NEURAL NETWORK-BASED SURVEY ANALYSIS OF RISK MANAGEMENT PRACTICES IN NEW PRODUCT DEVELOPMENT

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Abstract

The current study investigates the applicability of Artificial Neural Networks (ANNs) to analyse survey data on the effectiveness of risk management practices in product development (PD) projects, and its ability to forecast project outcomes. Moreover, this study presents the relations between risk management factors affecting the success of a PD project, such as cost. ANNs were chosen due to the fact that hidden inherent relations can be revealed through this type of quantitative analysis. Flexibility in terms of analysis and adaptability on the given dataset are the great advantages of Artificial Neural Networks. Dataset used is a filtered survey of 291 product development programs. Answers of this survey are used as training input and target output, in pattern recognition two-layer feed forward networks, using various transfer functions. Using this method, relations among 6 project practices and 13 outcome metrics were revealed. Results of this analysis are compared with existent results made through statistical analysis in prior work of one of the authors. Future investigation is needed in order to tackle the lack of data and create an easy to use platform for industrial use.

Keywords: Project management, Risk management, New product development, Uncertainty, Organizational processes

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1 INTRODUCTION

Risk management is a field widely concerning both industry and academics. Its application extends to any field of the human activity, from construction to finance. The core definition of risk in projects can be expressed as the exposure to economic loss or gain, as part of involvement in a specific process (Akintoye and MacLeod, 1997). Moreover, definition of risk, specifically targeting the field of project management, is an "uncertain condition or event that can have positive or negative effect on projects objectives" (Project Management Institute, 2013). However, in order to have a closer contact to practitioners' concept of risk, especially in New Product Development (NPD) projects, risk is defined as the effect uncertainty has, in order to achieve a projects objective (International Organization for Standardization, 2009). As a result of those definitions given above, risk management for projects can be expressed as the identification, analysis and response to factors that create risk in a project's course and its objectives completion. In order to have efficient control of the forthcoming events, it is necessary for managers to be proactive than reactive, so a way to predict future problems is necessary. This prediction can be enhanced through forecasting. Hoping to highlight the need of risk management in NPDs, association between risk undertaking and control is made. Through literature, is evident that the innovative character of NPD projects, embeds risk concepts in their framework (DiMasi et al., 2016; Gemser and Leenders, 2011; Tang et al., 2011). Low quality of ideas on initial project stages (Ernst et al., 2010), incomplete information (Nepal et al., 2011) and high costs of development (Lee et al., 2009) are some of the factors that contribute to the high vulnerability on failure of a NPD project. More about those factors can be retrieved through various studies (Blau et al., 2000; Calantone et al., 2003; Mu et al., 2009). The high amount of risk in such products has been tackled throughout various methodologies, both qualitative and quantitative. Design collaborations across the supply chain, especially with suppliers (Petersen et al., 2005), customer input in order to get further market insight (Fang et al., 2008) and collaboration in design with other institutions and businesses (Blau et al., 2000) has shown evidence of helping in risk avoidance (Gemünden et al., 1992; Håkansson, 1990). In terms of qualitative risk management on the specific area, ranking of raw material suppliers through multi-criteria methods (Wang et al., 2004), as well as using such methods in NPD decision making (Büyüközkan and Feyzıoğlu, 2004) have been implemented. Moreover, statistical analysis (Olechowski et al., 2016) indicating the factors of success of an NDP or practices ranking (Page, 1993), is another procedure of qualitative risk management. However, an assessment of risk management practices and their impact on overall design project success based on empirical evidence remains rare.

This paper is aimed at making a further contribution to evidence-based assessment of risk management practice, by applying Artificial Neural Network (ANN) analysis technique to an extensive set of risk management performance related survey data.

