

A new dynamic two-stage mathematical programming model under uncertainty for project evaluation and selection

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ABSTRACT

Project portfolio evaluation and selection is a complex task involving an exhaustive assessment of competing projects with interdependencies and synergies based on multiple and often conflicting criteria. The additional factor of uncertainty further complicates this complex task. This study proposes a two-stage hybrid multi-criteria decision making and mixed-integer linear programming for evaluating and selecting projects with interdependencies under uncertainty. In Stage I, we use the fuzzy technique for order of preference by similarity to ideal solution (TOPSIS) to evaluate the alternative projects under uncertainty. In Stage II, we formulate a bi-objective mixed-integer linear program to optimize profit and qualitative values for each portfolio by considering project synergies, human resources capabilities, and employee training opportunities under different scenarios. The proposed model produces portfolios with quantitative and qualitative values for each scenario under consideration. We demonstrate and validate the applicability and efficacy of the proposed approach through a real-world case study in the cybersecurity industry.

1. Introduction

Project portfolio evaluation and selection is a complex task that involves the use of qualitative and quantitative factors for choosing project portfolios with the most positive organizational impact. The additional elements of project interdependencies and synergies, along with environmental uncertainties, add to this already complex task. The purpose of information technology (IT) portfolio management is to ensure IT projects are selected according to the overall organizational strategies and the successful execution of those strategies. Despite the best efforts of management to improve project portfolio evaluation and selection, an unacceptable number of IT projects continue to miss their target.

1.1. Project and portfolio selection

Zanakis, Mandakovic, Gupta, Sahay, and Hong (1995) divided project evaluation and selection methods into three groups of

descriptive methods (e.g., checklist and un-numerical ranking, scoring models, Delphi method, AHP pairwise comparison, utility theory, fuzzy set theory), decision analysis (e.g., decision tree, risk analysis, linear regression, and correlation analysis), and data envelopment analysis (DEA). Chu, Hsu, and Fehling (1996) classified the project selection methods into two major categories of compensatory models and non-compensatory methods. The compensatory methods embrace such models as cost-benefit analysis and analytical hierarchy process (AHP), and the non-compensatory models include two major types of multi-criteria decision making (MCDM) and ranking models. Cooper, Edgett, and Kleinschmidt (2001) categorized project selection methods into financial methods (e.g., net present value and return on investment), methods based on business strategies, bubble diagrams or portfolio maps, scoring models, and other models, which include multi-criteria models.

Unsurprisingly, the field of project portfolio selection has been active, considering the importance of project evaluation and selection.

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An early study, carried out by Sharpe (1967), focused on quantitative methods where a linear programming modeling approach was applied to project selection problems. Several studies have modeled the project selection problem using mathematical programming models such as 0–1 programs (Aaker & Tyebjee, 1978; Kyparisis, Gupta, & Ip, 1996; Ghorbani & Rabbani, 2009; Carazo et al., 2010; Hassanzadeh, Nemati, & Sun, 2014), mixed-integer programs (Beaujon et al., 2001; Naderi, 2013; Li, Wang, Yan, & Zhao, 2019; Li, Huang, Fang, & Zhang, 2020), and quadratic programs (Seydhosseini et al., 2016). Except for Beaujon et al. (2001), who used an MS Excel spreadsheet, and Hassanzadeh et al. (2014), who used an interactive and robust weighted Tchebycheff procedure, all of the studies mentioned above, used heuristic or meta-heuristic methods to solve their models. Santhanam and Kyparisis (1995), Santhanam and Kyparisis (1996), Badri, Davis, and Davis (2001), Ghahtarani and Najafi (2013), and Bagheri (2019) used goal programming methods to model the portfolio selection problem. Data envelopment analysis (DEA) was used in project selection problems by Oral, Kettani, and Lang (1991), Oral, Kettani, and Çınar (2001), Dey (2006), Chang and Lee (2012), and Chen, Li, Zhang, and Mehlatat (2020).

