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Shipbuilding Supply Chain Framework and Digital Transformation: A Project Portfolios Risk Evaluation

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Abstract

Program portfolio managers in digital transformation programs have a need for knowledge that can guide decisions related to the alignment of program investments with the sustainability and strategic objectives of the organization. The purpose of this research is to illustrate the utility of a framework capable of clarifying the cost-benefit tradeoffs stemming from assessing digitalization program investment risks in the military shipbuilding sector. Our approach uses Artificial Neural Network to quantify benefits and risks per project while employing scenario analysis to quantify the effects of operational constraints. A Monte Carlo model is used to generate data samples that support the execution of the Neural Network. This enables the use of Portfolio Management Theory principles to organize and estimate measures of performance of the digitalization project portfolio. We demonstrate the utility of the framework by means of a theoretical case study presenting several digitalization project investment scenarios. We conclude that the framework makes a contribution and call for additional work to extend this framework to formalize the portfolio assessment activity while including acceptable risk ranges that constrain the final fractions of budget allocations.

Keywords: Project Management; Portfolio Management; Neural Networks; Cost Analysis; Training

1. Introduction

Operational and financial pressures in tandem with the increasing demands of customers have intensified stress for competent operations. The evolution of industrial systems operating within intricate competitive environments has placed substantial constraints on the configuration and performance of agile, efficient, and flexible business and institutional operations. Successful firms recognize that the continual enhancement of existing operations is essential to gaining and maintaining a competitive edge. These organizations engage in strategic management initiatives by employing effective project, program, and portfolio management techniques to improve their operational efficiency and responsiveness. However, while 88 percent of executives assert that strategy implementation is critical to their firms, only 61 percent recognize that their organizations frequently have struggled in bridging the gap between strategic goals and their everyday operation [1]. Furthermore, in the digital transformation era, a smaller fraction of executives confesses to truly engaging in digitalization projects as they might be considered a risky endeavor [2]. This gap suggests a lack of understanding that projects and programs are catalysts in strategic change [3] as they represent versatile structures that enable the realization of distinctive and innovative organizational offerings [4].

Aligning digitalization projects or programs with strategic objectives has the greatest potential to add value to an organization [5,6]. Although, average organizations report that three of five projects and programs are not aligned to

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strategy, those that are aligned to an organization's strategy are successfully completed (71%) more frequently than projects that are misaligned (48%) [3]. Problems caused by misalignment include: confusion; waste of time, money and opportunity; diminished productivity; de-motivation of individuals and teams; internal conflicts and power struggles and ultimately project failure [7]. In a shipyard, resources that have been initially allocated to specific shipbuilding projects may be pulled away to temporarily serve other projects (e.g., maintenance, emergency repairs) [8]. For example, in the US shipbuilding industry, important delays caused by a high number of interactions from liberal concurrent engineering policies has led to an 18 year maintenance backlog [8,9].

The alignment of projects and programs to strategic goals requires stakeholders to develop a consistent means of identifying, prioritizing, and defining metrics/outcomes and their aligned outputs [10]. In this alignment process, a program or project may be seen as a line of organized activities that is intended to advance a product, practice, procedure, or service towards meeting a need within the government or marketplace, contribute to some type of benefits (e.g., readiness, revenue), and contribute to the sustainability of the organization. In an intensive capital industry sector such as the military shipbuilding, this organizational configuration by project/program makes sense given the large number of non-repetitive and complex activities and tasks associated to it [11]. Firms and institutions that use this managerial perspective, generally group projects and programs that have the potential to advance a common organizational goal into portfolios that require continuous control and evaluation [12]. Thus, an organization may have several concurrent programs and each program may encompass one or more projects or programs that address the development of a product or capability that is understood to contribute to longer-term institutional sustainability.

The shipbuilding industry that is largely characterized by using a project-based approach to manufacture ships, submarines, and engage in ship repair and overhaul [9] would largely benefit from the implementation of novel technological and operational means that seek to enhance its questionable performance. Digital transformation programs emerge as a means that seek to convert slow-, outdated-, and ill-defined operations into data-driven agile and at the same time lean operations based on the extensive use of Industry 4.0 technology [13–15].