2 APPLICATION OF ANN TO THE ANALYSIS OF SURVEY DATA

ANN is a methodology of data analyzing first proposed during WW2 (McCulloch and Pitts, 1943) and is an effort to simulate the procedure of which the human brain creates knowledge and solves problems, through prior given information. Despite the computational power needed for this method, due to its non-linear character (Zhang et al., 1998), the uses of this method are almost limitless. Especially, in cases of pattern recognition and forecasting, the uses have shown great promise. The literature on application is vast and here only applications on questionnaire data will be briefly discussed. More information on the general topic of ANN is available in recent literature reviews (e.g. Misra & Saha,2010; Schmidhuber,2015). Using ANNs for data analysis from questionnaires was introduced in a study aiming to rank and select appropriate supplier for a company in Taiwan (Kuo et al., 2010). Through this study, a specific questionnaire was given to experts, in order to obtain the appropriate factors for analysis. This qualitative data were combined with quantitative data, and through the introduction of fuzziness, a combined dataset was created. Utilizing Particle Swarm Optimization method, initial weights of the networks were selected. This procedure was further developed for industrial application. Moreover, ANNs have been used in order to generate missing data in various questionnaire-based studies (Nelwamondo et al., 2007). The comparison with Expectation Maximization techniques has shown that ANNs can better highlight non-linear relationships between variables, in cases where there is inherent interdependency. Although, forecast results were inferior to the Expectation Maximization technique, poor quality of survey answers is the root of this result, according to the researchers. The use of ANNs in forecasting costs of building projects is the application that created the initial idea for this research (Emsley et al., 2002). Through literature review, researchers created a questionnaire, answered by practitioners. This questionnaire created a dataset for analysis on cost per square meter and the log of cost per square meter. Use of ANNs did not create a much more accurate way of forecasting cost, however the non-linear relationships among cost factors was highlighted as well as proving the ability of ANNs in modeling such cases. In another application of ANNs, data from questionnaires was embedded in a quantitative analysis of building projects in Singapore (Ling and Liu, 2004). Identification of ANN input factors through formal questionnaires in the building industry is another way that survey data can be integrated in this type of analysis (Boussabaine, Lewis, Wanous, 2003). Those factors were used as an input to create ANNs giving information on a binary decision, bid/no bid. This way, the contractor could enhance his knowledge on whether a project showed sufficient suitability and profit margin, in order to begin in the costly bid preparation. A comparison of the results of classical statistical analysis and results of ANNs using questionnaire data was performed in a case of the hotel industry (Tsaur et al., 2002). Predictions made through linear regression were considered inferior to those of created from sets of neurons. Moreover, researchers concluded that the flexibility of ANNs in terms of data handling creates an ideal method for forecasting. In summary, ANNs have shown great promise as an analysis tool for survey-based data with unforeseen relationships between the items. Their ability of being flexible, their relative ease-of-use and examples of better results than statistic methods applied to survey data, despite difficulties in results interpretation, has motivated their use in this paper to analyze survey data relating to risk management practices in design projects.

The two research questions are: 1. Can we uncover hidden relationship between risk management practices and design project success, especially in achieving the cost target? 2. Do the results of the ANN data analysis contradict, support or expand the results that were previously achieved through conventional statistical data analysis?

3 EMPIRICAL DATA COLLECTION: SURVEY

The analysis presented in this paper is based on an extensive survey dataset of risk management professionals. The preparation, testing and administration of the survey is described in detail in Oehmen et al. (2014). Because of space restrictions, the description will not be reproduced here in its entirety. The survey included questions on company and PD project profiles, risk management practices, risk and mitigation actions, as well as risk management and project success. A total of 381 respondents, mostly from the US Aerospace and Defense sector, participated in the survey. Due to the method of survey administration, some parts were randomized and only shown to a sub-group; partially due to job profiles (e.g. respondents indicating that they were risk managers were presented with additional questions to those indicating that they were project managers). Due to this reason, and overall completion and answer rate differences for the various survey items, the total number of valid responses for each item varies between 112 and 291, with a typical value of 140. The proportion of respondents from the aerospace and defense is 51%, while the rest of them are from other industrial sectors. Statistical tests were employed to investigate possible differences among industries, and they were found not to be significant, as shown by a preliminary analysis. The size of organizations participating was relatively equally distributed. The product orientation of participants was divided in: 27% integrated mechatronics, 25% software, 17% integrated electronics and software and 13% mechanical components

