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Project selection in project portfolio management: An artificial neural network model based on critical success factors

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Abstract

While a growing body of literature focuses in detecting and analyzing the main reasons affecting project success, the use of these results in project portfolio management is still under investigation. Project critical success factors (CSFs) can serve as the fundamental criteria to prevent possible causes of failures with an effective project selection process, taking into account company strategic objectives, project manager's experience and the competitive environment.

This research proposes an innovative methodology to help managers in assessing projects during the selection phase. The paper describes the design, development and testing stages of a decision support system to predict project performances. An artificial neural network (ANN), scalable to any set of CSFs, classifies the level of project's riskiness by extracting the experience of project managers from a set of past successful and unsuccessful projects.

Keywords: Critical success factors; Project selection; Artificial neural network; Project risk

1. Introduction

The contemporary competitive environment, with its widespread lack of information, misleading signs and difficulties in forecasting future scenarios, makes the acquisition and management of projects investments always more risky. A recent research (Bloch et al., 2012) on more than 5,400 IT projects by McKinsey and the University of Oxford shows that half IT projects with over $15 million budget run, on average, 45% over budget and 17% fail to a point of threatening the very existence of the company.

Companies should align project portfolio with their strategic business objectives, combining performances of its components in order to maximize the shareholders' value while balancing resource allocation and risks. Some of the main objectives of the project portfolio management are the identification, the ranking, the prioritization, the selection and the authorization of projects or programs. Uncertainty and volatility are increasing day by day and managers take strategic decisions on project portfolio (like a tender's participation or a project authorization) under non-deterministic conditions. Only through the definition of accurate project selection criteria, any organization can reach its targets.

As a matter of fact, once started, a significant level of complexity affects project life cycle and different sources of risk influence its success (Cagno et al., 2007):

- indeterminateness, ambiguity or poor definition and sharing of targets;
- lack or low measurability of targets and a consequent low capability of evaluating and recognize performances;
- inadequate resource allocation, i.e., right resources but wrongly managed or insufficient resources due to a wrong estimation;
- incorrect and not detailed identification of all the customer's and company's requirements;

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- fast evolving markets and industries with a continuous need of targets re-alignment and re-planning;
- inaccurate planning or errors in implementation of project management processes.

Having a clear identification of threats and opportunities that can arise (Hillson, 2002; Ward and Chapman, 1995) allows containing the level of uncertainty and evaluating any possible alternative in terms of project sustainability (Ghosh and Jintanapakanont, 2004). Investments in project management capability should support project portfolio strategies while enhancing operations management during the execution phase, ensuring project performances in terms of value for customers, market share and competitiveness (Elkington and Smallman, 2001). As the project success is the ultimate objective of a company, critical success factors (CSFs) affecting its future implementation should be pillars of the selection criteria.

An early evaluation of the expected economic or financial return of a project is a very tough process, pushing organizations to set up managerial levers that could help to forecast performances (Ibbs and Kwak, 2000; Thomas and Mullaly, 2007). During the tendering stage, risk analysis can support decisions, drawing all the possible scenarios that could cause an early and unsuccessful conclusion. As managers have to investigate and control risks, any tool that evaluate how critical success factors can affect performances will support in implementing adequate actions of mitigation, making the risk assessment process more reliable. Managers can reach a proper control of the projects' portfolio, balancing the overall exposure to risks, only with a clear perception of the expected results on every single project.

In this context, risk analysis can help project managers to handle a portfolio of projects with different characteristics. The process of protection from risks represents a fundamental component of the project portfolio and project management activities (Cooke-Davies, 2002; Jaafari, 2001; Raz et al., 2002) and needs systematic procedures to enable its correct application. These procedures can vary according to different organizational environments, having an effect in the planning stage and during the whole life cycle of the project, considering the requirements of all the stakeholders. Project risk management supports managerial and organizational control (Kloppenborg and Opfer, 2002; Söderlund, 2004) to minimize inconveniences, shifts and gaps from the target values, recognizing further potential risks and their relative protections (Milosevic and Patanakul, 2005) to avoid project failure.

Our research, collocating in the "factor school" according to the extensive review by Söderlund (2011), deals with the issue of making an early assessment of projects for portfolio selection as a risk management technique. Critical success factors (CSFs) are the levers that can address toward project success. According to different industries and environments, project managers have to identify the most opportune set of CSFs, trying to implement the right practices that satisfy all the stakeholders' requirements. To this extent, the paper presents an innovative approach to design a decision support system to evaluate the correlation between a desired set of CSFs and the future projects' performances. Extracting and consolidating implicit knowledge from past projects, an artificial neural network toolbox is able to analyze a given set of CSFs' and identify, with a certain degree of error, the expected level of success for project selection process in the project portfolio management.

The following sections present the development and implementation of the research path. The first section discusses the strategic importance of project selection and the project success as a crucial point in definition of selection criteria. After we examine project selection methodologies and the role of critical success factors (CSFs) and key performance indicators (KPI) in the project selection process, deepening the project implementation profile (PIP) model. The second section describes the research methodology. The subsequent sections present the model for early assessment of project success based on critical success factors of project implementation using artificial neural network (ANN). The results of the analysis on the data coming from 150 projects of a leader Italian EPC contractor and the relative academic and managerial implications are in the last section.

