29) \\ (.02,.07,.23) \end{bmatrix} = \begin{bmatrix} (.07,.18,.50) \\ (.06,.16,.44) \\ (.04,.13,.36) \\ (.02,.06,.16) \\ (.02,.06,.17) \\ (.02,.06,.16) \\ (.01,.04,.11) \\ (.01,.04,.12) \\ (.01,.04,.11) \\ (.03,.07,.19) \\ (.03,.08,.23) \\ (.03,.08,.22) \end{bmatrix}$$

Step 9. The results of step 8 are crucial for performing the Monte Carlo simulation. Based on the Monte Carlo simulation principles, 10,000 simulation trials are conducted in order to eliminate the impact of random variations. During the calculation of the normalized weighted fuzzy decision matrix, the weights of the evaluation criteria are used to define the range in which Monte Carlo simulation random numbers can change to produce different sets of weights. At each run of the simulation, a new set of weights is multiplied with the normalized fuzzy decision matrix. The simulation produces 10,000 matrices, and the additional calculations are based on the means results of the matrices.

Steps 10-11. The next step presents development of an aggregated fuzzy decision matrix for the three alternatives which data comes from 16 respondent questionnaires. The aggregated fuzzy decision matrix evaluates each alternative against the defined criteria using the linguistic scale established in Chapter 4.3 (Table 19). Each of the 16 respondents has evaluated the three projects against the defined criteria, so that ultimately the data for each alternative is based on 16 responses. Each response has been turned into a triangular fuzzy number and adapted form of equation described in methodology has been used to calculate the result. An example for calculating the rating NPV/IRR for Alternative 1 would lead to the following result:

$$\tilde{a}_{ij} = (\tilde{a}_{ij}^{1} \otimes \tilde{a}_{ij}^{2} \otimes \ldots \otimes \tilde{a}_{ij}^{K})^{1/K}$$

$$\tilde{a}_{NPV/IRR-A1} = (126610091973225)^{1/16}$$

$$\tilde{a}_{NPV/IRR-A1} = 7.6103$$

Table 19. Aggregated Fuzzy Decision Matrix

Criteria	Alternative 1	Alternative 2	Alternative 3
C_{11}	(5.55,7.61,9.19)	(4.71,6.89,8.69)	(3.27,5.43,7.49)
C_{12}	(4.59,6.64,8.56)	(4.59,6.64,8.56)	(3.94,6.26,8.22)
C_{13}	(4.59,6.67,8.46)	(4.17,6.23,8.17)	(3.45,5.64,7.66)
C_{21}	(3.96,6.01,7.99)	(4.91,7.11,8.80)	(4.59,6.67,8.46)
C_{22}	(5.73,7.77,9.34)	(4.24,6.40,8.31)	(4.84,6.89,8.76)
C_{23}	(4.24,6.40,8.31)	(3.85,6.19,8.07)	(3.79,6.04,7.94)
C_{31}	(4.54,6.61,8.49)	(3.41,5.78,7.73)	(4.74,6.78,8.70)
C_{32}	(4.54,6.61,8.49)	(2.91,5.18,7.23)	(3.01,5.29,7.35)
C_{33}	(3.75,5.97,7.96)	(5.38,7.41,9.16)	(4.94,7.00,8.81)
C_{41}	(4.69,6.75,8.62)	(3.52,5.73,7.71)	(4.38,6.53,8.44)
C_{42}	(4.73,6.82,8.60)	(5.15,7.22,8.93)	(4.84,6.89,8.76)
C_{43}	(5.38,7.41,9.16)	(4.69,6.75,8.62)	(4.89,6.96,8.73)

Steps 12-14. The aggregated fuzzy decision matrix (Table 19) is then normalized using equations described in methodology. In practice, this means that the lowest possible value and the most likely value of each triangular fuzzy number is represented as a percentage of the highest possible value, which is reduced to 1. The resulting data (Table 20) represents the basis for calculating the weighted normalized fuzzy decision matrix, for which Monte Carlo simulation is needed.