In some studies, project selection is accomplished in two or more stages. Golabi, Kirkwood, and Sicherman (1981), Mavrotas, Diakoulaki, and Capros (2003), Mavrotas, Diakoulaki, and Kourentzis (2008), and Tavana, Khosrojerdi, Mina, and Rahman (2019) used a two-step approach for project selection. In these studies, the first stage involved a multi-criteria assessment of projects using MCDM methods. In the second stage, the obtained information is used as input in the objective function of a linear programming model, which is then solved. Henriksen and Traynor (1999) and Lee and Kim (2001) utilized multi-criteria scoring methods based on MCDM techniques. Eilat, Golany, and Shtub (2006) developed a model based on DEA and balanced scorecard (BSC), which first eliminated projects based on the three factors (effectiveness, risk, and balance) and then analyzed the strategic framework of each project using BSC. Halouani, Chabchoub, and Martel (2009) used the MCDM method of PROMETHEE-MD-2 T. Carazo (2015) referred to the evolution of key dimensions and the advantages and disadvantages of different methods in project selection. To help decision-makers invest in scarce resources, the author developed a highly flexible universal mathematical model. Benaija and Kjiri (2015) proposed a three-step method for project selection. In the first step, projects are classified based on three criteria: maximizing value, minimizing risk, and strategic alignment. In the second step, according to the classification of projects obtained from the previous step, replacement portfolios are created by managers. The final step identifies the alternative projects (along with the interaction among them) to be included in the portfolio to achieve organization objectives. A practical approach based on fuzzy TOPSIS was developed for sustainable project portfolio selection by Ma, Harstvedt, Jaradat, and Smith (2020). The efficiency of the proposed approach was validated through implementation in a large-scale manufacturing company.

Several studies have considered the uncertainties in project selection problems. Bhattacharyya, Kumar, and Kar (2011), Khalili-Damghani et al. (2012), Khalili-Damghani and Sadi-Nezhad (2013), and Tavana, Khalili-Damghani, and Abtahi (2013) proposed various project and portfolio selection models with fuzzy mathematical programming. Perez and Gomez (2016) proposed a multi-objective nonlinear binary mathematical model for project portfolio selection and scheduling using fuzzy parameters. Guo, Wang, Li, Chen, and Cheng (2018) suggested a fuzzy bi-objective model for project portfolio selection by taking the balance between strategic contributions and financial returns into consideration. Zhang, Hipel, and Tan (2019) used fuzzy theory to formulate a nonlinear multi-objective mathematical model for portfolio selection under uncertainty. Dutra, Ribeiro, and de Carvalho (2014) used combined economic and probabilistic approaches to model uncertainty. Panadero, Doering, Kizys, Juan, and Fito (2018) analyzed a stochastic version of the project selection problem and solved it using a variable

neighborhood search heuristic integrated with Monte Carlo simulation. Li, Zhu, Sun, Aw, and Teo (2018) used uncertain variables in two single-objective optimization models, which are solved using a genetic algorithm combined with the penalty function method.

Alvarez-García and Fernández-Castro (2018) and Gomez et al. (2018) both incorporated project interactions into the project selection problems they studied. The former utilized fuzzy techniques, while the latter developed a strategy based on Ant Colony Optimization. Recently, studies have focused on project selection problems that consider uncertainty as well as project interactions and interdependencies. The majority of studies combine fuzzy techniques and mathematical programming to model their problems. These models are then solved using DEA (Ghapanchi, Tavana, Khakbaz, & Low, 2012), metaheuristics (Wu et al., 2019; Guo et al., 2018; Wu, Xu, Ke, Chen, & Sun, 2018), optimization software Lingo (Takami, Sheikh, & Sana, 2018), or a proposed resolution procedure (Pérez et al., 2018). Isikli, Yanik, Cevikcan, and Ustundag (2018) used a simulation-based integer programming model, which was solved using Crystal Ball version 7.2.1, while Jafarzadeh, Akbari, and Abedin (2018) combined fuzzy Quality Function Deployment with DEA.

1.2. Information technology portfolio management

Milis and Mercken (2004) stated, “There is a large consensus among academics and practitioners that information and communication technology investments should be carefully justified, measured and controlled.” The dynamics that exist between IT projects are such that the failure of one project could impact the portfolio. For example, Neumeier, Radszuwill, and Garizy (2018) show: (1) A predecessor project that fails to deliver the promised technical output may negatively impact dependent projects, or (2) A project may overuse shared resources, leading to a shortage of resources for the remaining projects in a portfolio.