Mostly organized with a project-based configuration as well, resources are temporarily assigned to carry on digital transformation assignments that seek to increase industrial capabilities and become more efficient and largely flexible while increasing process and product integrity. These digitally-oriented initiatives are mostly based on data sharing and processing resulting in a paradigm shift in the way that organizations, such as shipbuilding, engage in decision-making processes toward a data-driven approach [16]. Thus, a set of digital transformation projects may be further represented within a larger project or program portfolio, supervised by a digital transformation portfolio manager. The management of either a portfolio containing several projects, or a specific program encompassing a set of projects, entails an understanding of the mission of the organization and decision-making that will realize benefits that are of strategic importance [17,18]. Since the pursuit of programs and the continuation of projects require expenditure of finite organizational resources, the identification of digitalization projects that are most aligned with strategic priorities is critical for the success of the organization [19,20].

Digital portfolio and project managers must necessarily determine the variations in the amount of support among the projects in an effort to maximize the utility of the mix in advancing the organization towards its digital transformation strategic goals. This prioritization process frequently involves evaluating the relative risks, benefits, and costs among the projects [21]. Maximizing benefit-cost relationships while minimizing risks are common tasks performed in the planning and controlling stages of project portfolio management.

Project portfolio managers seek to select or support projects within the project's portfolio that traditionally balance benefits (mean) and risks (variance). Risk, however, may be measured using other forms, e.g., conditional value at risk (CVaR), Tail value at risk (TVaR), also known as tail conditional expectation (TCE), or conditional tail expectation (CTE). In this paper, the minimum variance opportunity set indicates combinations of risks and benefits that yield the minimum variance for a particular benefit. Hence, an efficient digitalization project portfolio frontier may identify investments in a set of projects where it is not possible to obtain less risky project combinations relative a desired benefit level.

The following sections of this paper presents a background section that positions this work within the industrial context, presents an innovative digital shipbuilding supply chain framework; outlines a neural network analysis to examine digital projects using a digital shipbuilding supply chain perspective; presents a brief description of stochastic portfolio analysis; and introduces a framework integrating these approaches. This is followed by a brief analysis of a case study in the development research industry illustrating the application of the framework. The results stemming from the analysis of theoretical scenarios are presented and discussed. We then revisit and summarize the contributions of this work.

2. The Shipbuilding and Shipyard Supply Chain Management Context

In general, supply chain refers to all parties involved, directly or indirectly in fulfilling customer requests [22]. In the shipbuilding supply chain management context, activities upstream include procuring material and components from numerous, complex suppliers to managing the deactivation of ships and submarines downstream once they have reached their end-of-life. The basic elements of a shipbuilding supply chain management framework that seek to guide an understanding of a value chain of these processes is presented in Figure 1.