Table 20. Normalized Fuzzy Decision Matrix

Criteria	Alternative 1	Alternative 2	Alternative 3
C_{11}	(.60,.83,1.00)	(.54,.79,1.00)	(.44,.72,1.00)
C_{12}	(.54,.78,1.00)	(.54,.78,1.00)	(.48,.76,1.00)
C_{13}	(.54,.79,1.00)	(.51,.76,1.00)	(.45,.74,1.00)
C_{21}	(.50,.75,1.00)	(.56,.81,1.00)	(.54,.79,1.00)
C_{22}	(.61,.83,1.00)	(.51,.77,1.00)	(.55,.79,1.00)
C_{23}	(.51,.77,1.00)	(.48,.77,1.00)	(.48,.76,1.00)
C_{31}	(.53,.78,1.00)	(.44,.75,1.00)	(.54,.78,1.00)
C_{32}	(.53,.78,1.00)	(.40,.72,1.00)	(.41,.72,1.00)
C_{33}	(.47,.75,1.00)	(.59,.81,1.00)	(.56,.79,1.00)
C_{41}	(.54,.78,1.00)	(.46,.74,1.00)	(.52,.77,1.00)
C_{42}	(.55,.79,1.00)	(.58,.81,1.00)	(.55,.79,1.00)
C_{43}	(.59,.81,1.00)	(.54,.78,1.00)	(.56,.80,1.00)

Steps 15-17. At this point, a series of calculations based on the equations in methodology are made with each run of the Monte Carlo simulation. In essence, the fuzzy positive-ideal solution (A^{+}) and fuzzy negative-ideal solution (A^{-}) are identified, as well as the distances of each alternative from the FPIS (d_i^{+}) and the

FNIS (d_i^-). Finally, the relative closeness to the ideal solution (CC_i) is calculated for each alternative.

Step 18. Based on the generated mean values of the simulation, it is possible to rank the different solutions (Table 21). What follows is an example of the calculation CC_i for alternative A_1, given mean values for 10,000 Monte Carlo simulation trials based on equation. The same calculation is applied to alternatives A_2andA_3.

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} = 1.6532/(4.1210 + 1.6532) = 1.6532/5.7742 = 0.2876$$

Table 21. Ranking of Alternatives

Alternatives	d_i^+	d_i^-	CC_i	Rank
A_1	4.1210	1.6532	.2876	1
A_2	4.1151	1.6472	.2859	2
A_3	4.1095	1.6416	.2854	3

Based on this analysis, the best alternative for the new financial database in this real-world study case is alternativeA_1. If the evaluation team is uncertain of the results, they could run the simulation several times to verify the conclusion. The Monte Carlo simulation is useful to assure the individuals involved in the selection process that there is little probability that alternatives A_2 and A_3perform better than alternative A_1.

5.2 GUI Application and Test Case Scenario

To ease the calculations of the research a GUI is developed from scratch by use of JavaScript and HTML (HyperText Markup Language) compatible for internet browsers. GUI is adapted to work for all browsers without additional plugins or installations. GUI, simply has a form of two text boxes for number of projects (n) and number of participants (m) who are going to evaluate criteria for the projects (Figure 11).

