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Critical managerial factors affecting defense projects success: A comparison between neural network and regression analysis

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Abstract

A comparison between neural networks and linear regression analysis is used for identifying critical managerial factors affecting the success of high-tech defense projects. The study shows that neural networks have better explanatory and prediction power, and it enables the exploration of relationships among the data that are difficult to arrive at by traditional statistical methods.

The study yielded some new results: The chances to success of a project that was acknowledged by its prospected customers as essential for improving their performance are much higher than other projects. Furthermore, organizational learning and social cohesion of the development team are of extreme importance for success.

Keywords: Defense development projects; Managerial success factors; Neural networks

1. Introduction

Some of the most important ideas and concepts constituting the modern project management approach were conceived in the defense industry (Tishler et al., 1996). Recent trends, such as the drive for global competitiveness and the associated demands for high-quality products and services, reduced project life cycle and rapid technology development have fueled an increased reliance on project management (Grant et al., 1992). The downsizing of the defense industry during the last decade has further increased the importance of an efficient defense project management.

Artificial neural networks (ANN) are used in this study for identifying the most important managerial factors associated with defense projects and their relation to the overall projects' success. The results are compared with those obtained via linear regression. Some critical factors, which were found less important by linear regression, turned out to be important while using ANN. It is shown here that the use of ANN enables to create a more accurate list of critical success factors of defense projects when compared with regression: The predictions of ANN over previously unseen data are more accurate than those of regression, and this advantage is statistically significant.

The data used in this paper were gathered in a study of 89 defense projects executed in Israel during the 80s and beginning of the 90s. The analysis of the data yielded some new results that were not found earlier by using linear analysis methods.

2. Theoretical background

2.1. The measurement of project success

The difficulties involved in assessing project success from several points of view have traditionally driven project managers to ascribe to simplistic formulae in rating project success. 'Projects are often rated successful because they have come in, or near budget and schedule and achieved an acceptable level of performance' (Pinto and Slevin, 1988). These internal measures of efficiency are partial and sometimes misleading. They disregard incidents where a

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project which ran very efficiently, did not meet customer needs and requirements.

Pinto and Mantel (1990) identified three distinct aspects of project performance as benchmarks against which the success or failure of a project can be assessed: The implementation process itself, the perceived value of the project, and, client satisfaction with the delivered project. This multidimensional approach was also used in a previous study of the Israeli industry, which was focused at the project level (Dvir et al., 2003). Its findings, together with the results described in the literature guided the formulation of the current measures of defense projects' success (see Section 3.1).

2.2. Success factors of defense projects

Only a few studies in the project management literature concentrate on the critical success factors that affect project success or failure. Whereas many of these studies generate lists of critical success factors, each list varies in its scope and purpose (Belassi and Tukel, 1996). Even fewer studies concentrated on factors affecting defense projects success. The main driving force was the potential of budget savings in defense projects which created great interest by the governments in research into the factors affecting their success.

One of the early studies that tried to measure the payoff to defense of its own investments in science and technology was conducted by the US Department of Defense and is known as Project Hindsight (Sherwin and Isenson, 1967). Although Project Hindsight concentrated on the payoff of science and technology, one major finding was that 'it tells us once again that recognized need is the key to efficient utilization'. Furthermore, they recognized that psychological and other behavioral factors are affecting the generation and utilization of scientific and technical knowledge and initiated a follow-up study to explore the impact of such factors.

Tubig and Abeti (1990) investigated the effect of four contractual variables on the success of defense R&D projects, type of R&D, type of solicitation, type of contract and size of business of the contractor. They found that except for the size of the business, all variables had an effect on some of the performance measures.

Another approach for identifying the main factors affecting defense project success was used by the US Government Accounting Office (GAO, 1990). They analyzed the program to build a submarine ballistic missiles, which was considered a successful project, schedule and performance-wise, and identified five factors that were considered the main contributors to the program success: stability of funds and stability of the operational plan; full responsibility for the whole program by one organization; stability of key personnel in the program office; professional and technical expertise in the program office; open communication channels within and outside of the project.

Tishler et al. (1996) studied the impact of managerial variables on the success of defense projects in Israel. According to their study, organizational and management style variables have considerable impact on project success. The most important variables out of this list are 'esprit the corps' of the development team; managers who are also leaders; high level of technical qualifications among the development team; stability of 'key' personnel along the entire duration of the development phase; and a professionally experienced project manager.