2. Theoretical background

Since many years, project management research has been trying to discover how to improve the ability of organizations to reach success in implementing projects (Maylor, 2001; Patanakul et al., 2012). Project portfolio management extends the objective of realizing successful projects to the alignment with strategic business objectives, but expected project success remains the main determinant for projects selection, if success means the maximization of the shareholders' value while balancing resource allocation and risks. Therefore, project selection is a process of strategic significance (Cooper et al., 2001) aimed at evaluating individual projects or groups of projects and then choosing to implement a set of them so that the objectives of the parent organization are achieved ((Meredith et al., 2015). However, too often it fails (Ghapanchi et al., 2012) due to complexity in project portfolio management caused by many factors, such as uncertainty, interrelationships among projects, changes over time and success factors that are difficult to measure (Coldrick et al., 2005).

Given the success of the project as crucial to the definition of the criteria, there is no consensus on what criteria should be used. As a matter of fact, "companies have considerable leeway in the development of their selection criteria, and different measures as well as the wide variety of industries, project types and strategy choices make inter-organizational standardization impractical" (Kaiser et al., 2015).

The process of project assessment for project portfolio selection should always consider criteria, factors and key performance indicators (KPIs). Factors are the independent variables of a project that organizations can drive, while key performance indicators (KPIs) are the significant dependent variables that measure outcomes and performances of the project (for a complete review of project management KPIs, see Luu et al. (2008). Furthermore, the definition of the criteria is fundamental. A criterion is "a principle or standard by which anything can be judged," while a factor can be described as "any circumstance, fact, or influence which contributes to a result" (Lim and

Mohamed, 1999). Criteria are the basis to express judgments, whereas factors are the influential forces that contribute to the success or failure of a project. Bryde (2008) extensively investigated relationship between success factors and criteria. Criteria are the lens through which determine if the project is a success or a failure, considering the results of the KPIs (further considerations about these issues are available in Ika (2009).

2.1. Project selection methodologies

Since 80s of last century, project selection has gained an increasingly attention in project management literature, e.g., researches on R&D project selection (Cooper, 1981) or on MIS project selection (Ginzberg, 1979). In the project portfolio management, the gathering of possible projects, their prioritization and selection usually involve particular optimization algorithms or management techniques that make use of specific project selection criteria (Kaiser et al., 2015). Project selection approaches can be distinguished between financial and non-financial models (Gray and Larson, 2003). Moreover, project selection methodologies range from single criteria cost–benefit analysis to multicriteria scoring and ranking methods, or subjective committee evaluation methods (Lee and Kim, 2001). For instance, as regards financial models, researchers proposed an R&D options selection model for investment decisions based on risks (Coldrick et al., 2005). Jafarizadeh and Ramazani Khorshid-Doust (2008) considered as principal selection criteria the semi-deviation of return, i.e., the measure of risk of projects that is more consistent with the definition of risk as the probability of unwanted outcomes. (Dutra et al., 2014) used an economic–probabilistic model for project selection and prioritization.

The literature presents a number of studies addressing project selection using multicriteria scoring. For instance, Mohanty (1992) proposed a multiple-criteria decision-making model to assist in the selection of project proposals, while Henriksen and Traynor (1999) adopted a project selection scoring tool.

Moreover, there are several researches adopting different methodologies: genetic algorithm-based multicriteria (Wang et al., 2012), fuzzy decision support system (Lin and Hsieh, 2004), multiobjective particle swarm optimization for project selection problem (Rabbani et al., 2010), Data Envelopment Analysis (Ghapanchi et al., 2012) and analytic network process (Meade and Presley, 2002). Fox and Baker (1985) used a simulation model that include simplified market and production characteristics of a hypothetical firm and a specific project selection decision mechanism.

Artificial neural networks (ANNs) have been used in project selection to "learn" the knowledge from historical project selection (Flintsch et al., 1996) and in the very specific case of Arizona Department of Transportation (Flintsch and Zaniewski, 1997). Nevertheless, neural network decision support system can guide managers when they make complex new product development decisions (Thieme et al., 2000). Furthermore, an artificial neural network model is a non-parametric method; therefore, it is superior in the ranking and the selection of projects compared to regression analysis, that is, a parametric method (Olanrewaju et al., 2011). Consequently, even if in PM literature the examples of application of artificial neural networks in project selection are limited to specific cases, we considered the use of this methodology in our research for the following three reasons:

(1) Ease of use because ANN extracts implicit knowledge from past experience without involving managers in complex and fallible judgments
(2) Applicability to any industry, project types and company because customizable to any critical success factors framework
(3) Dynamic learning capacity of ANN models which can allow a review of project evaluation during the project lifecycle

2.2. Project success evaluation

Literature review and empirical analysis suggested that attaining performances in terms of time, cost and quality of the final product are not always enough to consider a project as successful. Quality is becoming more and more considered by managers as the main target to achieve, in terms of the quantity of work that does not require rework: doing the job right the first time in order to eliminate the reworking of tasks, reducing time and costs of implementation, represents a main source of success. Customer and stakeholder's satisfaction and deliverables' acceptance are the key dimensions of analysis in order to underline the role of the value perceived by the client (Tukel and Rom, 2001). Well-defined objectives, communication of project's aims to team members and the approval of deliveries by a multiplicity of stakeholders are crucial. Management of customers' change requests is a critical issue to add to the traditional ones such as project managers' competence, project team members' capacity of problem solving or project innovativeness. A formal method of recording change requests and assessing the effect of the change on the project approval process is necessary to control ad-hoc changes to the project (Carù et al., 2004).