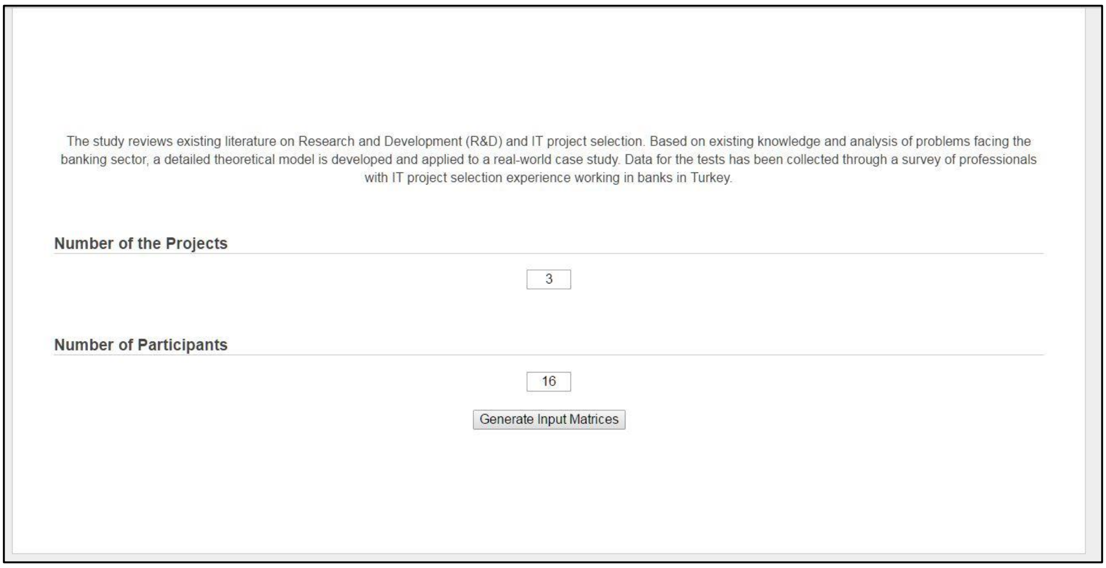
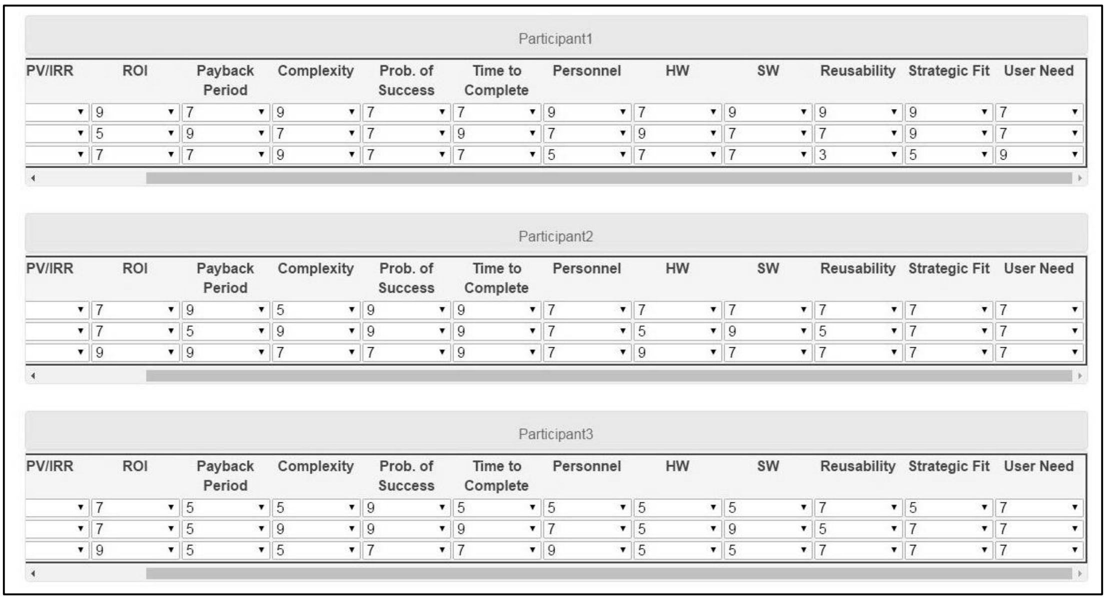


Figure 11. GUI for simulation - initial page

After submission of these text boxes, a second form of n x m combo boxes appears and requires input for projects scores with respect to criteria (Figure 12).



Participant1

PV/IRR	ROI	Payback Period	Complexity	Prob. of Success	Time to Complete	Personnel	HW	SW	Reusability	Strategic Fit	User Need
	9	7	9	7	7	9	7	9	9	9	7
	5	9	7	7	9	7	9	7	7	9	7
	7	7	9	7	7	5	7	7	3	5	9

Participant2

PV/IRR	ROI	Payback Period	Complexity	Prob. of Success	Time to Complete	Personnel	HW	SW	Reusability	Strategic Fit	User Need
	7	9	5	9	9	7	7	7	7	7	7
	7	5	9	9	9	7	5	9	5	7	7
	9	9	7	7	9	7	9	7	7	7	7

Participant3

PV/IRR	ROI	Payback Period	Complexity	Prob. of Success	Time to Complete	Personnel	HW	SW	Reusability	Strategic Fit	User Need
	7	5	5	9	5	5	5	5	7	5	7
	7	5	9	9	9	7	5	9	5	7	7
	9	5	5	7	7	9	5	5	7	7	7

Figure 12. GUI for simulation - inputs page

Finally, a text box accepts the number of iterations for Monte Carlo simulation (10000 by default) (Figure 13).