A previous study, focusing on the effect of team characteristics and management style on defense project success (Dvir and Ben David, 1999) also used neural networks for identifying the most important cultural variables for project success. The main variables identified by their study are: outside of work activities (activities which are not directly related to the project and usually done after working hours) for improving the cohesion of the development team; the importance of the work as perceived by the development team members; readiness of the project management to accept new ideas; creating an atmosphere of partnership, involvement and identification among the development team members; the existence of a mechanism for distribution of lessons learnt in previous development projects; and, creating an organizational culture that encourages cooperation and a sense of identification with the project goals. The current study is much more comprehensive than the previous work as it also considers technological and managerial variables. For comparison, only ten team characteristic-related variables were tested in Dvir and Ben David (1999) by regression and neural networks, compared with 85 in this experiment. The addition of more potential explanatory variables covering all aspects of project management proved to be very important. As will shortly be described, the addition of managerial and technology factors resulted in other factors which proved to be more important than team cohesion.

Another comprehensive study (Dvir et al., 2003) employed multivariate statistical analyses for identifying the common managerial factors affecting projects. About half of their sample was of defense projects and therefore the results are relevant to the current paper too. The use of a very detailed data set and multivariate methods enabled to address several perspectives which have not been adequately analyzed by previous research. The main results of this study are: (i) A well-designed initiation phase is the most important factor in project success; (ii) organizational setup and project structure are not good predictors of project success; (iii) formal design and planning documents are instrumental in meeting project time and budget constraints, as well as in ensuring customer satisfaction from the end-product; (iv) design changes during the execution of the project are usually detrimental to the customer's satisfaction, and contribute little to the improvement of the end-products.

The current study opens a wider window and examines 85 managerial variables relevant to the various phases of project execution in order to isolate the most important

Table 1
Summary of critical success factors of defense development projects

CSFs	Sherwin and Isenson	Tubig and Abeti	US GAO	Tishler et al.	Dvir and Ben David
Recognized need	√				
Type of R&D		√			
Type of solicitation		√			
Type of contract		√			
Stability of funds			√		
Stability of the operational plan			√		
Full responsibility for the whole program by one organization			√		
Stability of key personnel along the entire duration of the development			√	√	
Open communication channels within and outside of the project			√		√
"Esprit the corps" of the development team				√	√
Managers who are also leaders				√	
High level of technical qualifications among the development team				√	
Professionally experienced project manager				√	
Work perceived important by the development team					√
Readiness of the project management to accept new ideas					√
Atmosphere of partnership					√
Involvement and identification among the development team members					√
Organizational culture that encourages cooperation and identification with the project goals					√

ones by using two analysis methods, neural networks and stepwise linear regression.

Table 1, summarizes the critical success factors found in previous research of defense projects.

2.3. *Artificial neural networks*

ANNs mimic some basic aspects of the brain. They are currently used in a wide spectrum of tasks: from simple calculations to high-level decision making such as credit card and loan approval, bankruptcy prediction, fraud detection, control and scene understanding for surveillance purposes, to name a few.

The pioneering step in ANN research is attributed to Minsky and Papert (1969). Similar to the human brain, ANNs are built of many simple computational elements, called *nodes*. Each node can have many inputs and many outputs. A *weight*, W, which reflects the strength of a link, is associated with each incoming input. These weights model the strength of the chemical connections among brain neurons. Each node j sums its weighted input:

$$\mathrm{net}_j = \sum_{j=1}^{n} W_j X_j. \tag{1}$$

The output of a node, Y_j, is a non-linear function of its weighted input:

$$Y_j = f(\mathrm{net}_j). \tag{2}$$

Nodes are arranged in layers. In the simplest ANN model, there are only two layers of nodes: One layer is connected to inputs (independent variables), and therefore it is frequently referred to as an *input layer*. The second layer is connected to the output (dependent variables). It is therefore called the *output layer*. Later ANN models have included one or more intermediate layers between the input and the output layers. These layers are called *hidden layers*. Similar to the brain structure, each node is connected to every node in the next layer. An ANN in which signals flow in one direction, from the input layer to the output layer is called a *feed-forward ANN*. Other types of network topologies are possible as well. However, since feed-forward ANNs were used in this study, only they will be discussed here.