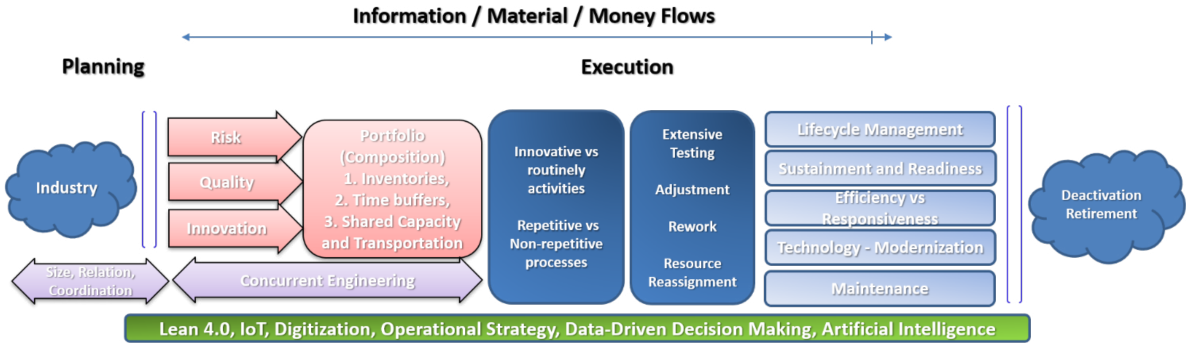

Fig. 1. Shipbuilding Supply Chain Framework

3. Digital Project Portfolio: Balancing Risk and Returns

A balance among risks and returns is required for each combination of projects that compose the portfolio frontier. In an industry sector such as military shipbuilding, monitoring risk is an important endeavour as delays, labour availability, and large expenditures may drastically affect the readiness and sustainment of the fleet. The selection of these opportunity sets may be determined by the indifference curve map that describes the project strategic preferences and policies. Accordingly, an optimal risk management portfolio maximizes the average benefit while minimizing variance. The risk associated with a project portfolio containing multiple projects may be different from the risk associated with an individual project. The different associated risks and potential relationships among projects make project portfolio management a complex subject.

The risk-benefit relationships associated with digital transformation projects in a shipbuilding project-based institution further increases the complexity as different types of risk exert compounding effects on the already multifaceted nature of the shipbuilding process. A proficient mechanism to assess this compounding effect is important for assessing and prioritizing digital transformation programs.

We assert that Artificial Neural Network (ANN) and Monte Carlo simulation may be combined to offer a capable framework that assists digital transformation portfolio managers in performing an effective portfolio evaluation. The objective of this research is to describe this framework and its capacity to clarify the cost-benefit and risk trade-offs stemming from modifying project investments. The framework uses a hybrid between ANN and Monte Carlo capabilities to determine the benefits and risks per digitalization project considering the relationships that exist among multiple relevant projects' attributes, e.g., time, control, and information. This Monte Carlo simulation approach generates complementary samples that assist in training the network model to increase its accuracy.

4. Digital Transformation Risk Evaluation Framework

A framework based on ANN to analyse project portfolios is presented in this section and illustrated in Figure 2. The approach uses ANN to determine the benefits and risk associated with projects within a portfolio of projects. A scenario analysis is performed to gain knowledge regarding impacts of new constraints per project. This knowledge is used to determine portfolio management measures of performance that include overall benefits and variances. In addition, project portfolio optimization can be potentially used to minimize the overall portfolio variance while maintaining risk-aversion and budget-constrained range restrictions. This framework adequately captures the complexities associated with determining risks and returns, relevant cost and benefit considerations guided by a proven assignment method. ANN assists by providing the critical elements that guide the resource assignment process. This framework consists of three stages summarized as follows.

4.1. Quantifying risks and benefits of digital transformation projects

Risk in projects is commonly defined in terms of exposure to explicit factors that present a threat to attaining the expected results. For example, the probability-weighted impact of an event on a project usually defines risk in software development projects [23]. The notion of risk, usually measured in dollars or time, may be characterized by $R = P \times I$, where R represents the risk exposure that is related to an explicit risk issue while P is the probability the adverse event will be realized, and I is the effect of the loss if the undesired event materializes [24]. Often digital transformation development risks are managed by lists which are ranked by subjective qualitative measures resulting in excessive expenditure of risk management resources. Risk identification is the most critical step in risk management, yet often is poorly done [25]. As fundamental aspects of digitalization projects resemble those factors in software and hardware development, the uncertainties considered in this paper are guided by [26]. These uncertainties include time uncertainty, which reflects uncertainties about the occurrence of expected and unexpected events and the ability to react to them; control uncertainty that concerns with inadequate authority to make or influence decisions or inconsistency on processes; and information uncertainty, which concerns with inadequate or inaccurate information on which to base decisions. These authors also suggest an extensive list of potential project development risk concerns that includes but is not limited to creeping user requirements, large size and complexity of projects, complex applications, unnecessary features, and lack of user support.