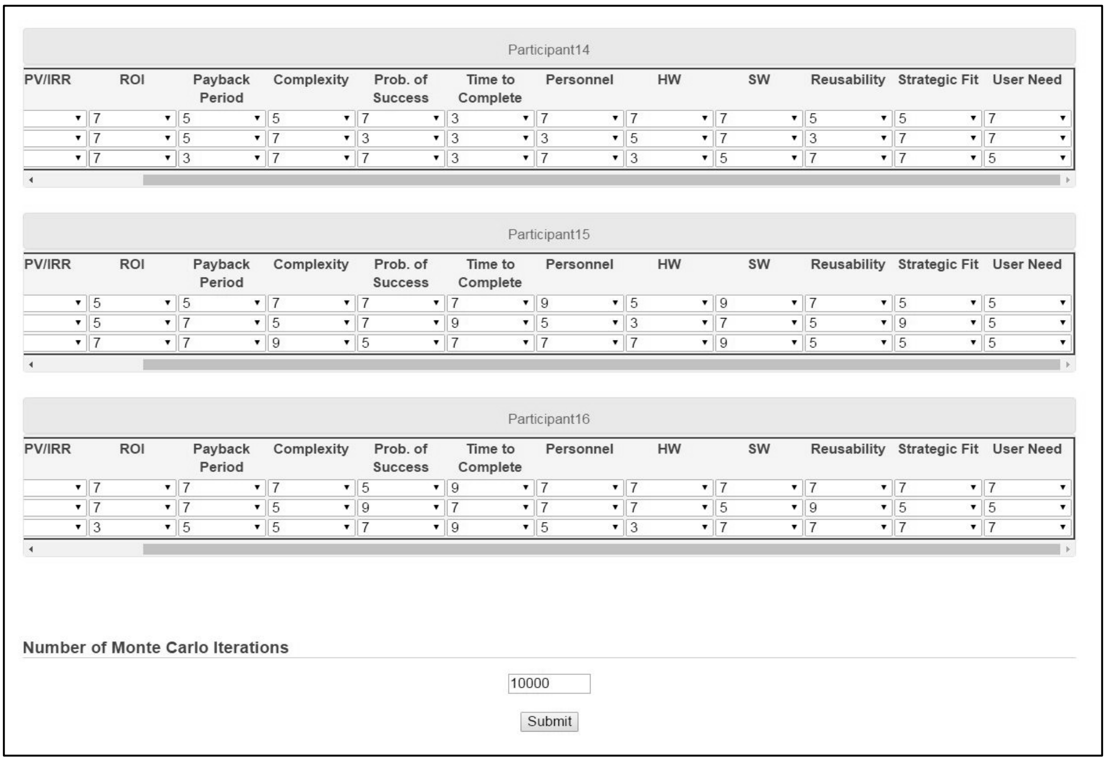


Figure 13. GUI for simulation - submission page

After submission of the second form, calculations are made behind the screen and result appears on the browser screen. Detail calculations are logged in browser console for debugging purposes. (Figure 14)

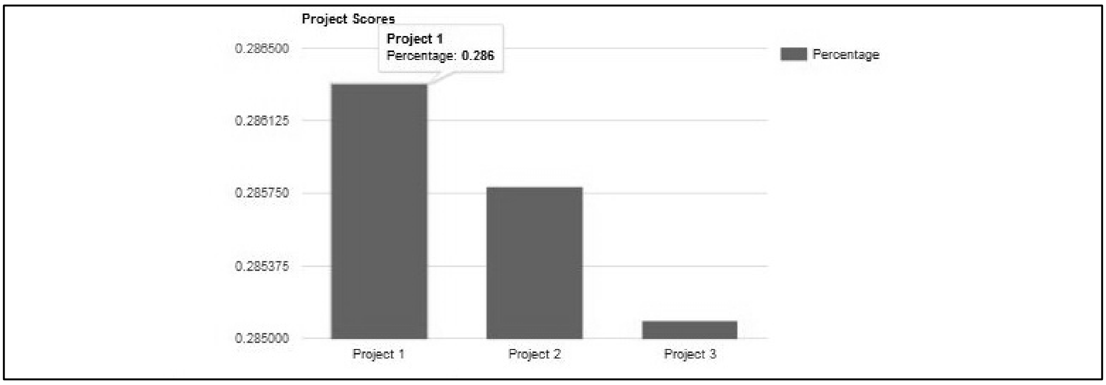


Figure 14. GUI for simulation - result page

5.3. Discussion

The main purpose of this study was to establish a model, which would find the optimal solution for selection of IT projects in the context of banks. The proposed solution combines the previously tested technique of fuzzy ANP with Monte Carlo simulation analysis, suggesting that such a move would provide better results when thinking of subjectivity of decision making committee. To verify if this is true, one needs to compare the results of the technique with and without Monte Carlo simulation analysis.