Adapting an ANN as much as possible to patterns in the data must be done before the network can be used. This process is called *training*. While the training begins, random weights are assigned to all the connecting arcs. During training, the input signals propagate from the input nodes via the arcs to the hidden layers' nodes and from the hidden layers to the output nodes. The actual output values are compared now to their true (known) values. If a difference (error) exists, the training algorithm continues backwards through the hidden layers in the opposite direction (i.e., from output nodes to input nodes), adjusting the values of the weights using first-order gradient descent method to reduce the error. The training algorithm proceeds repeatedly forward (i.e., calculating new output values and errors) and backwards (adjusting the values of the weights) until the error is minimized to an acceptable level.

ANNs are frequently used in many application areas since, by adjusting the number of hidden layers and the number of nodes in each layer, they can model any smooth non-linear mathematical function (Leshno et al., 1993; Hornik et al, 1989; Spangler et al., 1999). This important theoretical aspect of ANNs implies that neural networks can perform better accuracy-wise than linear models such as regression while approximating non-linear phenomena. This observation has been confirmed by many researchers: Rumelhart and McLelland (1986), Hertz et al. (1991), Weiss and Kulikowski (1991), Ben-David and Pao (1992), Jain et al. (1996), Sung et al. (1999), Lim and Loh (2000) are some examples. For that reason ANNs have become an important research tool. When the data at hand are not linear, ANNs have a very good potential to provide the researcher with more accurate predictions than linear methods such as regression or discriminant analysis. The latter are traditionally used for identifying critical success factors. In addition, while using ANN, the researcher does not have to assume anything about the inherent input–output relationship within the data. This is not the case while using non-linear statistical methods such as non-linear regression. For these reasons, this study has utilized ANN for identifying critical success factors and for predicting project success. The results were compared with those obtained by regression.

3. Data organization

The data came from 89 defense R&D projects performed in Israel during the 80s and beginning of the 90s and contracted by the Israeli Defense Armament Development Authority. Overall, at that period of time about 110 projects were conducted under the auspices of Defense Armament Development Authority. Data regarding all the 110 projects were gathered, but only 89 of them were sufficiently detailed to perform a thorough analysis. The data were gathered using a structured questionnaire and interviews. This kind of project is usually intended to provide the Israeli Defense Forces with weapon systems and various types of support equipment. The procurement process involves three main entities: the end-user, the contracting office and the contractor.

The end-user represents the personnel who will be using the systems and equipment that the project is intended to develop and produce. The need for the project originates with the end-user, who is significantly involved in defining the functional requirements. The contracting office is a unit of the Ministry of Defense. Its role is to manage the procurement process on behalf of the end-user, and includes, among other responsibilities, monitoring the performance of the contractor selected for carrying out the project. The contractor is a commercial firm or a government R&D facility that has been awarded the contract for carrying out the project. The project manager is an employee of the contractor who has full responsibility for successful execution of the project.

The projects in the sample were performed by a variety of contractors in the areas of electronics, computers, aerospace, mechanics and others. The respondent population included many types of defense projects: new weapon systems, communication, command and control systems, electronic warfare equipment and other support equipment development projects, they all were completed or terminated by the time of the survey. The questionnaires were filled out within not more than 3 years after the completion of the projects by at least three key personnel related to the project and representing the various stakeholders (the end-user, the project manager within the contractor organization and the contracting office).

The questions solicited subjective evaluations on a seven-point scale. For example, the level of improvement of the end-user capabilities by using the new product was determined by asking the respondent the following question: ‘According to your assessment, were the end-user capabilities significantly improved?’ The answer was marked by the respondent on the scale: 1 (not at all) to 7 (extremely improved). The questionnaire was administered in a face-to-face session by specially trained interviewers, all of whom had been previously involved with this type of projects in various capacities. For each project there were three respondents: The project manager (or a senior representative from the project office); a representative from the end-user community; and a representative from the contracting office. Later, the interviewer completed a separate questionnaire that integrated the three sets of responses while accounting for the relative weight given by the interviewer to the three interviewees. This method was used since not in all cases the most informed respondent was tracked and interviewed. In such cases a greater weight was given to the answers of the respondents who were better informed than the others. The analysis presented here is based on the integrative responses compiled by the trained interviewers.