Santhanam, Muralidhar, and Schniederjans (1989) designed a multi-objective model to model the selection of IS projects when contradictory or inexecutable goals are at play. Jiang and Klein (1999) examined the project selection criteria for different organizations with the help of IS experts, where their findings can be used to improve the methods of project selection.

Yap, Raman, and Leong (1992) presented the AHP and Simple Multi-Attribute Rating Technique (SMART) for the selection of IS projects in an empirical study and compared them with each other. The results showed that SMART outperforms AHP for problems with a large number of options and selection criteria.

Schniederjans and Santhanam (1993) proposed a nonlinear 0–1 programming model as a decision-making method for the selection of IS projects. The model was of importance in the use of multi-objective problems and limited resource modeling in decision-making on the selection of IS projects. Santhanam and Kyparisis (1996) formulated a nonlinear 0–1 programming model for IS project selection based on project interdependencies. Chen and Gorla (1998) provided managers with a fuzzy logic decision model to facilitate project selection based on the existing constraints. Chen (2002) converted expert opinions to trapezoidal fuzzy numbers and proposed a new algorithm based on the fuzzy measurement and fuzzy integral to solve the problem of IS project selection.

Sherer (2004) developed a model of the selection process of IT-based projects because the strategic perspective influences the project type, the resources allocated to IS, and the justification of investments in the domain of IT. Sorrentino (2004) used the model developed by Soh and Markus (1995) in the selection process of Italian governmental projects and for the overall assessment of the role of information and communication technology in modernizing the public sector and its application for the realization of e-government.

De Reyck et al. (2005) proved the existence of a correlation between project performance and IT portfolio management implementation. For

this purpose, they presented a three-stage scheme to implement project portfolio management.

Huang (2008) proposed an approach for the selection of an appropriate IS through the integration of entropy weighting method and TOPSIS method. Rosacker and Olson (2008) highlighted the importance of assessment methods of cost control and examined the selection of IT projects and their financial and qualitative evaluations to determine project success. Fasanghari and Roudsari (2008) designed a fuzzy integer linear program for the selection of information and communication technology projects so that indefinable or incomplete information can be used as input for the system.

A hybrid approach based on MCDM and multi-objective linear programming model were developed by Zandi and Tavana (2010) for selecting the best IT project with qualitative and quantitative features and competitive values. The authors implemented their integrated model to a problem faced by a textile factory in Philadelphia, USA. Bai and Zhan (2011) considered the IT project selection problem as an MCDM problem and, accordingly, they proposed a fuzzy analytic network process. Shakhsi-Niaei, Torabi, and Iranmanesh (2011) proposed a framework based on Monte Carlo simulation for project selection by considering the constraints of an IT case study. Pendharkar (2014) used dynamic programming for portfolios with independent projects and mixed-integer programming for portfolios with interdependent projects. Oztaysi (2015) used Interval Type-2 Fuzzy AHP for the problem of organizational IS project selection.

Shollo, Constantiou, and Kreiner (2015) studied how managers prioritize IT projects and found that managers used a toolbox that included the following tactics: supplementing, substituting, interpreting, and reframing. Mohagheghi, Mousavi, and Vahdani (2016) proposed an MCDM approach with interval-valued fuzzy sets for considering uncertainty in project portfolio selection. In addition to sustainability criteria, this proposed approach also includes practical criteria, which embrace non-beneficial advantages, strategic alignment, and project risks. The relationship between the three components of IT management, project management, and project performance was examined in Sirisomboonsuk, Gu, Cao, and Burns (2017) as they assessed project efficiencies. Tavana et al. (2019) proposed a hybrid approach based on a fuzzy AHP, fuzzy inference system, and mathematical programming for IT project portfolio selection. They used fuzzy AHP for determining the weight of criteria, fuzzy inference system for calculating the final score of projects, and mathematical modeling for selecting the portfolios.

The review of the literature shows that a large number of MCDM models have been developed for project portfolio evaluation and selection. Some of these models use qualitative criteria, and some use quantitative parameters and mathematical programming. While qualitative models focus on managerial intuition and subjective judgment, quantitative models use mathematical programming for optimization subject to a set of constraints or restrictions. It is often difficult to ignore qualitative judgments or quantitative solutions in real-world problems. The combination of these two perspectives brings the best of both worlds together by taking advantage of managerial intuition within a structured and mathematical framework. This comprehensive approach leads to the development of a practical strategic-operational approach. Hence, this study proposes a hybrid approach based on fuzzy TOPSIS and mathematical modeling. Fuzzy TOPSIS extends the applicability of conventional TOPSIS by considering ambiguous, uncertain, and fuzzy data in MCDM (Kannan, de Sousa Jabbour, & Jabbour, 2014). The status of each project is evaluated using a qualitative assessment. The output of the qualitative assessment is used in a bi-objective optimization model with tactical and operational objectives. These two objective sets bridge the gap between strategic management and project management by choosing an optimal project portfolio based on qualitative and quantitative criteria.