A key point of contention is that while the Monte Carlo simulation enables a complete characterization of uncertainty and variability in the results inherent to the range of potential scenarios, it also requires a large amount of data to adequately function for all input parameters. The information required for accurate characterization of an input parameter may not be readily available to a pure Monte Carlo model. As demonstrated in the proposed hybrid model, in order to generate the necessary data for proceeding with the Monte Carlo simulation, it was necessary to first process the fuzzy global weights and the aggregated fuzzy decision matrix. By comparison, while the fuzzy ANP does not provide as thorough statistical characterization of the outcomes as the Monte Carlo analysis, it is fairly independent and can function on its own. In essence, the two techniques should result in a similar conclusion, but it is questionable how much the added step of Monte Carlo simulation adds value to the project selection process.

For this purpose, calculation is made based on the available data, but taking into account that the process of the fuzzy TOPSIS is completed without an integrated simulation component. To achieve this, first a unique weighted normalized fuzzy decision matrix needs to be produced (Table 22).This is achieved by multiplying the fuzzy global weights (Table 18) with the normalized fuzzy decision matrix (Table 20).

The equations of TOPSIS are then performed on the basis of the above data. This results in a new set of distances from the FPIS (d_i^+) and the FNIS (d_i^-), and the final result is CC_i calculated for each alternative and another ranking of the alternatives (Table 23).

Table 22. Weighted Normalized Fuzzy Decision Matrix

Criteria	Alternative 1	Alternative 2	Alternative 3
C_{11}	(.04,.15,.50)	(.04,.15,.50)	(.03,.13,.50)
C_{12}	(.03,.12,.44)	(.03,.12,.44)	(.03,.12,.44)
C_{13}	(.02,.10,.36)	(.02,.10,.36)	(.02,.09,.36)
C_{21}	(.01,.04,.16)	(.01,.04,.16)	(.01,.04,.16)
C_{22}	(.01,.05,.17)	(.01,.05,.17)	(.01,.05,.17)
C_{23}	(.01,.04,.16)	(.01,.04,.16)	(.01,.04,.16)
C_{31}	(.01,.03,.11)	(.01,.03,.11)	(.01,.03,.11)
C_{32}	(.01,.03,.12)	(.01,.03,.12)	(.01,.03,.12)
C_{33}	(.01,.03,.11)	(.01,.03,.11)	(.01,.03,.11)
C_{41}	(.01,.06,.19)	(.01,.05,.19)	(.01,.06,.19)
C_{42}	(.02,.07,.23)	(.02,.07,.23)	(.02,.07,.23)
C_{43}	(.02,.07,.22)	(.02,.06,.22)	(.02,.06,.22)

Table 23. Ranking of Alternatives without Monte Carlo Simulation

Alternatives	d_i^+	d_i^-	CC_i	Rank
A_1	5.3339	2.4554	.3152	1
A_2	5.3308	2.4525	.3151	2
A_3	5.3278	2.4497	.3150	3

The results of this technique also show that the alternative A_1 is the best solution, and the ranking is the same, but the differences between the results appear to be much closer. This may be because of two factors. First, the use of fuzzy global weights to produce the results in Table 22 leads to fuzzy numbers which appear to be equal when rounded to two decimals. The implication of this method is that all three alternatives have the same score for some subcriteria, such as ROI (.03,.12,.44), which is clearly not the case if one compares aggregated decision matrix with ranking of projects. If the numbers are rounded to four decimals, the differences would be clearer. For this reason, some applications of TOPSIS (e.g. Sodhi and Prabhakar, 2012) avoid using the global weights and instead use the weights defined in the pairwise comparisons (Table 11 - Table 14). This technique does make some differences more apparent, but it is still limited. Using the pairwise comparison weights means that the scores for ROI for alternativesA_1, A_2, and A_3would be (.11,.24,.48), (.11,.24,.48), and (.10,.24,.48), respectively.

More importantly, the differences in the results can be attributed to the focus of the Monte Carlo simulation on the entire range of possible values in between the lowest and highest possible solutions. By exploring the different implications of the fuzzy decision, and not just its extremes, it should be easier to spot the overall trends in the distribution of the possible results. This is a quality, which makes the Monte Carlo simulation an important contribution to fuzzy ANP and ANP-based techniques in general. As the case demonstrates, optimization of the, results through simulation is especially influential in the definition of the fuzzy ideal-positive solution and the fuzzy ideal-negative solution, as well as the subsequent calculation of distances for each alternative. For the same reason, the results seem to be more balanced, and the values are slightly smaller overall.