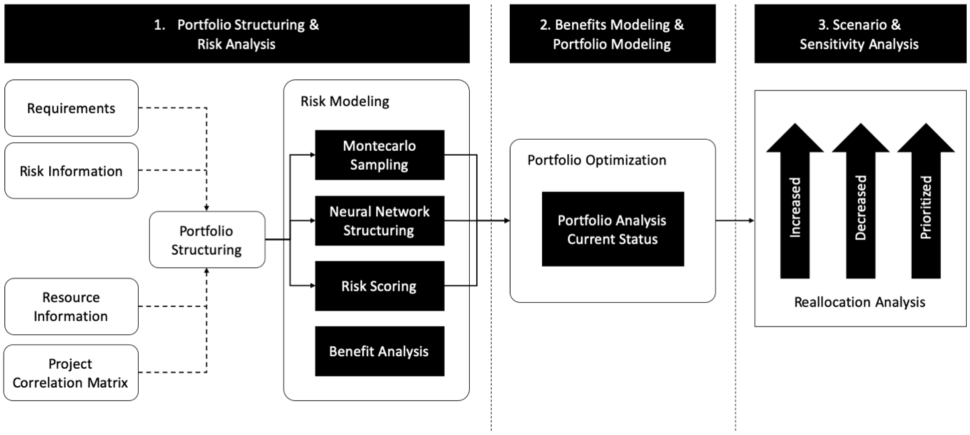

Fig. 2. Digital Transformation Risk Evaluation Framework

Project portfolio evaluations require reasonable estimations of the risks and associated benefits per project. The complex and stochastic nature of project risks makes the analysis of investment choices intended to mitigate risks, a candidate for ANN analysis. ANN models have been recognized in the IT development context as competent tools to reasonably estimate these values accurately [27].

ANN models employ the concept of hidden layers which are composed of a number of neurons (hidden neurons). These models use mathematical functions to map inputs to outputs and may be conceived as a massively parallel adaptive network of simple nonlinear computing neurons, which are intended to characterize and mimic some of the functionality of the human nervous system in an effort to partially capture some of its computational strengths [28]. ANN can be described as a complex nonlinear characterization where the task of variable transformation, composite variable transformation, and model estimation are done simultaneously in such a way that a specified error function is minimized [29]. An appropriate number of hidden units depend on a relationship between the number of input and output units, the number of training cases, the type of hidden unit activation, and the training algorithm [30].

As a rule of thumb, it is well known that 30 observations are required in the input layer per neuron in the hidden layer. The ANN model cycles through an iterative process until a termination criterion is reached.

In the studied context, the response model may reflect the risk related to the likelihood of the occurrence of undesirable events. Thus, an overall project risk factor that relates individual risk elements per project can be defined as a target output. The ANN model obtained with historical data (supervised training) is then executed with new information about the assessed project portfolio, and thus the overall risk per project can be obtained (scoring process).

4.2. Sampling Enhancement via Monte Carlo

Empirically generated continuous or discrete probability distribution per risk component can be elicited from historical data, subject matter expert (SME) information, or a combination of both. These probability distributions per project risk level can be used to generate samples through a Monte Carlo simulation, and thus, to train the data that is used to calculate overall risk to projects. The historical data reflects a set composed of individual project risk factors and overall risk scores per project information. Additional Monte Carlo samples can be used to extend the historical and SME input data set to an acceptable number of observations to improve the accuracy of the ANN analysis. In this machine learning process, the sample data is partitioned into three major groups that include: learning (40%), training (30%), and testing (30%). The Levenberg-Marquardt optimization technique (see [31] for details) is used to train the data.

4.3. Neural Network Scoring

The knowledge created during the machine learning training and testing process may be described as the behavioral pattern of the effects resulting from different factor risk arrangements. Given a selection criterion, such as minimizing a set of error functions, the neural network model is generated. A second data source that corresponds to the risk scores of the assessed projects is obtained by applying the neural network model to calculate the overall risk per project as a target layer. To ensure the best neural network model is obtained for computing overall risk per project, different types of neural architecture can be used to train the data. However, workers are required to carefully assess these opportunities as each one might contain unacceptable risk levels (e.g., additional cyber risks) that can jeopardize the operational integrity.