4 APPLICATION OF ANN TO DESIGN RISK MANAGEMENT SURVEY DATA

In order to discover the hidden relationships in the data through ANN analysis, certain analysis steps have to be followed to enhance the quality of results. These steps include the filtering and “cleanup” of the raw data, the specifics depending on the particular requirements of the analysis method. For example, in cases where a respondent had more than one unanswered item in a set of input data, his/her response was completely eliminated from the sample in order to have more coherent set of input data. The number of valid data sets varied case by case, from 158 to 211 valid responses. Data filtering was followed by an exploration of various designs of possible architecture of the ANNs, which are subsequently selected on a case-by-case basis to produce best results. The procedure was implemented in Matlab 2015a, running on a computing cluster to shorten the overall processing time. Each computer of this cluster was equipped with Intel Core i3-3250 and 4 GB of RAM memory. The chosen number of layers for the analysis was one hidden layer and one output layer, as this is not only a common choice of architecture, but also it is proven that only one hidden layer can be efficient enough for a wide variety of applications(Csáji, 2001) . As training algorithm, the Levenberg–Marquardt training algorithm was chosen, as a preliminary series of trials had shown that it provided, in most of the cases, better results than alternative algorithms. The comparatively fast convergence of this specific algorithm (Foo et al., 2002; Zarei, 2012) was another supporting its selection. The transfer functions used in each of the hidden layers were not selected ex-ante, but a combination of soft max, log-sigmoid and tan-sigmoid transfer functions was explored. Each case was analyzed through combinations of these three transfer functions. In order to determine the ideal number of neurons needed for each ANN, there was a gradual increase of neurons between each case, beginning with one neuron, to a maximum of 70, in increments of five neurons. The weights for each ANN were initialized randomly, with an iteration of 10 different sets of initial weights for each case. The input of each case was set as a category of risk management activities (see Oehmen et al. 2014 for details), and the output of the ANN was set as a project and risk management outcome metric. This represents an effort to create a forecast of design and risk outcomes, depending on different risk management process factors. The dataset was randomly separated into three sets: the training set (70%), the validation set (15%), and the test set (15%). For each case, the ANN finally chosen was the one with the highest accuracy, as indicated by each of those sets. In order to evaluate the quality of the ANN models, several additional metrics were used. Cross-entropy (Roe et al., 2005), and mean absolute error (Chai and Draxler, 2014) were the metrics of choice for this procedure. Different optimal ANNs can be seen in Table 1, where the transfer function of each layer, number of neurons and summary of data used in each case, is given. Completion of training was followed by the extraction of weight of each factor, through a specific procedure of matrix multiplications, as obtained through previous studies (Garson and David, 1991; Goh, 1995)

5 RESULTS & DISCUSSION

In this section, the results of analysis are presented as well as the relations uncovered between input and output data. ANNs with over 65% forecasting capability, satisfactory cross-entropy and mean absolute error will be presented, as these can provide reasonably credible information about the relation of factors and outcomes. Despite the fact that there were cases with higher forecasting capability, the ones with lower cross-entropy and mean absolute error were chosen, as it was considered that those metrics could give a more holistic image of the model created. Explanation of input factors and output metrics can be found in the Appendix, Tables 2 and 3. The forecasting accuracy of each successful configuration is shown in Table 1. Moreover, the input data with the corresponding output that gave the best results are shown. Finally, the number of neurons, cross entropy and mean absolute error are given. As evident from Table 1, input groups 1, 4 and 6 are the most appropriate ones to obtain adequate insight of the outcomes. Moreover, for the majority of analyses, the Tangent Sigmoid transfer function in the hidden layer can more effectively adapt to the data. That applies for the output layer too, as 50% of the successful configurations contain this transfer function on that stage. Despite the literature-based expectation that the Softmax transfer function would be more appropriate (Bishop, 2006), as pattern recognition procedures were followed, it appears in the results just twice. As cross-entropy and mean absolute error are quality metrics, there is a relation among them, whereas the cross-entropy increases, mean absolute error increases as well (see Figure 1).