In contrast to stand-alone projects, there is synergy in project portfolios because of the interdependencies and interactions among the projects (Cho & Shaw, 2013). For this reason, the structure of the models proposed for project portfolio selection is different from stand-alone projects. To address this difficulty, we propose a new two-stage approach that considers the concept of synergy among the projects. Moreover, fuzzy logic is used to represent uncertainties and ambiguities inherent in project portfolio evaluation and selection. Archer and Ghasemzadeh (1999) argue there is no consensus on the most effective methodology for portfolio selection. They suggest the methodology chosen must be consistent with the needs of the project class(es) under consideration. Furthermore, Lopes and Almeida (2013) state that methodologies used for developing portfolios for one particular class of projects may not be the best for other classes, and that the choice of methodology depends greatly on the decision context.

The remainder of this paper is organized as follows: The problem statement and the proposed model are defined in the next section. Section 3 is devoted to a case study and its results. Finally, the conclusions are drawn in Section 4.

2. Problem statement and our proposed model

A multi-level approach is needed for portfolio selection because isolating the interrelationships among the IT projects is often a difficult task. For this purpose, we divided the project selection problem into two levels: the market study level and the operational level. Project feasibility is first assessed using a market study. The result of the market study determines the project's chances of success. If the results are satisfactory, the project will move into the operational level.

One of the most important factors in project selection is competition. For example, consider two different companies, A and B, in direct competition working on similar projects. Company A is in the midst of conducting a market study for its product. At the same time, Company B, who started working on their project earlier, has completed its market study and moved into the operational level building and testing their product. It is risky for Company A to consider a project at the market study level when their competition, Company B, is already considering a similar project at the operational level. We consider the competition during the market study and operational levels in the portfolio evaluation and selection process.

Another important factor is the synergies between projects since projects have positive or negative impacts on each other in terms of costs and benefits. Cho and Shaw (2009) present the following example as positive synergy between projects. Consider a situation where IT resources can be shared and utilized remotely by multiple users simultaneously as long as traffic congestion does not become a problem. Rivera et al. (2013) present the following example as negative synergy between projects. Consider two projects that would benefit 100 and 200 people if they are undertaken separately. However, if the two projects are undertaken together, they would only benefit only 250 people. In this paper, this positive/negative synergy factor is considered as a parameter in the portfolio selection process. The proposed model aims at creating the highest positive synergy by increasing revenues and reducing costs.

This study presents a two-stage model to analyze and select the optimal IT project portfolio, considering the problem dynamics and synergy among the projects. In this study, projects are analyzed and ranked using fuzzy TOPSIS, and the obtained scores from project analyses are utilized as the closeness coefficient for the (second) objective function that maximizes the total non-cost values of the chosen portfolio. In our proposed mathematical model, projects are assessed in a pilot study at the market study level. The project selection at the operational level will be analyzed according to project synergies, human resource planning, employee training, and project profitability under multiple

Table 1
Linguistic terms to weight the relative importance of the criteria (Wang & Elhag, 2006).

Fuzzy triangular numbers	Linguistic Terms
(0, 0.2, 0.4)	Very low
(0.2, 0.4, 0.5)	Low
(0.4, 0.6, 0.8)	Medium
(0.6, 0.8, 1)	High
(0.8, 0.9, 1)	Very high

different scenarios if there are no competitors at the operational level. In the following, we present our proposed approach:

Stage I: Fuzzy TOPSIS

We perform project analysis and scoring via fuzzy TOPSIS techniques. For this purpose, a group of k experts (D_1, D_2, \dots, D_k) and m projects are available (A_1, A_2, \dots, A_m) where these projects are compared with one another using n criteria (C_1, C_2, \dots, C_n). The proposed approach for this process is as follows:

Step 1: Determine criteria weights

The experts are asked to weight the criteria according to Table 1. Then, using the following formula, the fuzzy triangular numbers are defuzzified:

$$W'_{jt} = \frac{a_{jt} + 4b_{jt} + c_{jt}}{6} \tag{1}$$

where a , b , and c represent the pessimistic value, the most likely value, and the optimistic value of triangular fuzzy numbers, respectively, and W'_{jt} is the weight of the j th criterion by the t th expert. Then, using the following formula, the final weight of each criterion is obtained:

$$W_j = \frac{\sum_{t=1}^T W'_{jt}}{T} \tag{2}$$

Step 2: Score projects

The experts are requested to assign a score to each project using the linguistic terms presented in Table 2. The mean score of the expert opinions is then calculated using the following formula:

$$R_{ij} = (a_{ij}, b_{ij}, c_{ij}) = \frac{\sum_{t=1}^T (a_{ijt}, b_{ijt}, c_{ijt})}{T} \tag{3}$$

The fuzzy triangular matrix R_{ij} is defined as:

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \tag{4}$$

Thereafter, R_{ij} is normalized using the formula below:

$$r_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right), j \in B$$

$$c_j^+ = \max_{ij} c_{ij}, j \in B$$

$$r_{ij} = \left(\frac{a_j^-}{c_{ij}^-}, \frac{a_j^-}{b_{ij}^-}, \frac{a_j^-}{a_{ij}^-} \right), j \in C$$

$$a_j^- = \min_{ij} a_{ij}, j \in C$$

C and B represent the positive and negative sets of criteria, respectively.

Step 3: Construct weighted normalized decision matrix

The weighted normalized decision matrix is formed as follows:

Table 2
Linguistic terms to score the relative preference of the alternatives (Wang & Elhag, 2006).

Fuzzy triangular numbers	Linguistic terms
(0, 0, 1)	Very weak
(0, 1, 3)	Weak
(1, 3, 5)	Medium-weak
(3, 5, 7)	Medium
(5, 7, 9)	Medium-strong
(7, 9, 10)	Strong
(9, 9, 10)	Very strong

$$v_{ij} = r_{ij} \cdot W_j \quad \begin{matrix} i = 1, 2, \dots, m \\ j = 1, 2, \dots, n \end{matrix} \tag{6}$$

Step 4: Determine positive and negative ideal solutions

The positive ideal solution (A^*) and negative ideal solution (A^-) are determined. The positive ideal solution is the highest value for positive indices and the lowest value for negative indices. The negative ideal solution is the lowest value for positive indices and the highest value for negative indices.

$$A^* = (v_1^*, v_2^*, \dots, v_n^*)$$

$$A^- = (v_1^-, v_2^-, \dots, v_n^-)$$

$$v_j^* = \max\{v_{ij}\}$$

$$v_j^- = \min\{v_{ij}\}$$

Step 5: Determine the distance from positive and negative ideal solutions

The distance of each project from the positive and negative ideal solutions is measured as follows:

$$d_i^* = \sum_{j=1}^n d_v(v_{ij}, v_j^*), i = 1, 2, \dots, m \tag{8}$$

$$d_i^- = \sum_{j=1}^n d_v(v_{ij}, v_j^-), i = 1, 2, \dots, m \tag{9}$$

The fuzzy triangular numbers are as below:

$$d(A, B) = \sqrt{\frac{1}{3} [(a - a_1)^2 + (b - b_1)^2 + (c - c_1)^2]} \tag{10}$$

Step 6: Determine closeness coefficients

This step determines the closeness coefficients for each project as follows:

$$cc_i = \frac{d_i^-}{d_i^- + d_i^*}, i = 1, 2, \dots, m \tag{11}$$

The closeness coefficient of each project is used as the coefficient of the (second) objective function that maximizes the total non-cost value of the chosen portfolio.

Stage II: Formulating and solving the mixed-integer linear programming model

We propose a bi-objective mixed-integer linear programming model for project selection. We begin with definitions for the indices, parameters, and variables used in the model.