3.1. Measures

3.1.1. Managerial success factors

About 400 managerial variables derived from the theoretical and practical literature for their influence on the success of defense projects were collected. These variables were organized into groups in such a way that each group covered, a specific issue related to project management, such as project structure, project team or use of control methods. The groups are also related to the various phases of project execution, from the concept formulation, through definition of the technical and operational requirements, product design and development to acceptance tests by the end-user. The content validity of each group was checked by calculating Cronbach’s Alpha coefficients (Cronbach, 1951, 1984). A detailed description of the data set and the division into groups and then, further division into factors related to specific activities within each group, as well as the elimination method of variables not exhibiting enough variability or having high linear combination with other variables, can be found in Tishler et al. (1996).

Each variable describes how well a certain managerial task (i.e., preparation of a detailed operational requirement, evaluation of technical alternatives, project planning, etc.) was executed during the development process. Out of the 400 variables, only 85 variables were selected for this study using two criteria: first, all variables are at least ordinal variables (on a scale of 1–7) and second, there are at least 80 data points per variable. The size of data collected in the field research, did not allow the use of more strict selection methods to ensure random selection of variables. Although the rule for selection was arbitrary, the variables that were eventually selected for this study cover all phases of the project execution and represent all groups that constitute the original questionnaire.

3.1.2. Success measures

Project success was measured according to four dimensions which were applied and validated in a previous research by Tishler et al. (1996) and Lipovetzky et al. (1997). These dimensions are: (A) *Meeting design goals*, refers to the contract that was signed with the customer. (B) *Benefit to the end-user*, the benefit to the customers from the projects end-products. (C) *Benefit to the developing organization*, the benefit gained by the developing organization from executing the project and (D) *Benefit to the defense and national infrastructure*, which measures the benefit to the national technological infrastructure as well as to the technological infrastructure of the firm that was engaged in the development process.

All items in the four dimensions (a total of 20) were measured on a 1–7 scale, where 1 represents a complete failure and 7 represents full success. Table 2 provides the four success dimensions along with the specific measures comprising each dimension.

In addition to the four sets of success measures described above, the questionnaire included an item dealing with overall success of the project. The *overall success* was also measured on a 1–7 scale.

4. Data analysis

Data analysis was conducted using both neural networks and linear regression. The data set contained one dependent variable (the *overall success,* see above) and 85 independent variables (see Section 3.1.1 above). As has been mentioned, there had been 110 observations representing 110 R&D defense projects. However, some observations had missing values. The intersection of all variables with full information (no missing values) was 35. In order to prevent the loss of so many records, the data were inspected and 21 observations containing 20 missing values each were removed. The original set was thus reduced to 89 observations with just a few (three) missing values. Those missing values were replaced by the average of the respective variable. This procedure allowed for effective usage of the information available in the original data set.

The error criterion was identical in both experiments. Both neural networks and regression used the mean squared error (MSE) which is traditionally used in regression analysis. In order to assure a good estimate of the real error (that is, the error estimates are not due to chance), a ten-fold pseudo-validation technique (Weiss and Kulikowski, 1991) has been used in both analyses. The

Table 2
Success dimensions and measures

Success dimension	Success measures
Meeting design goals	Functional specifications Technical specifications Schedule goals Budget goals
Benefits to the customer	Meeting acquisition goals Meeting the operational need Product entered service Reached the end-user on time Product had a substantial time for use Product yields substantial improvement in user's effectiveness and/or capability User is satisfied with the product
Benefits to the developing organization	Project yielded relatively high profit Project opened new markets Project created a new product line Project developed a new technological capability Project improved reputation
Benefits to the defense and national infrastructure	Project contributed to critical fields Project maintains a flow of updated generations Project decreases dependence on outside sources Contribution to other projects

entire data set was randomly shuffled ten times, creating ten data files, each containing the same data in different (random) order. Each data file was further sub-divided into two mutually exclusive groups: (1) The data that were used for training the ANN and for calculating the regression equations (usually referred to as *in-sample* data) and (2) The previously unseen data which have been used for making the predictions after the ANN and the regression models were built (frequently called *out-sample data)*. The in-sample data containing 70 project records were used for model building (neural network or regression). The out-sample data, on which the prediction capability of the model generated was tested, contained the remaining 19 records. Later, a paired *t*-test was carried out for checking whether the difference between the out-sample predictions' accuracy of both models was statistically significant.

4.1. Finding success factors with neural networks

Neural networks are known in their capability to adjust to non-linear data (Minsky and Papert, 1969; Spangler et al., 1999). However, while facing as noisy data as the one used for this research, one must be careful not to over-train the neural networks. Over-training means a 'too tight' or 'over-fitted' approximation of the data, such as in a curve-fitting problem. By adjusting 'too well' to the input data, neural networks can easily adjust themselves to noise instead of to the underlying patterns (assuming, of course, that such patterns do exist in the data). Over-training typically leads to poor prediction performance when applied to previously unseen, out-sample, data (Wary and Green, 1995).