5. Case Study

A Research and Development (R&D) institution that investigates and develops digital solutions in the military domains is engaged in three types of digitalization development programs categorized by three risk levels (low, medium, and high) with equal possibility as exhibited in Table 1.

Table 1. Risk Factor Probability per Project Risk Level

		Low Risk Level					**Medium Risk Level**					**High Risk Level**				
		1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Creeping user (CR) requirements	Probability	.50	.25	.15	.06	.04	.10	.25	.40	.10	.15	.10	.15	.20	.35	.20
	CR Risk	.10	.30	.45	.50	.60	.20	.30	.45	.50	.70	.30	.35	.45	.55	.60
Large and Complex Projects (LCP)	Probability	.50	.20	.15	.10	.05	.10	.30	.35	.20	.05	.01	.05	.34	.40	.20
	LCP Risk	.05	.30	.40	.50	.60	.20	.30	.40	.50	.60	.30	.20	.35	.50	.60
Delay (D)	Probability	.65	.15	.10	0.06	0.04	.05	.30	.40	.20	.05	.05	.10	.25	.40	.20
	D Risk	.10	.25	.40	0.45	0.5	.15	.25	.40	.55	.60	.30	.30	.40	.65	.70
Control (CON)	Probability	.65	.15	.10	0.07	0.03	.05	.40	.35	.15	.05	.10	.20	.20	.30	.20
	CON Risk	.15	.25	.35	0.50	0.60	.20	.25	.35	.50	.60	.10	.25	.30	.50	.60
Complex User Requirements (CUR)	Probability	.65	.25	.05	0.04	0.01	.05	.30	.35	.25	.05	.10	.20	.25	.30	.15
	CUR Risk	.10	.30	.40	0.60	0.80	.20	.30	.40	.60	.80	.30	.35	.40	.60	.80
Unnecessary Features (UF)	Probability	.70	.15	.08	0.05	0.02	.10	.25	.35	.25	.05	.05	.15	.20	.50	.10
	UF Risk	.05	.10	.15	0.20	0.80	.05	.10	.15	.20	.80	.30	.10	.15	.20	.80
Lack of User Support (LUS)	Probability	.50	.20	.15	0.10	0.05	.10	.30	.35	.20	.05	.01	.09	.20	.45	.25
	LUS Risk	.10	.40	.50	0.60	0.90	.30	.40	.50	.60	.90	.30	.40	.50	.60	.90

Unlike most project studies that consider risk probabilities as a continuous distribution (e.g., beta or normal distributions), in this paper, we consider an empirically discrete modeled distribution for characterizing these probabilities. Thus, each individual risk probability is partitioned into five sub-levels (1-5). Each level considers both the probability of occurrence and associated risk degree represented nominally and measured from 0 to 1. For each factor, the probability mass function adds up to 1. The risk factors considered in these projects include: 1. Creeping user requirements, 2. Large and project complexity, 3. Application complexity, 4. Unnecessary features, and 5. Lack of user support [26]. In addition, the manager ponders uncertainties within three additional dimensions that include 60% in time uncertainty, 10% in control uncertainty, and 30% in information uncertainty. Notice that as explained before, risk value represents a convoluted measure that characterizes the probability that a project will fail to meet its objectives.

Table 2 presents the financial and individual risk factors for ten ongoing projects A through J which requires evaluation. The costs of each project as well as its cost as a share of the entire portfolio (estimated by the portfolio manager to be $124.7 million) are presented in the second and third columns, while individual project risk information is presented in columns four to eleven.

5.1. Determine benefits and risks

The portfolio manager computes the overall risk associated with each project in the portfolio during a risk analysis phase. This is done by assessing the importance, or weight, of the individual risk factor for each project. ANN is used to generate a model that can be used to relate individual risk factors and produce an overall risk score for each individual project. A simple ANN with 2 hidden layers with 8 neurons each and a single output is used to produce these risk scores (8-8-1) [32]. Eight was selected as this corresponds to each the five project risks and three uncertainties. SAS Miner 7.1 is employed to configure, execute, and compare the ANN models.