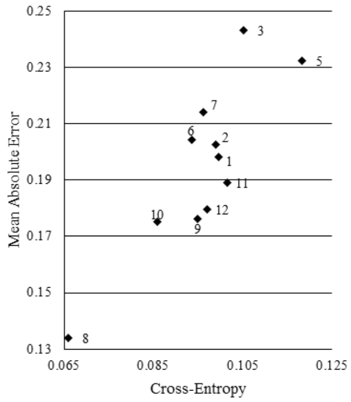

Figure 1. Cross Entropy Mean Absolute Error Diagram

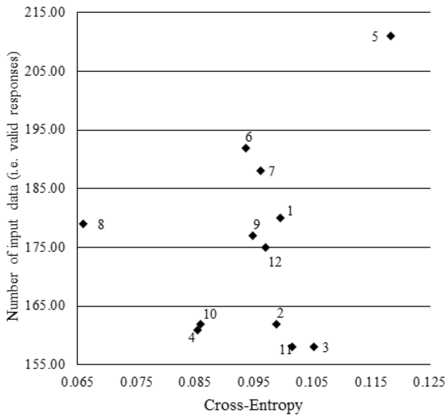

Figure 2. Cross Entropy Number of Input Data Diagram

The same relationship is not as evident between accuracy and quality metrics. The number of input datasets affects the cross-entropy, with a tendency that a larger amount of input datasets (i.e. survey responses) results in lower cross entropy (Figure 2). Similar conclusions cannot be drawn for the relationship of number of neurons and cross-entropy mean absolute network, accuracy or number of inputs. This justifies the experimentation procedure followed to construct the networks. After the completion of the analysis of the quality and properties of ANN architectures, the results were analyzed to obtain hidden relations among the input factors and the output metrics (see Table 1), i.e. the forecasts of the ANN. The Cost Target (D.1) shows high relative importance of with the Available Human Resources to Conduct Risk Management (1.2) and the Ability of Teams Conducting Risk Management Actions to Be Cross-Functional and Cross Organizational (1.4). These factors have the biggest impact on forecasting the Cost Target (D.1), a relationship that was only indirectly visible through standard statistical methods(Oehmen et al., 2014). Similarly, risk management taking account of cultural and human factors (1.5) is also showing significant impact on Cost Target (D.1) according to this analysis. Timely Resource Allocation for Risk Reduction (4.1) and Consideration of Risk Analysis in Making Various Tradeoffs (4.3) are the ones with higher relative importance on Support of Managers Risk Management Activities (C.4). Those factors have significant importance for Technical Performance (E.1) And Overall Customer Satisfaction (E.2), too. About the Influence of Risk Management Results on Tradeoff Decisions (A.2), the greatest relative importance is seen on Transparency and Inclusivity towards All Stakeholders (6.2). This factor along with the Explicit Address of Uncertainty from Risk Management (6.3), are having a great impact on Overall Customer Satisfaction (E.2) outcome forecast. Available Information on Risk Management (6.1) combined with this explicit identity of risk management (6.3), have great influence on forecasting the Ability to Identify Key Risk and their Successful Mitigation (B.2). A similar relation of those factors seems to exist for Technical Performance (E.1). Almost equal importance is shown on RM experts sufficiency (1.2) and RM team characteristics (1.4), on Overall Customer Satisfaction (E.2). Addressing Stakeholder Concerns (C.2) is more related with transparency and uncertainty address (6.2) than available information (6.1). On Addressing Stakeholder Concerns (C.2), all but one factor, the Cross-Function and Cross-Organization Ability of the Team (1.4), have almost the same impact on forecasting this output. Finally, this ability of the risk management team (1.4) has the greatest impact on forecast of E.1. Generally, the relative importance of various factors on Cost Target significantly extends the knowledge on the factors effecting the success of a project in terms of cost, expanding previously found results through classical forms of statistical analysis (Oehmen et al., 2014). So, despite the inability to gain direct connection through Goodman–Kruskal Gamma association, with the use of neural networks, cost success was linked with sufficient resources and personnel and the functionality of risk management teams. Some contradictions with the results of statistical analyses such as the importance of factors of Group 4 with outcome C.4 were revealed, but these were minor ones. Finally, there were agreements with previous results, especially the importance of factor 4.1 on the outcome of E.2.