According to de Wit (1988) and Cooke-Davies (2002), a main issue to consider when assessing projects is the difference between *project success*, which measures the achievement of the overall objectives, and *project management success*, which measures the performance of the management process. Project success is next to the idea of effectiveness (achieved vs. targeted objectives), while project management success is next to the idea of efficiency (consumed resources vs. achieved targets). Turner and Müller (2005) showed the complexity of identifying the set of factors, criteria and KPIs through an extensive survey, demonstrating that success or failure might vary in relation to different characteristics:

- Selection of criteria: changing the perspective from which the project should be seen implies differences in the KPIs that project managers have to check during the whole life cycle
- Organizational structure: functional, project oriented or matrix structures present different approaches to coordination and control, affecting performances (Larson and Gobeli, 1989)

- Size of the project: the number of activities can change the level of importance of the factors, e.g., shifting the central role of top management support to team commitment when passing from small to large projects (Turner and Müller, 2005);
- Industrial sector: different industries (Pinto and Covin, 1989) can present different degree of priorities in results to achieve (e.g., budget control in construction, delivery times in manufacturing, quality in utilities);
- Different perspectives of the stakeholders: project success depends on the structure of preferences of the assessor. Different stakeholders (owner, developer, contractor, user, general public) may not have the same expectations while looking at it (Chen et al., 2013; Pokharel, 2011);
- Different stages of the life cycle: each project cycle implies a different intensity of efforts as well as different tasks and actors (Pinto and Slevin, 1988). Modern markets present rapidly occurring changes and managers have to adapt to a dynamic definition of success. During project's progress, both the relative importance of the performances and the factors to control can vary (Belout and Gauvreau, 2004; Lipovetsky et al., 1997; Pinto, 1988).

2.3. Project critical success factors

The critical success factors (CSFs) are the main factors that increase the ability of organizations to carry a project through its full implementation. In this sense, a continuous assessment of all the decisions taken during project life cycle which impact on project risks (Baccarini and Archer, 2001) and on CSFs (Pinto and Kharbanda, 1996) allows managers to set the priorities and determine the actions that can drive toward success.

Pinto and Slevin in their fundamental researches (Pinto and Slevin, 1988, 1989; Pinto, 1990) identified ten critical factors, crucial for the implementation of a successful project, and developed a diagnostic tool for project managers, the project implementation profile (PIP).

Since then, several studies tried to verify and discuss the PIP, going deep into the specific effect of any factor like project sponsorship (Bryde, 2008) or human resource management (Belout and Gauvreau, 2004; Pant and Baroudi, 2008). On the other side, researches also aimed at declining some results of the PIP. For example, Belout and Gauvreau (2004) submitted a questionnaire to the project managers of 142 projects, concluding that "Personnel" factor was not significant for success. Successive investigations did not confirm this evidence, but literature proposes the existence of conflicting opinions and the discussion is still acting. An extensive review (Ika, 2009) showed that many authors traced alternative sets of project CSFs, identifying a wide range of models that could best suit any project or industry. Other models are more practitioners-oriented as presenting a more comprehensible terminology to project managers. Cooke-Davies (2002) analyzed 136 projects (by 23 organizations) obtaining 12 CSFs that do not deny nor confirm PIP. In fact, their CSFs have different names and partially overlap PIP considering some additional issues. For example, the PIP does not cover the topic of risk management, a practice that Cooke-Davies includes in four CSFs (company-wide education on risk management, organization's processes for assigning ownership of risks, risk register, up-to-date risk management plan). Similarly, the definition of monitoring is different between PIP ("Systematic control of information, progresses and deliverables at each stages of the implementation process") and Cooke-Davis ("Maintain the integrity of the performance measurement baseline") with slightly different meanings. Chua et al. (1999) used an AHP model to identify 27 CSFs from a panel of 67 factors, in which the PIP's CSF "Institution of an appropriate network of communication for all the necessary data to all key actors in the project implementation" is split in "Formal communication during design" and "Formal communication during implementation." Furthermore, Thomas Ng et al. (2009) mixed 24 internal and 7 external critical factors, going beyond the structure of PIP while adding a different point of view that increases the complexity of the analysis.

This debate on the identification of project management CSFs and on their correlation with project success is still open. Taking as the starting point the PIP, still the most commonly recognized set of CSFs, our research proposes a model of project early assessment whose methodology could fit any of the above-mentioned CSFs' profiles based on ANN.

3. Research methodology

The design process of this research ensures the consistency of the data, to maximize the validity, reliability and scalability of the model and, consequently, of the results.