As mentioned earlier, each data file had been randomly divided into two mutually exclusive groups: in-sample data and out-sample data. Of the 89 project records available in each file, 70 were used for model building (i.e., network training) and 19 for testing the resulting network performance (out-sample) in terms of MSE. In the neural networks analysis, the in-sample data were further sub-divided to model building data (50 project records), according to which the neural networks were trained and to in-sample testing data (20 records), for determining when to stop the training. In this study, the training continued as long as the predicted error over the in-sample testing data decreased.

The above-mentioned strategy has an advantage. Assuming the in-sample testing data shares patterns similar to those of the out-sample data (a reasonable assumption only when both sub-groups are large and are taken at random from the same population), 'accurate' predictions in the in-sample data during training should imply 'good' predictions in the unseen, out-sample, data. Indeed, due to the small size of the entire date set, over training (or under training) could have occurred to some extent despite of the above counter measures. However, as we later show, this strategy has resulted good predictions when compared with those of regression.

A forward stepwise MATLAB program was written for the data analysis. At each step, the program tests the inputs and selects the one that (in the presence of previously selected inputs) minimizes the in-sample error. Only inputs that significantly improved the error were selected, otherwise they were ignored. Under this strategy, each input testing involves new neural network training, so an exhaustive search of all possibilities (i.e., all input permutations) was clearly not practical. Instead, a hill climbing like algorithm without backtracking was used. Under this policy, once input is declared 'meaningful', it is not considered again. Consequently, the results presented shortly are to be considered as 'good' rather than as optimal.

4.2. Linear regression analysis

Similar to the procedure used for neural networks, regression analysis was performed on the in-sample set only and the best model for a predetermined number of variables was selected. Later, the estimated model was used to forecast the success of the 19 projects in the out-sample data set. The above process was repeated ten times, one for each different data set. The variables for each run were marked along with the corresponding MSE.

5. Results

Important variables with considerable impact on the variance of the dependent variable appeared in many runs (p value $\leqslant 0.05$). The relative importance of each variable was determined by number of times that this variable was included in the model, out of the ten runs. Obviously, the maximum number was ten and the lowest zero.

The variables that were found by both methods to be important to the projects' success were categorized into eight managerial characteristic factors, each factor containing one or more variables (see Table 3). The frequency of appearance of the participating variables in the ten runs was therefore counted according to their managerial characteristic factors. Variables, which entered the model only in few cases, were excluded. Only those consistently participating in the ten runs were considered in the comparison between the regression and the neural network analysis results.

Regarding the predictive ability of the two methods, ANNs provided better results than regression. This can be shown in Table 3, where the MSEs are shown for each run. The mean out-sample MSE of the neural networks was 0.0476, compared with 0.0579 of the regression analysis. A paired t-test on the results shown in Table 3 was carried out for checking the statistical significance of the above observation:

$$H_0: \ \mu_{\text{reg}} - \mu_{\text{nnet}} \leqslant 0,$$
$$H_1: \ \mu_{\text{reg}} - \mu_{\text{nnet}} > 0,$$

where μ_{reg} and μ_{nnet} are the MSEs of Regression and Neural Networks respectively. At 95% level of significance the null hypothesis could be rejected (t value of 2.100 versus the critical value of 1.833), so we could conclude that the advantage of Neural Network over Regression was statistically significant at 95% confidence level.

These results show that the models which were built by ANNs are more accurate on average, when compared to those of regression, with respect to their ability to predict project success. The improvement, about 10% relative to regression, though not as dramatic as we have initially anticipated, cannot be ignored either.

The ranking of the success factors, which was the focus of this research (to be shortly described in the Discussion section), which was provided by both methods was not identical as well. Since the ANNs models proved better in predicting project success, their ranking of the most meaningful success factors should be regarded as more reliable than those of the regression. Table 4 compares the two lists, where the first factor in each list is the most important one and the last, is the least important.