Table 1. Neural Network Results

	1	2	3	4	5	6	7	8	9	10	11	12
Hidden Layer Function	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Softmax	Logistic Sigmoid	Logistic Sigmoid
Output Layer Function	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Tangent Sigmoid	Softmax	Logistic Sigmoid	Logistic Sigmoid	Logistic Sigmoid	Tangent Sigmoid	Softmax
Input Group	1.x	4.x	4.x	4.x	6.x	6.x	1.x	1.x	6.x	1.x	6.x	6.x
Output Metric	D.1	C.4	E.1	E.2	A.2	E.2	E.1	C.2	B.2	E.2	C.2	E.1
Number of Neurons	33	17	9	21	41	21	17	57	49	45	51	61
Summary of Input Data	161	211	192	188	179	158	162	180	175	158	177	162
Cross-entropy	0,0996	0,0989	0,1052	0,0855	0,1183	0,0937	0.0962	0.066	0.0949	0.0859	0.1015	0.097
Mean Absolute Error	0,1982	0,2025	0,2432	0,1234	0,2323	0,2043	0,2140	0,1338	0,1762	0,1752	0,1890	0,1796
Accuracy	77	66,8	66,1	70,7	68,2	69,6	67,9	76,1	65,7	68,4	70,4	67,3
Relative Importance %	1.1 15,83 1.2 17,12 1.3 23,22 1.4 22,55 1.5 21,28	4.1 35,52 4.2 30,19 4.3 34,29	4.1 32,77 4.2 22,09 4.3 45,14	4.1 37,17 4.2 26,72 4.3 36,11	6.1 28,11 6.2 40,89 6.3 31,00	6.1 24,75 6.2 37,46 6.3 37,79	1.1 21,01 1.2 18,33 1.3 18,95 1.4 23,42 1.5 18,29	1.1 20,99 1.2 20,49 1.3 19,65 1.4 18,79 1.5 20,08	6.1 37,17 6.2 26,72 6.3 36,11	1.1 21,53 1.2 20,85 1.3 18,88 1.4 20,31 1.5 18,43	6.1 30,55 6.2 36,08 6.3 33,37	6.1 36,16 6.2 31,40 6.3 32,44

6 CONCLUSIONS AND FUTURE WORK

ANNs and other machine learning methods are constantly evolving. Applications on real world data, acquired from experts through questionnaires can give insights through statistical procedures, but ANNs can model complex non-linear relations, and forecast future events or outcomes. In this specific research, there was an effort to relate specific strategies and situations during NPD projects. Moreover, specific aspects in construction of ANNs were highlighted, such as the significance of cross-entropy and mean absolute error in choosing an appropriate ANN, and the impact of amount of data in order to create accurate models. Moreover, the importance of input factors on forecasting the outcome of various aspects of a project was shown, revealing relationships of risk management practices on projects' success. Tangent Sigmoid functions are shown to be more appropriate for the hidden layer of this survey. The experimental procedure followed is validated through the lack of relation between the number of neurons and the quality of forecasts. The main limitation of this research derives from the nature of the survey data and not only in terms of quantity but also quality.