The data collection processes adopted a combination of primary and secondary sources. Data from primary sources derived from 10 structured interviews, relying on a questionnaire for individual assessment of CSFs, and a group-based assessment of projects. Data from secondary sources came from internal documents of a leader Italian EPC (engineering, procurement and construction) contractor in constructions, engineering, healthcare, industrial plants, mining and steel industry. This large enterprise employs more than 50,000 workers and operates worldwide with a benchmark expertise in project management.

The research followed these steps:

- Presentation of the research objective and requirements to the top management of the EPC contractor to receive their sponsorship for the subsequent data collection
- Selection of a sample of 150 projects from different areas of the EPC portfolio (mainly construction, hardware or equipment development, serve or test, feasibility study and reorganizations), with different budgets (from €5 million to €20 million) and duration (from 18 months to 36 months) to have an high differentiation, reducing the effect of project typology on success evaluation
- Collection of the projects' documentation and their synthesis in executive business cases, containing all the KPIs used by the company
- Involvement of a pool of 10 IPMA (International Project Management Association) certified project managers (one Program Manager, three Senior Project Managers and six Project Managers) according to a minimum level of experience

in PM of 10 years; these PM experts assessed the CSFs of each project

- Development of the questionnaire for the CSFs assessment, according to the PIP, describing all the ten factors (see the first table in Appendix 1); the PIP model is still the most accepted and used model by researchers and practitioners as highlighted in the previous section
- Interview with experts for the individual assessment of the ten CSFs (15 assessments for each expert) and delivery of projects' documentation and business cases
- After 1 month, organization of a workshop involving the ten experts for group-evaluation of the degree of success of each project (see the second table in Appendix 1);
- Use of the experts judgments to train and test an artificial neural network model, to verify the correlation among the sets of CSFs' values and the degree of success of any project, to provide a decision support system to evaluate future projects
- Discussion on the research result with the top management of the EPC contractor

4. A model for early assessment of project success

As highlighted before, the research aimed at proposing a model for early evaluation of project success based on critical success factors of project implementation using an artificial neural network (ANN) model.

4.1. Artificial neural network

An artificial neural network is a tool inspired by the functioning principles of the biological nervous system of the human brain: elementary computational units (neurons) are the nodes of an oriented network, endowed with processing capacity. Each node receives in input a combination of signals, coming from the external environment or from other nodes, and applies a transformation through an activation function. Oriented and weighted connections send the output of each node to other nodes or out of the ANN. In details, the nodes have two functions: extracting knowledge from the external environment through an adaptive learning process and storing knowledge into the network's parameters (in particular, into the connections' weights). Consequently, an ANN is as a non-linear and non-parametric model that searches relations between data to solve two different kinds of problems:

- *functions approximation (regression):* inputs represent a vector of independent variables while outputs are the dependent variables of an unknown functional relation
- *classification:* inputs represent a vector of features of a phenomenon while outputs express the belonging to a set of identified classes

These tools have aroused a great interest because of their capability to execute an operation that is impossible to most of other Artificial Intelligence's techniques: answering correctly (with a certain degree of confidence) to inputs not previously encoded, handling the uncertain, unpredictable and noisy external environment.

Some authors used ANN in project management field of research to determine project performances and understand risks at an early stage. In particular, two main streams, limited to few specific experiences, exist:

- *Cost approach:* the introduction of ANN (functions approximation type) is targeted at controlling budget and provide risk protections, through forecasting and early assessment (Chua et al., 1997a, 1997b; Emsley et al., 2002; Jin and Zhang, 2011; Murat Günaydın and Zeynep Doğan, 2004; Wang et al., 2012). Most of these experience come from the construction industry where an high standardization of processes allows the creation of a common knowledge base.
- *Managerial approach:* ANN (classification type) identify the relation that exists among project performances and key project management levers, as for organizational and managerial factors (Chen et al., 2012; Dvir et al., 2006; Ling and Liu, 2004; Zhang et al., 2003). This paper below belongs to this second research stream.

4.2. Model design

The choice of developing an artificial neural network model derived from the first analysis of the results of the CSFs and project success evaluation (see Table 1). Table 2 shows the results collected from the expert in terms of correlation values among the degree of success and each CSF and among the whole set of CSFs. These unclear and partial correlations did not allow building a simple or a multiple regression model as the relations among the CSF resulted definitely non-linear as well as non-linearly separable. This property of the results suggested applying a classification model to understand if the relation with the project success existed in terms of a whole set of CSFs instead of any single CSF.

Table 1
The ten key factors of the project implementation profile (source: Slevin and Pinto [40], pp. 57–58).

Factors	Definition
Project mission	Initial clearly defined goals and general directions
Top management support	Willingness of the top management to provide the necessary resources and authority/power for project success
Project schedule/ plan	A detailed specification of the individual actions steps for project implementation
Client consultation	Communication, consultation and active listening to all impacted parties
Personnel	Recruitment, selection and training of the necessary personnel for the project team
Technical tasks	Availability of the required technology and expertise to accomplish the specific technical action steps
Client acceptance	The act of "selling" the final project to its ultimate intended users
Monitoring and feedback	Timely provision of the comprehensive control information at each stage in the implementation process
Communication	The provision of an appropriate network and necessary data to all key actors in the project implementation
Troubleshooting	Ability to handle unexpected crises and deviations from plan

Table 2
Squared correlation coefficient values among CSFs and project success.