The risk probability distribution presented in Table 1 per project risk level is used to generate samples through a Monte Carlo simulation, and thus, simulate the training data that is used to evaluate overall project risks of the projects presented in Table 2. Notice that some analysists and researchers might use the Monte Carlo technique to generate samples and then calculate averages in determining the overall project risks. However, in this paper the Monte Carlo simulation is limited only to determine samples that will feed the neural network model as other authors has considered. The machine learning approach used in this paper seeks to employ ANN as a better approximation of the real risk behaviour exhibited by the portfolio.

The historical data is based on a (disguised) data set comprising individual project risk factors and overall risk scores per project for 30 projects. More specifically, the Monte Carlo samples obtained using the probability distribution presented in Table 2 are used to extend the historical input data set from 30 project observations to 300 observations. The sample data is further partitioned into three major groups that include: learning (40%), training (30%), and testing (30%).

As previously discusses, the knowledge created during the training and testing process are assessed using 1. classical multilayer perceptron (MLP), 2. ordinary radial basis function with equal widths (ORBFEQ), 3. ordinary radial basis function with unequal widths (ORBFUN), 4. normalized radial basis with equal heights (NRBFEH), 5. normalized radial basis with equal volumes (NRBFEV), 6. normalized radial basis with equal widths (NRBFEW), 7. normalized radial basis with equal widths and heights (NRBFEQ), 8. normalized radial basis with unequal widths and heights (NRBFUN). As mentioned, the Average Square Error from the validating stage is used as the reference for model selection. Table 3 shows the statistical results of this comparison that suggests the normalized radial basis with equal widths and heights (NRBFEQ) architecture outperforms the alternative assessed ANN architectures. Thus, the NRBFEQ architecture is employed to determine the risk data. Once the ANN model using the NRBFEQ architecture is selected to execute the ANN model, the target variable which is overall risk per project is obtained as presented below in Table 4.

Table 2. Current Project Investment and Risk Level per Risk Factor

Project	Cost ($ millions)	CR	LCP	D	CON	CUR	UF	LUS	Information
A	15.0	.20	.30	.25	.35	.20	.10	.30	.22
B	20.1	.30	.40	.15	.20	.30	.10	.45	.31
C	2.30	.45	.50	.25	.35	.30	.20	.45	.38
D	14.0	.10	.05	.10	.25	.50	.10	.50	.25
E	9.0	.55	.50	.70	.30	.60	.30	.55	.50
F	12.3	.50	.05	.10	.15	.05	.05	.10	.15
G	7.0	.10	.05	.10	.15	.05	.15	.10	.09
H	11.0	.10	.05	.25	.15	.05	.10	.10	.08
I	16.0	.30	.30	.15	.35	.30	.15	.50	.31
J	18.0	.30	.50	.10	.15	.60	.10	.10	.32

6. Summary and Managerial Implications

Organizations may benefit from applying investment allocation approaches traditionally employed in financial markets analyses. A framework that combines the principles of Artificial Neural Network and Monte Carlo Simulation to analyze project portfolios may assist portfolio managers in their resource allocation activities. Our approach uses ANN to quantify benefits and risks per project while employing scenario analysis to quantify the effects of constraints per project. Monte Carlo simulation is used to obtain sample data that facilitates the execution of the neural network. The results from these simulations could be used to enable the use of Portfolio Management Theory principles to organize and estimate measures of performance and the utilization of nonlinear programming tools to minimize the overall portfolio variance while maintaining risk-aversion and budget-constrained parameters.

The digital transformation project risk evaluation framework offered follows a logical approach. First, it uses ANN to capture individual risk factors and quantify the overall risk of each project. Cost-benefit analysis is then employed to provide the foundation for performing a scenario analysis. An examination of the effects of selected scenarios can subsequently be performed. This examination is required to understand variations in the potential resources assigned per digitalization projects. Afterward, correlation and covariance matrices can be determined. These correlations may represent elicited perceptions that indicate how individual projects are related. The covariance matrix can relate the project correlations, the returns, and the variability or risk required. The overall digitalization project portfolio returns, and the portfolio variance can be then determined. Returns and variances can be subsequently recalculated given additional constraints. Thus, portfolio managers are able to optimize the distribution of available resources while preserving portfolio integrity.