In a next step, more detailed advice for real world application should be given. A sensitivity analysis should be conducted to gain more information on the type of impact each factor has (Olden and Jackson, 2002). Also, a graphical user interface that embeds the developed ANN architectures would be appropriate in order to transform the ANN into a tool that is useful for practitioners. This would enhance their abilities in decision making in a more visual way. Moreover, the need for additional data could be tackled by a computational procedure of generating new datasets simulating previous ones. This would provide additional information for the training of the ANN; potentially further increasing the quality of the results. Another addition would be to explore and compare results of other Machine Learning methods, such as Support Vector Machine or Deep Learning, as ANN analysis was chosen due to literature review.

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APPENDIX

Table 2. Output Metrics

Output Metric	Reference
Risk management results are important in decision making	A.1
Risk management influences trade offs	A.2
ROI of risk management was positive	A.3
Stable execution and following defined processes	B.1
Identified key risks and mitigated them	B.2
Management was proactive in addressing risks and issues	C.1
Concerns were heard and addressed	C.2
OK to report “bad news” and concerns	C.3
Managers support risk management activities	C.4
Achieved cost target	D.1
Achieved schedule target	D.2
Achieved technical performance target	E.1
Achieved overall customer satisfaction target	E.2

Table 3. Input Names

Input Group	Factors
1. Develop Risk Management Skills and Resources	1.1 Our employees are motivated to perform/implement RM
	1.2 Our RM has available, qualified experts to help implement the processes
	1.3 There are sufficient resources and personnel to conduct RM
	1.4 RM teams are cross-functional and cross-organizational
	1.5 Our RM takes human and cultural factors into account
2.Tailor Risk Management to and Integrate it with new Product Development	2.1 Our RM is tailored to specific program/project needs
	2.2 We coordinate and integrate RM activities of different functions and across the hierarchy
	2.3 RM is an integral part of all organizational processes
	2.4 Risks and RM activities are communicated to stakeholders (including management)
	2.5 The RM process is effectively integrated with other project/program management processes
3.Quantify Impact of Risks on your Main Objectives	3.1 The impacts of risks are quantified using cost as a dimension
	3.2 The impacts of risks are quantified using technical performance or quality as a dimension
	3.3 The impacts of risks are quantified using schedule as a dimension
	3.4 Assessment of risk on scales, e.g.1-5 scale for probability and impact
	3.5 Before they are implemented, risk mitigation actions are evaluated based on the reduction of impact of risk through the mitigation action
4.Support all Critical Decisions with Risk Management Results	4.1 Resources are allocated to reduce largest risks as early as possible
	4.2 Forecasts and projections (e.g. cost, schedule, and performance) are adjusted based on risk assessment.
	4.3 The results of the risk analysis are considered in making technical, schedule and/or cost trade-offs.
5.Monitor and Review your Risks, Risk Mitigation Actions, and RM Process	5.1 Risks were escalated to senior management according to guidelines
	5.2 Risks were regularly re-assessed according to guidelines, e.g. after specific events or after a certain time interval
	5.3 The risk management process was regularly reviewed and improved
	5.4 A formal feedback system was used to monitor the execution of risk mitigation actions
	5.5 A nearly warning system was used to track critical risks and decide on activating mitigation measures
	5.6 Risk mitigation plans are used for monitoring
	5.7 Tracking of error/issue/failure rates is used as a key performance indicator to track risks
	5.8 Our RM is dynamic, iterative and responsive to change
	5.9 Our RM is systematic, structured and timely
6.Create Transparency Regarding New Product Development Risks	6.1 Our RM is based on the best available information
	6.2 Our RM is transparent and inclusive towards all stakeholders
	6.3 Our RM explicitly addresses uncertainty