	SUCCESS	CSF1	CSF2	CSF3	CSF4	CSF5	CSF6	CSF7	CSF8	CSF9	CSF10
SUCCESS	1.000	0.383	0.481	0.580	0.310	0.675	0.714	0.156	0.414	0.167	0.222
CSF1		1.000	0.822	−0.168	0.088	0.591	−0.044	0.185	0.047	0.108	−0.082
CSF2			1.000	−0.111	0.094	0.711	0.049	0.258	0.090	0.105	0.002
CSF3				1.000	−0.012	0.166	0.604	−0.007	0.344	−0.014	0.105
CSF4					1.000	0.131	0.092	0.079	−0.217	−0.003	−0.019
CSF5						1.000	0.463	0.324	0.129	0.130	0.039
CSF6							1.000	0.134	0.276	−0.026	0.108
CSF7								1.000	0.005	−0.517	−0.021
CSF8									1.000	−0.069	0.335
CSF9										1.000	−0.009
CSF10											1.000

In this case, only an artificial neural network could catch and share the knowledge of the experts. In fact, the key property of this application is the ability to replicate the reasoning of skilful managers, extracting and keeping the implicit knowledge from experiences, even if affected by uncertainty or incompleteness. The process of design and implementation, mainly a combination of previous experiences with a set of rule of thumb, followed available guidelines (Rafiq et al., 2001; Kriesel, 2005; Hagan et al., 2014) that supported the selection of all the characteristics of this architecture.

The analytical model is a hetero-associative net (multilayer perceptron, MLP) where all the inputs connected to the external environment are distinct from the output that express the answer of the system: the input is a vector of project managers' evaluations on the CSFs and the output is the project degree of success. The choice of MLP is in accordance with the general literature of neural network design for classification problems. Due to the characteristics of this kind of network, after the training process the results are not integers and need a rounding after the classification process. Classification networks that work with integers generally present a high computational effort and lower performances if not designed properly while MLP, whose design and training processes are easier, can produce satisfying performances under this simple assumption.

The network elements combine a hierarchical frame of synapses in a *feed-forward* topology (Fig. 1), where all the nodes of a layer link in a unidirectional way to the ones of the following, to create the possibility of identifying non-linear characteristics. The capacity to detect non-linear relations without defining a formal expression, not requiring "a priori" hypothesis on variables' behavior, depends essentially on

- the number of nodes,
- the number of layers,
- the transfer function *f* of each node,
- the weights *w* of the connections.

This architecture elaborates CSFs inputs in a black box of weighted connections and transfer functions that generate the success value with a combination of interlaced non-linear functions that does not allow an analysis of each singular CSF contribution to the results.

The MLP traditional training method is the *back-propagation, online mode, with momentum updating rule*. This learning algorithm achieves the automatic linear scaling of real world data ranges into the network target ranges. In detail, the training process is the stage of implementation of the neural network to set the unknown network's parameters (*weights*); this concerns the process of repeatedly presenting examples of historical data to the system (*patterns*) and altering the connection weights basing on a learning rule. In the online mode, the network receives the patterns in a random and always changing order.

At a general level, parameters are set in two steps:

- Defining a subset of data (training set) that represents an example of input/output associations
- Solving an optimization problem:

$$min\ \ E(w) = \sum E_p(w)$$

with E_p representing a measure of the error related to the p-pattern (subset) of the training set.

This error estimates the gap between the output given in the training set and the output predicted by the network. The back-propagation algorithm is an iterative method, a heuristic version of the *gradient method*, commonly applied in multilayer networks

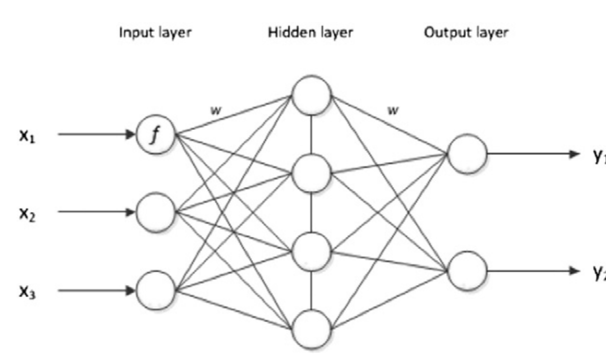

Fig. 1. General MLP network.

because of its high performances in terms of time and precision. The interaction defining back-propagation is:

$$w^{k+1} = w^k - \alpha \nabla E_{p(k)}\left(w^k\right) + \eta\left(w^k - w^{k-1}\right)$$

where

- $\nabla E(w^k)$ is the gradient of the error function in the current vector w^k of weights;
- the scalar α (*learning rate*) defines the step along the anti-gradient direction $d^k = -\nabla E(w^k)$, using at each step only the current pattern of inputs and output ($x^{p(k)}$, $y^{p(k)}$);
- the scalar $\eta > 0$ (*momentum*) executes an adaptive choice of the step or modifies the research direction to ensure the convergence of the algorithm.