Although in a classical project selection methodology takes longer time for analysis of the alternative opinions, in this study analysis is relatively faster than the data collection. The process is only marginally longer than the fuzzy ANP process presented in similar studies (e.g. Mahmoodzadeh et al., 2007; Liu and Lai, 2009; Sodhi and Prabhakar, 2012), which is due to the Monte Carlo simulation step. Similarly, from the perspective of the project selection committee, the evaluation process is virtually the same as it would be for a basic ANP evaluation. In this sense, the benefit of evaluating the fuzzy decisions in more detail compared to other ANP-based processes represents a significant benefit of the proposed model.

The data collection method may have also affected the presentation of the final results. Because the responses were not focused on specific projects, the distribution of scores has been randomized to a certain extent, which would make the evaluations of each alternative rather similar to each other. The implication here is that even though the findings showed similar values for the relative closeness to the ideal solution, it is likely that project selection teams should find more distinctive results when applying this method in practice.

The questionnaire responses suggest that the generic criteria/subcriteria can be applied to a multitude of IT projects in the banking sector. This includes software solutions for payment systems, projects related to migration of ERP data, and building the IT architecture for central warehouse databases. These projects are related to problem sizes in scope and should have significantly different price tags, even though the questionnaire itself did not ask for a price range of the project. While no respondents skipped a field when evaluating the projects, it is still possible that the respondents have used the evaluation options given without necessarily considering it relevant to the given project. For situations like this the respondents were given the option to leave a comment or clarification, but virtually no respondent used it. A future research on this topic could improve on the proposed criteria/subcriteria by allowing the respondents to evaluate the projects only with the criteria/subcriteria that they actually consider to be relevant. Nevertheless, since the hybrid model allows for project selection committees to define the important evaluation criteria based on the project requirements, the process proposed in chapter 4 and the calculation methods employed should remain the same. It is for this reason that the proposed model could be applied in areas out of the scope of the banking sector.

The major limitation of this study is that the real-world case on which it is based may not necessarily be representative of the decision making practices of the respondents in day-to-day scenarios. In this sense, the presented results are an approximation of what an actual project selection process would look like if it uses the proposed method. This needs to be taken into account when evaluating the merits of the proposed model either for research or for practical purposes. The absence of an actual comparison regarding the alternative projects, which are the subject of the project selection process, should also be considered an opportunity for future projects to research the applicability of the model in different scenarios, ranging from cases in the banking industry to capacities in production plants.

CHAPTER 6

CONCLUSION

The purpose of this study was to find an efficient technique to resolve the IT project selection problem for qualitative and quantitative criteria. As the case study demonstrates, the focus of the study was on the banking sector, but alternative applications could be performed in a variety of areas where a similar mix of qualitative and quantitative criteria is needed to reach a decision. In this sense, the study expanded on similar IT project selection methods that deal with MCDM such as the AHP/ANP models and its fuzzy versions. This is achieved by adding a simulation component to optimize the comparison between different alternatives before the final choice is made. Thus, the final version of the proposed model represents a hybrid of three methodologies that are commonly used for decision making: ANP, fuzzy TOPSIS, and Monte Carlo analysis. The results from a series of simulation trials make it clear that this method would benefit its users by taking into account an entire range of data instead of a set of crisp numbers or a limited set of fuzzy numbers. By comparison, the fuzzy ANP considers only the extreme cases (the lowest possible value, the most likely value, and the highest possible value). Some concerns over the ease of simulation performance and the effort versus usefulness of outcomes might exist, but as discussed, the method does not add much in resources needed or complexity compared to the fuzzy ANP. Other conclusions include:

- For the banking sector, finance, organizational goals, risk and technical items are the most important criteria respectively, and NPV/IRR, ROI, payback period and strategic fit are the most effective subcriteria under these criteria;

- The results generated using a fuzzy ANP approach are comparable to those using the Monte Carlo simulation, but are less detailed;
- As indicated early on, the fuzzy results are a better representation of the uncertainty inherent in the IT project evaluation process;
- The Monte Carlo simulation needs the preceding fuzzy ANP process to provide it with sufficient data; and
- The process could be easily adapted for a variety of different criteria used, based on the project conditions.

This study has contributed to both theory and practice by proposing and testing a new project selection model. In this context, this study should be useful to IT project selection committee members and researchers in the field of decision making, but it should also be of interest to managers in general. The proposed model is recommended for all the decision making situations where purely qualitative or quantitative methods are insufficient to choose from multiple options. The hybrid method is part of an on-going movement for adoption of fuzzy solutions, recognising that fixed inputs and outcomes tend to ignore a large portion of relevant data, or rely on data that is uncertain or inaccurate. The fact that the inputs used for demonstrating the model is based on a real-world scenario suggests that it should be applicable to a wide range of IT projects in the banking sector, as well as other use cases.