It is important for training analysts and managers to perform risk evaluations as the organization moves through digital transformation process while achieving strategic goals. In particular, organizations engaged in becoming data-driven managed and operated might consistently reveal vast opportunities to digitalize their operations. However, workers are required to carefully assess these opportunities as each one might contain unacceptable risk levels (e.g., additional cyber risks) that can jeopardize the operational integrity. Digital project portfolio analysts and managers are required to learn the type of risks that their portfolio may contain. Likewise, they should be trained in the use of competent tools to elicit projects risks and determine desired risk thresholds for their firm. This enables the anticipation of actions and plans that makes the organization more resilient as vulnerability might increase if risks are not properly elicited. Training modules might include introduction to digital supply chain to provide an overview of the shipbuilding context and risk quantification methodologies as they apply to specific settings of the shipbuilding process.

Future research endeavours include extending this framework to consider calculating the overall portfolio performance, optimizing resource allocation, and determining acceptable risk ranges per project that constrain the final fractions of budget allocations as well as including the examination of portfolio actions that balance resource allocations considering risks and benefits. This might trigger project removal decisions for those projects whose acceptable risk ranges violate upper or lower boundaries.

Table 3. Neural Network Architectures: Statistical Evaluation (AIC: Akaike's Information Criterion; SBC: Schwarz's Bayesian Criterion; ASE: Average Squared Error; MAE: Maximum Absolute Error; RASE: Root Average Squared Error; SSE: Sum of Squared Errors; FPE: Final Prediction Error; MSE: Mean Squared Error; RFPE: Root Final Prediction Error; RMSE: Root Mean Squared Error; AEF: Average Error Function; EF: Error Function)

ANN Architecture	Valid: ASE	AIC	SBC	ASE	MAE	RASE	SSE	FPE	MSE	RFPE	RMSE	AEF	EF
NRBFEQ	3.33E-06	-1372.62	-1169.13	3.19E-06	.0093	.0018	.0004	1.310E-05	8.15E-06	.0036	.0029	3.19E-06	.0004
NRFEW	4.36E-06	-1366.40	-1140.61	2.94E-06	.0057	.0017	.0004	1.518E-05	9.05E-06	.0040	.0030	2.94E-06	.0004
MLP	5.25E-06	-1323.98	-1098.19	4.19E-06	.0095	.0020	.0005	2.157E-05	1.29E-05	.0047	.0036	4.19E-06	.0005
NRBFUN	1.09E-05	-1198.70	-953.40	1.06E-05	.0107	.0033	.0013	6.888E-05	3.97E-05	.0083	.0063	1.06E-05	.0013
ORBFUN	1.38E-05	-1217.82	-992.03	1.01E-05	.0102	.0032	.0012	5.227E-05	3.12E-05	.0072	.0056	1.01E-05	.0012
NRBFEV	2.48E-05	-1311.71	-1088.71	4.72E-06	.0063	.0022	.0006	2.379E-05	1.42E-05	.0049	.0038	4.72E-06	.0006
ORBFEQ	3.39E-05	-1212.57	-1006.30	1.19E-05	.0086	.0035	.0014	5.024E-05	3.11E-05	.0071	.0056	1.19E-05	.0014
NRBFEH	1.31E-04	-1511.94	-1288.94	8.89E-07	.0037	.0009	.0001	4.446E-06	2.67E-06	.0021	.0016	8.89E-07	0.001

Table 4. Neural Network Architectures: Statistical Evaluation

Project	Project Cost (millions)	Percent of Portfolio Cost	Scored Risk
A	15.00	.1203	.25
B	20.10	.1612	.20
C	2.30	.0184	.30
D	14.00	.1123	.16
E	9.00	.0722	.60
F	12.30	.0986	.12
G	7.00	.0561	.10
H	11.0	.0882	.19
I	16.0	.1283	.22
J	18.0	.1443	.17

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