The problem with the training process is to understand a point where the network received enough training on the training set (*learning capacity*) and can give the best results on all the possible new patterns (*generalization capability*). Continuous training of a neural network aims at making it working always better, but eventually it arrives to a point where the forward progress is too slow to be practical. Moreover, over-training is dangerous because it can bring to *over-fitting*. It occurs when the mapping function, resulting from the training process, fits the training set too well, losing the ability of processing new data and producing only results by heart. In order to assess these capabilities, a stage of validation run the neural network on the same set of data, evaluating the accuracy of the outputs without adjusting the weights of the nodes at each step. Furthermore, its generalization ability strictly depends on the existent inner correlations between different input variables that determine the output. To this extent, the existence of a certain degree of correlation among the CSFs and with the degree of success (as for Table 2) helps the training process, reducing the computational effort and improving the performance of the algorithm.

According to these principles, the 150 projects divided into two subsets, 120 to train the neural network and 30 to test the performances of the resulting model.

The 120 projects for the training followed a ten-fold cross-validation process. Each round of cross-validation partitioned the sample of 120 data into complementary subsets, applying the training process on one subset and validating the analysis on the other subset. To reduce variability, multiple rounds of cross-validation used different partitions and the validation results in an average over the rounds. The ten-fold cross-validation partitioned the original sample randomly into 10 equal size subsamples (each one of 12 projects), assigning 9 subsamples (108 projects) to training and 1 sample to validation (the remaining 12 projects).

The subset of the remaining 30 projects for the test contains the most recent projects executed by the EPC contractor with a significant sample of all the possible risk levels (from two to six occurrences for each risk value), to really assess the learning process from the past data.

The performances of the network during the training stage are a proxy of the learning capacity while the performances during the validation stage are a proxy of the generalization capability, in terms of:

- R^2 = squared correlation coefficient between MLP input and output
- RMSE = Root mean square error between the expected output (degree of success given by experts) and the MLP output (degree of success predicted by the network).

Furthermore, the topology that ensured the best performances during training and validation is the result of a recurrent trial and error process, balancing the properties of learning capacity of the nodes and the generalization capability of the layers. The different experiments on the network configuration followed this path:

- Set the input layer with 10 nodes corresponding to the 10 CSFs of PIP, with a linear [0;1] transfer function to conserve their native values
- Set the output layer with 1 node corresponding to the risk value, with logistic [0.0;1.0] transfer function
- Start with a hidden layer, train and validate the network for all the configurations of nodes from 1 (number of outputs) to 10 (number of inputs) with tanH [−1.0;1.0] transfer function and identify the best performances; as the best performances resulted with the maximum value of nodes for the hidden layer (10), with adequate performances in learning capacity and improvable performances on generalization capability, try to improve the learning capability
- Add an hidden layer with the same number of nodes, always with tanH [−1.0;1.0] transfer function, in front of the previous hidden layer, and gradually increase the number of nodes of this layer until the performances of training and validation are similar

The learning algorithm, set to 20,000 repetitions, gave the best performances with a learning coefficient $\alpha = 0.1$ and a momentum $\eta = 0.6$ with the results shown in Table 3.

Table 3
Performance of the different neural network topologies.

Nodes of the hidden layer 1	Nodes of the hidden layer 2	Training		Validation	
		RMSE	R^2	RMSE	R^2
15	10	0.065	0.9564	0.087	0.9214
14	10	0.072	0.9518	0.137	0.9108
13	10	0.124	0.9212	0.084	0.9352
12	10	0.084	0.9383	0.151	0.9086
11	10	0.097	0.9088	0.163	0.9265
10	10	0.123	0.9045	0.152	0.8847
n.a.	10	0.079	0.9648	0.161	0.8958
n.a.	9	0.087	0.9141	0.221	0.8767
n.a.	8	0.095	0.9389	0.122	0.9271
n.a.	7	0.101	0.9100	0.078	0.9317
n.a.	6	0.087	0.9298	0.167	0.8307
n.a.	5	0.099	0.9685	0.072	0.9365
n.a.	4	0.167	0.9238	0.102	0.8552
n.a.	3	0.186	0.9170	0.197	0.9156
n.a.	2	0.129	0.8566	0.314	0.7369
n.a.	1	0.228	0.8134	0.299	0.7259

The choice of the non-linear transfer functions is in accordance with the literature on MLP with back-propagation learning algorithm for pattern recognition, requiring differentiable, smooth, monotonic and bounded functions. The logistic transfer function commonly fits the property of classification, in particular when the output of the network should be integers and positive, to represent qualitative values. The tanH transfer function, which has almost the same properties of the logistic transfer function, best fits for hidden layers as it does not generates zeros (maintaining the nodes actives) when the argument of the function is substantially negative, thus lowering the learning rate for all the subsequent weights.

The final configuration with the best performances presents two hidden layers, the first with 15 nodes and the second with 10 nodes. The resulting two hidden layers confirm the hypothesis that only by selecting a neural network as a decision support system, it could be possible to try a classification of data that are not linearly separable and their interconnections are very relevant.

4.3. Results and classification error

The ANN assessment model supports the classification of projects, identifying their degree of success according to an early evaluation of CSFs. An application to the remaining 30 projects tested the best MLP configuration, showing a satisfying performance. Fig. 2 presents the comparison between the output of the MLP and the experts' evaluation, with an $RMSE_{test} = 0.34$.