Finally, the study could be improved in a number of ways, mainly related to the data collection method. A similar study where the data is collected from a single IT project selection committee, which evaluates several clearly identified alternatives to the same problem would be a more realistic test of the model. Furthermore, while the model is tested on IT projects in the banking sector, a similar study could validate its use in other industries or theoretical cases. It is generally hoped that the study has helped to broaden and deepen the understanding of complex decision making processes, as well as the specifics of IT project selection. Similar studies could build on the model by choosing alternative methods in formulating the fuzzy ANP or modifying the Monte Carlo simulation parameters.

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APPENDIX A

CONCEPTS OF AHP AND ANP

Analytic hierarchy process

1. Elements of the problem, goal, subgoals, time horizons, scenarios, actors and stakeholders, their objectives and policies, criteria, subcriteria, attributes, and alternatives.

2. Hierarchic structure.

3. Judgments - absolute numbers, homogeneity, clustering, pivot elements, tangibles and intangibles.

4. Comparisons, dominance and reciprocity with respect to an attribute, inconsistency and the eigenvector, use of actual measurements.

5. The number of judgments; how to take fewer judgments.

6. Derived ratio scales - in AHP the priorities are derived and are proven to belong to a ratio scale.

7. Interval judgments, stochastic judgments.

8. Synthesis - multilinear forms - density.

9. Rank - the dominance mode, the performance mode with respect to an ideal.

10. Absolute measurement - rating alternatives one at a time.

11. Benefits, opportunities, costs and risks hierarchies.

12. Parallel with human thinking - neural firing creates awareness and intensity of stimuli for both tangibles and intangibles. Measurements are data to be interpreted.

13. Group Decision Making and the reciprocal property; Pareto optimality: if each prefers A to B, then the group does.

14. Sensitivity Analysis.

15. Learning and revision as a process.

Analytic network process

1. Feedback, inner and outer dependence.

2. Influence with respect to a criterion.

3. The control hierarchy or system.

4. The supermatrix.

5. The limiting supermatrix and limiting priorities.

6. Primitivity, irreducibility, cyclicity.

7. Make the limiting supermatrix stochastic: why clusters must be compared.

8. Synthesis for the criteria of a control hierarchy or a control system.

9. Synthesis for benefits, costs, opportunities, and risks control hierarchies.

10. Formulation to compute the limit.

11. Relation to Neural Network Firing - the continuous case.

12. The density of neural firing and distributions and their applications to reproduce visual images and symphonic compositions. Further research in the area is needed.

APPENDIX B

SURVEY QUESTIONNAIRE

Dear participant,

We would appreciate it if you could take the time to participate in our survey. Through this brief questionnaire, your responses will be helpful for the researcher to complete the research paper titled: "A Simulation Based Project Selection Method for Information Technology Projects in the Banking Sector".

It should take approximately ten minutes of your time.

Your participation is voluntary. You can ask any questions you may have before or during the questionnaire. You are free to withhold answering some questions, and/or not complete the questionnaire.

Your responses will not be shared with third parties, all responses will be compiled together in an effort to analyse the group, and results will be only used for studies of this researcher.

Researcher:

Communication:

Please respond the following questions based on your experience.

1. How many years of professional experience in banking and finance do you have? (Please select one)

□ 1-5 years
□ 6-10 years
□ 11-15 years
□ 16-20 years
□ 20 years or more

2. Approximately how many times have you been involved in a project evaluation committee? (Please select one)

□ 1-5
□ 6-10
□ 11-15
□ 16-20
□ 20 or more

3. Please evaluate the following pairs for importance/influence in relation to the IT project selection, using the rating scale provided below.

CLUSTER / NODES	Importance																
	-9	-8	-7	-6	-5	-4	-3	-2	-1 = 1	2	3	4	5	6	7	8	9
NPV/IRR																	
NPV/IRR – ROI																	
NPV/IRR – Payback period																	
NPV/IRR – Complexity																	
NPV/IRR – Probability of success																	
NPV/IRR – Time to complete /duration of project																	
NPV/IRR – Personnel																	
NPV/IRR – Hardware																	
NPV/IRR – Software																	
NPV/IRR – Module reusability																	
NPV/IRR – Strategic fit																	
NPV/IRR – User need / market demand																	
ROI																	
ROI – Payback period																	
ROI – Complexity																	
ROI – Probability of success																	
ROI – Time to complete /duration of project																	
ROI – Personnel																	
ROI – Hardware																	
ROI – Software																	