Table 3
Mean square errors of out-sample data

Run #	Regression MSE	ANN MSE
1	0.0540	0.0274
2	0.0592	0.0255
3	0.0625	0.0559
4	0.0755	0.0802
5	0.0438	0.0482
6	0.0475	0.0643
7	0.0609	0.0483
8	0.0866	0.0651
9	0.0510	0.0378
10	0.0376	0.0230
Average	0.0579	0.0476

6. Discussion

Table 4 presents the eight most important managerial factors for project success according to the two analysis methods.

Four factors out of the eight identified by the neural network as the most important for project success are also included in the list produced by the regression analysis. An essential and urgent operational need is identified by both methods as the most important managerial factor. This finding is not new: Sherwin and Isenson (1967) as well as Tishler et al. (1996) have already identified this factor as one of the most important one. Nevertheless, our study strengthens the understanding that a project that is considered by its end-user as important and urgent has a better chance to be completed successfully.

Both analysis methods also identified the importance of the development team cohesion; the need for learning mechanisms for dissemination of lessons learned during the project execution, and exact definition of all operational and technical requirements of the end-product. The importance of team cohesion was found in an earlier study by Dvir and Ben David (1999) mentioned earlier, which first used neural networks to identify the cultural and organizational success factors. In that study, the team cohesion factor was identified as the most important factor by both analysis methods.

Another important finding is the extreme importance of learning mechanisms to the success of defense projects. Knowledge management and organizational learning attracted a lot of attention in the last years (see, for example, Farr and Fischer, 1992). This study contributes to this issue by showing that learning from past experience; either experience gained from previous projects or even from the current project, can substantially improve chances for success.

Table 4
Eight most important factors—regression vs. neural network

Neural network		Regression	
Factors	No. of variables	Factors	No. of variables
Essential and urgent operational need	2	Essential and urgent operational need	1
Cohesion of the development team	2	Definition of operational and technical requirements	4
Quality of the escorting team	3	General-level management and delegation of authority	3
Involvement of the developing organization in the project definition	1	Existence of learning mechanisms in the development team	2
Existence of learning mechanisms in the development team	2	Existence of appropriate technological infrastructure at the developing organization	1
Budget and technical control	3	Involvement in the decision making process and open communication	2
Definition of operational and technical requirements	6	Managerial qualifications within the developing team	2
Managerial qualifications of the project manger	3	Cohesion of the development team	2

Four factors are quite different in the two lists. While the regression analysis designates four factors related to the way the development team is managed (factors 3, 6, 7 and 8), the neural networks analysis adds to the list the quality of the escorting team (meaning the team appointed by the Ministry of Defense to monitor the development process) and the involvement of the developing organization in the conceptualization of the project and the definition of the end-product requirements. The neural networks analysis also identifies the project manager as the most important figure in the development team while the regression results put the emphasis on the qualifications of the whole team.

The findings presented thus far show that ANN can better fit the data used in this experiment than linear regression. This statement is based on the fact that ANNs produced smaller errors on average than linear regression when applied to the hold-out samples, and this advantage was statistically significant at 95% confidence level. The findings can be explained by non-linear relations between project success and its explanatory attributes on one hand, and the non-linear features of ANNs discussed earlier. Therefore, we tend to accept the order of priority suggested by the neural network analysis as more meaningful than that suggested by the regression analysis.

Clearly, one could choose a non-linear statistical model to improve the regression results. However, with traditional non-linear statistical methods one must first guess a model, then to test it and so on, until a sufficiently accurate model is found. This task is much simpler with neural networks, where one only needs to adjust a few parameters such as the number of nodes rather than to find by trial and error the 'proper' input–output non-linear relationship.

7. Conclusions

The analysis of the data by ANNs yielded some new results. An important finding is the extreme importance of learning mechanisms to the success of defense projects. Team cohesion was previously shown to be one of the most important success factors; nevertheless, in the presence of other managerial factors not related to the organizational culture, other factors prove to be more important. The neural networks analysis also identifies the project manager as the most important person in the development process while the regression results put the emphasis on the qualifications of the whole team.

It has been shown here that neural networks have better explanatory and prediction power for assessing success of defense projects, and that they are capable of exploring relationships among the data that are difficult to arrive at by using traditional statistical methods. This study tried to extract the most important managerial factors, which are common to several types of defense projects. Clearly, not all projects have the same characteristics and different management methods should be applied to them. The study of project-specific management factors was not in the scope of this study. It is our intention to try and use the same methods for the identification of critical success factors, which are contingent on the level of technological uncertainty at the initiation point of the project or on the scope and complexity levels of defense projects.

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