In particular, the $RMSE_{test} = 0.34$ gives an average level of error lower than 0.5 that represents the threshold for wrong answers. In fact, having assumed that the evaluation of experts on the degree of success had to be expressed in integer values, an output of the MLP can be considered correct only if the distance from the expected value is lower than 0.5, so that the MLP rounded value corresponds to the experts' one.

Only 3 projects (nos. 8, 22 and 25) presented and output value different from the expected one, overestimating the degree of success of 0.66, 0.54 and 0.55, respectively (anyway less than a category). There is no particular reason that lies under these errors,

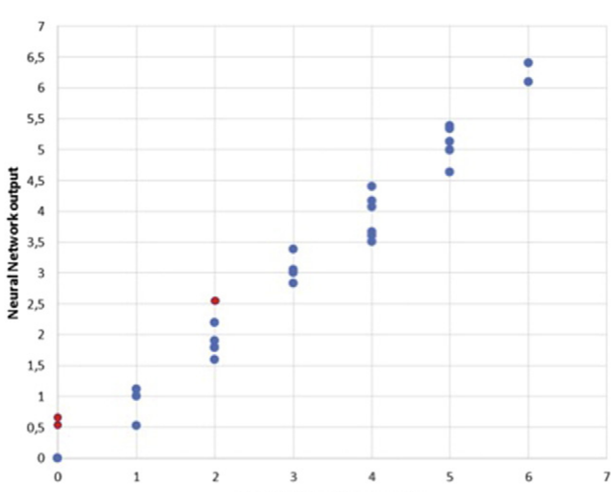

Fig. 2. Comparison between project manager and the neural network estimation.

as these projects present no specific or recurrent configuration of CSFs: it is possible to conclude that the degree of accuracy of the decision support system is about 90%. The top management of the EPC contractor considered acceptable the number of wrong answers and the marginal the specific errors, accepting the results and adopting the system in early project success' assessment for evaluating inclusion in project portfolio. Once accepted this level of accuracy, the model is able to assess any project maintaining the architecture and the set of parameters.

5. Discussion and conclusions

The results of the research have important implications, both academic and managerial.

5.1. Research implications

After more than 20 years, the debate around critical success factors is still ongoing. Many researches, as for the first part on the paper, recognize their role in determining project success, but two critical issues are still in discussion. First, a common view about a reference model to apply to any type of project or industry is missing due to the different opinions on the significance of the CSFs. In particular, modern authors prefer more to design new frameworks, specific to their researches, than to adjust or support already tested and validated model. This creates a wide range of alternative to project managers but, at the same time, limits their capacity of understanding differences and identifying practical solutions. Second, a major characteristic of the CSFs is evident: they all state an outcome with foggy advice, such as "improve the relationship with your customer" or "obtain management support" (Zwikael and Globerson, 2006). The main criticality is that CSFs are not specific enough to support decision-making but may be just useful to improve project manager expertise. For example, even if "planning" is one of the most cited factors, its role during the implementation and the relation with the success of a project is not always clear.

A main question remains unsolved: how many resources have to be dedicated to identify and improve CSFs to ensure success, balancing the project portfolio and facing the correct level of risk in a dynamic environment?

This paper gave an innovative way to answer this problem. The design, validation and test of an artificial neural network model automatically relates CSFs to project success, according to the company experience. The model acts as decision support systems for the project selection process highlighting early signs of failure by considering the alignment of a project with corporate strategy and the riskiness of the project acceptance.

Finally, it is important to underline that the purpose of the study was to define a systematic methodology for early project assessment that could fit any framework of CSFs in literature. The results, in fact, are not a general confirmation of the validity of the project implementation profile, but only an indication that PIP fits the requirement of the specific EPC contractor as its CSFs' profile presents an effective correlation to project success, with an accepted degree of accuracy. The ANN model correctly extracted the implicit knowledge of the experts, without involving them in a complex process of judgment of impacts of factors, criteria or KPIs but only interpreting their perceptions on input and results. This methodology can apply to any environment, industry or company, applying the process to any general or dedicated framework of CSFs, testing if it is able to reflect the real managerial levers that control success or failure. Project managers could have indications on what to improve or accept, determining in an early evaluation (or continuously, during the project) which resources have to be allocated and where.

5.2. Managerial implications

Fig. 3 shows how a company can use the ANN assessment model in the project selection and the two "learning processes" of the model. The enterprise environmental factors and knowledge gained in previous projects, the organizational process assets, are crucial for identifying and preparing accurate and viable tenders starting from the project statement of work (SOW) and, subsequently, the business case. However, managers can use the previous experience to define or to re-define project CFSs.

In this first learning process, portfolio managers can express their judgment for a new project on the same CSFs' questionnaire to provide the vector of inputs while the neural network gives as output an estimated degree of success, based on previous knowledge stored in its nodes and on the information coming from the business case. If the response is adequate, project fits the company's project portfolio strategy in terms of relevance and of a "standard" level of risk. If the response is not adequate (low degree of success), managers can modify the project characteristics related to the CSFs or accept and higher level of risk. The model supports the simulation of interventions, testing one or more CSFs, in both positive and negative way, to evaluate different project scenarios and the impact of improvements before their implementation.