Indices		
i, j	Project	($1 \leq i \leq I$)
k	Skill	($1 \leq k \leq K$)
e	The employee for project execution at the market study level (pilot)	($1 \leq e \leq E$)
\bar{e}	The employee for project execution at the operational level	($1 \leq \bar{e} \leq \bar{E}$)
s	Scenario	($1 \leq s \leq S$)

Parameters	
c_i^{plt}	The implementation cost of project i at the market study level without considering synergistic effects
c_{is}^{opr}	The implementation cost of project i at the operational level without considering synergistic effects under scenario s
$Income_e^{plt}$	Income obtained from the implementation of project i at the market study level without considering synergistic effects
$Income_{is}^{opr}$	Income obtained from the implementation of project i at the operational level without considering synergistic effects under scenario s
τ_{ij}^{plt}	Amount of cost synergistic effects of project i on project j through market study level
τ_{ijs}^{opr}	Amount of cost synergistic effects of project i on project j through operational level under scenario s
η_{ij}^{plt}	Amount of income synergistic effects of project i on project j through market study section
η_{ijs}^{opr}	Amount of income synergistic effects of project i on project j through operational level under scenario s
R_{is}	Results of project i execution under scenario s
MR_i	Minimum required result of project i at the market study level to be implementable at the operational level
$skill_{ik}^{plt}$	The number of required skill k to implement project i at the market study level
$skill_{iks}^{opr}$	The number of required skill k to implement project i at the operational level under scenario s
MP_i^{plt}	Maximum required employees to implement project i at the market study
MP_{is}^{opr}	Maximum required employees to implement project i at the operational level under scenario s
$cmp_{is} \begin{cases} 1 \\ 0 \end{cases}$	In case of the absence of competitors for the project i at the market study level under scenario s Otherwise
$A_{ek}^{plt} \begin{cases} 1 \\ 0 \end{cases}$	If employee e has skill k at the market study level Otherwise
$A_{ek}^{opr} \begin{cases} 1 \\ 0 \end{cases}$	If employee e has skill k at the operational level Otherwise
$cost_k^{train}$	Cost of training employee to acquire skill k
w_i	Closeness coefficient of project i
$wage$	The average wage of each employee
bg	Available budget
$bigm \sim \infty$	A very large number

Variables	
$x_i \begin{cases} 1 \\ 0 \end{cases}$	Binary • If project i is selected at the market study level • Otherwise
$y_{is} \begin{cases} 1 \\ 0 \end{cases}$	Binary • If project i is selected at the operational level under scenario s • Otherwise
$z_{ei}^{plt} \begin{cases} 1 \\ 0 \end{cases}$	Binary • If employee e is allocated to project i at the market research level • Otherwise
$z_{eis}^{opr} \begin{cases} 1 \\ 0 \end{cases}$	Binary • If employee e is allocated to project i at the operational level under scenario s • Otherwise
$\alpha_{ek}^{plt} \begin{cases} 1 \\ 0 \end{cases}$	Binary • If the k th skill of employee e is used at the market study level • Otherwise
$\alpha_{eks}^{opr} \begin{cases} 1 \\ 0 \end{cases}$	Binary • If the k th skill of employee e is used at the operational level under scenario s • Otherwise
$\beta_{ek}^{plt} \begin{cases} 1 \\ 0 \end{cases}$	Binary • If employee e is trained to acquire skill k at the market study level • Otherwise
$\beta_{eks}^{opr} \begin{cases} 1 \\ 0 \end{cases}$	Binary • If employee e is trained to acquire skill k at the operational level under scenario s • Otherwise
δ_k^{plt}	Integer Number of trained employees to acquire skill k at the market study level
δ_{ks}^{opr}	Integer Number of trained employees to acquire skill k at the operational level under scenario s
μ^{plt}	Integer Number of allocated employees to projects at the market study level

(continued on next column)

(continued)

Variables		
μ_s^{opr}	Integer	Number of allocated employees to projects at the operational level

The mathematical model

$$\begin{aligned}
 Max Z^{benefit} = & \sum_{ij} Income_i^{plt} \times x_i \times (1 - \eta_{ij}^{plt} \times x_j) \\
 & + \sum_{ijs} Income_{is}^{opr} \times y_{is} \times (1 - \eta_{ijs}^{opr} \times y_{js}) - \sum_{ij} c_i^{plt} \times x_i \times (1 - \tau_{ij}^{plt} \times x_j) \\
 & - \sum_{ijs} c_{is}^{opr} \times y_{is} \times (1 - \tau_{ijs}^{opr} \times y_{js}) - \sum_{k,s} c_k^{trn} \times (\delta_k^{plt} + \delta_{ks}^{opr}) - \sum_s wage \\
 & \times (\mu^{plt} + \mu_s^{opr})
 \end{aligned} \tag{12}$$

$$Max Z^{Total\ value\ of\ project\ portfolio} = \sum_i w_i \times x_i \tag{13}$$