ROI – Module reusability																	
ROI – Strategic fit																	
ROI – User need / market demand																	
Payback period																	
Payback period – Complexity																	
Payback period – Probability of success																	
Payback period – Time to complete /duration of project																	
Payback period – Personnel																	
Payback period – Hardware																	
Payback period – Software																	
Payback period – Module reusability																	
Payback period – Strategic fit																	
Payback period – User need / market demand																	
Complexity																	
Complexity – Probability of success																	
Complexity – Time to complete /duration of project																	
Complexity – Personnel																	
Complexity – Hardware																	
Complexity – Software																	
Complexity – Module reusability																	
Complexity – Strategic fit																	
Complexity – User need / market demand																	
Probability of success																	
Probability of success – Time to complete /duration of project																	

Probability of success – Personnel																	
Probability of success – Hardware																	
Probability of success – Software																	
Probability of success – Module reusability																	
Probability of success – Strategic fit																	
Probability of success – User need / market demand																	
Time to complete / duration of project																	
Time to complete /duration of project – Personnel																	
Time to complete /duration of project – Hardware																	
Time to complete /duration of project – Software																	
Time to complete /duration of project – Module reusability																	
Time to complete /duration of project – Strategic fit																	
Time to complete /duration of project – User need / market demand																	
Personnel																	
Personnel – Hardware																	
Personnel – Software																	
Personnel – Module reusability																	
Personnel – Strategic fit																	
Personnel – User need / market demand																	
Hardware																	
Hardware – Software																	
Hardware – Module reusability																	
Hardware – Strategic fit																	
Hardware – User need / market demand																	

Software																	
Software – Module reusability																	
Software – Strategic fit																	
Software – User need / market demand																	
Module reusability																	
Module reusability – Strategic fit																	
Module reusability – User need / market demand																	
Strategic fit																	
Strategic fit – User need / market demand																	
User need / market demand																	

4. Please evaluate the following pairs for importance in terms of IT project selection, using the rating scale provided below.

CLUSTERS	Importance																
	-9	-8	-7	-6	-5	-4	-3	-2	-1 = 1	2	3	4	5	6	7	8	9
1. Financial criteria – Risk criteria																	
2. Financial criteria – Technical criteria																	
3. Financial criteria – Organizational goals																	
4. Risk criteria – Technical criteria																	
5. Risk criteria – Organizational goals																	
6. Technical criteria – Organizational goals																	

Rating scale

Intensity of importance	Definition
1	Equal importance/influence
2	Equal to moderate importance/influence
3	Moderate importance/influence
4	Moderate to strong importance/influence
5	Strong importance/influence
6	Strong to very strong importance/influence
7	Very strong importance/influence
8	Very strong to extreme importance/influence
9	Extreme importance/influence
Negative numbers	The negative numbers indicate a relationship between two items that is inverse in direction to the one stated in the row. E.g. If the rating for the relationship NPV-IRR – ROI is 7 it means that NPV-IRR has a very strong importance/influence compared to ROI. If, on the other hand, the rating for the relationship NPV-IRR – ROI is -7 it means that ROI has a very strong importance/influence on NPV-IRR.

5. If you believe that other criteria/subcriteria should be used in the above tables, please indicate what are they and how they would be used to evaluate the projects in the provided context.

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6. Please provide any additional comment and clarifications

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APPENDIX C

PROJECT SCORING FOR CASE STUDY

Please evaluate the 3 most recent IT projects that you will be working on, by indicating the project's performance against the given criterion

Project #1: ________________________________

	Very low	Low	Medium	High	Very high
NPV/IRR					
ROI					
Payback period					
Complexity					
Probability of success					
Time to complete / duration of project					
Personnel – Hardware					
Hardware					
Software					
Module reusability					
Strategic fit					
User need / Market demand					

Project #2: ____________________________________

	Very low	Low	Medium	High	Very high
NPV/IRR					
ROI					
Payback period					
Complexity					
Probability of success					
Time to complete / duration of project					
Personnel – Hardware					
Hardware					
Software					
Module reusability					
Strategic fit					
User need / Market demand					

Project #3: ____________________________________

	Very low	Low	Medium	High	Very high
NPV/IRR					
ROI					
Payback period					
Complexity					

Probability of success					
Time to complete / duration of project					
Personnel – Hardware					
Hardware					
Software					
Module reusability					
Strategic fit					
User need / Market demand					