If the company's management approves the project and it advances to initiating phase, the project sponsor and/or the project manager will prepare the project charter, which serve as the basis for project evaluation. Key performance indicators, basing on the same project CSFs, will evaluate project performances, according to the project portfolio strategy. The final version of business case containing the project assessment, traditionally used to increase company's project knowledge base, will allow the model update (second learning process). Increasing the number of projects in assessment and the feedbacks on the performances enables the re-engineering of the model. Modifying the architecture or replicating the learning process on a bigger amount of data, the capability of classification improves, reducing the number of errors and increasing the level of accuracy.

5.3. Limitations and opportunities for future research

The main limitation of the research is that the empirical analysis relates on a sample of projects owing to the project portfolio of a unique EPC contractor. Although the sample size was significant in terms of number of projects from different areas of the EPC portfolio (150) and experts involved, its dimension cannot justify the broad generalization of the results. Therefore, our future efforts will be oriented toward obtaining an extension of the sample to increase the generalizability of the results or to confirm the application only to specific contexts.

Moreover, future developments will follow other two paths. First, the research will continue designing, implementing and testing different ANN model (e.g., for classification of integer values) on other frameworks of CSFs. Second, the research will improve its methodology by directly linking CSFs with KPIs and going over the experts/project managers' interpretation of project business case in order to increase the capability of risk analysis and shifting from a classification approach to a regression type. To this extent, it is necessary to develop an analytical mathematical structure, designing dedicated filters to treat results not consistent with the judgments of the experts (and vice versa), avoiding wrong correlations among CSFs and the degree of success.

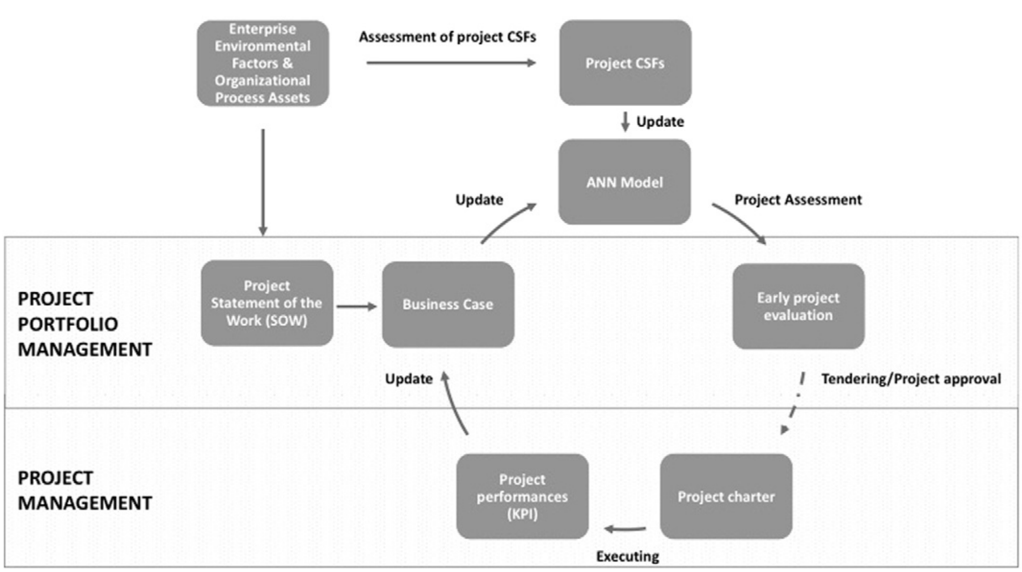

Fig. 3. Project and portfolio management using the ANN model.

Appendix 1. Questionnaire for the CSF and project success assessment

CSF	Description	Judgment						
		<<< Not at all						Totally >>>
Project mission	The project has a clear definition of goals and general directions	0	1	2	3	4	5	6
Top management support	The necessary resources and responsibilities to drive project success are provided by the top management	0	1	2	3	4	5	6
Project schedule/plan	Activities of project implementation are detailed, clear and the schedule provides a reasonable plan	0	1	2	3	4	5	6
Client consultation	All parties and stakeholders are regularly consulted and their impact and expectations are considered	0	1	2	3	4	5	6
Personnel	The personnel of the project has appropriate levels of experience and expertise	0	1	2	3	4	5	6
Technical tasks	Presence of the required technology and of specific expertise to accomplish technical tasks	0	1	2	3	4	5	6
Client acceptance	The project is supported and sponsored by the client and stakeholders	0	1	2	3	4	5	6
Monitoring and feedback	Each stage of the implementation is controlled, considering information, progresses and deliverables	0	1	2	3	4	5	6
Communication	All the key actors are part of an appropriate network of communication for all the required data and information	0	1	2	3	4	5	6
Troubleshooting	Unexpected crises and deviations from plans are managed with capacity and ability	0	1	2	3	4	5	6

Assessment of CSFs.

	Definition	Degree of success						
		<<< Not at all						Totally >>>
Success	The project accomplished its targets of schedule, cost, quality and stakeholders satisfaction	0	1	2	3	4	5	6

Assessment of project success.

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