Subject to:

$$y_{is} \leq x_i \quad i, s \tag{14}$$

$$y_{is} \leq x_i \times R_{is} \times \frac{cmp_{is}^{plt}}{MR_i} \quad \forall i, s \tag{15}$$

$$\sum_e z_{ei}^{plt} \leq MP_i^{plt} \quad \forall i \tag{16}$$

$$\sum_e z_{eis}^{opr} \leq MP_{is}^{opr} \quad \forall i, s \tag{17}$$

$$\sum_e \alpha_{ek}^{plt} \times z_{ei}^{plt} \times x_i \geq skill_{ik}^{plt} \quad \forall i, k \tag{18}$$

$$\sum_e \alpha_{eks}^{opr} \times z_{eis}^{opr} \times y_{is} \geq skill_{iks}^{opr} \quad \forall i, k, s \tag{19}$$

$$A_{ek}^{plt} + \beta_{ek}^{plt} \leq \alpha_{ek}^{plt} \quad \forall e, k \tag{20}$$

$$A_{ek}^{opr} + \beta_{eks}^{opr} \leq \alpha_{eks}^{opr} \quad \forall \widehat{e}, k, s \tag{21}$$

$$\alpha_{ek}^{plt} \leq bigm \times (A_{ek}^{plt} + \beta_{ek}^{plt}) \quad \forall e, k \tag{22}$$

$$\alpha_{eks}^{opr} \leq bigm \times (A_{ek}^{opr} + \beta_{eks}^{opr}) \quad \forall \widehat{e}, k, s \tag{23}$$

$$\mu^{plt} = \sum_{e,i} z_{ei}^{plt} \tag{24}$$

$$\mu_s^{opr} = \sum_{e,i} z_{eis}^{opr} \quad \forall s \tag{25}$$

$$\delta_k^{plt} = \sum_e \beta_{ek}^{plt} \quad \forall k \tag{26}$$

$$\delta_{ks}^{opr} = \sum_e \beta_{eks}^{opr} \quad \forall k, s \tag{27}$$

$$\sum_e z_{ei}^{plt} \leq bigm \times x_i \quad \forall i \tag{28}$$

$$\sum_e z_{eis}^{opr} \leq bigm \times y_{is} \quad \forall i, s \tag{29}$$

$$\sum_i z_{ei}^{plt} \leq 1 \quad \forall e \tag{30}$$

$$\sum_i z_{eis}^{opr} \leq 1 \quad \forall \widehat{e}, s \tag{31}$$

$$\begin{aligned}
 & \sum_{i,j} c_i^{pl} \times x_i \times (1 - \tau_{ij}^{pl} \times x_j) + \sum_{i,j,s} c_{is}^{opr} \times y_{is} \times (1 - \tau_{ijs}^{opr} \times y_{js}) \\
 & + \sum_{k,s} c_k^{trn} \times (\delta_k^{pl} + \delta_{ks}^{opr}) + \sum_s wage \times (\mu_s^{pl} + \mu_s^{opr}) \leq bg \tag{32}
 \end{aligned}$$

The first objective function maximizes the profit earned from the project in the selected portfolio. The implementation cost of the project at both the market study and operational levels, training costs, and wages are subtracted from the income gained from the execution of the projects at the market study and operational levels. The second objective function maximizes the total non-cost value of the portfolio of projects selected.

Constraint (14) ensures that for a project to be selected at the operational level, it must also be selected at the market study level. The following three conditions must be met to select the project at the operational level: The project should be selected at market study, the absence of competitors for the project at the market study level, and the project has achieved an acceptable result as represented by Constraint (15). The available human resource constraints at the market study and operational levels are defined in constraints (16) and (17), respectively. Constraints (18) and (19) ensure that the required skills for each project are covered at the market study and operational levels. Constraints (20) and (21) ensure that if an employee at the market study and operational levels (respectively) are only receives training for a particular skill if the skill is required, and if the employee is untrained in the skill. Constraints (22) and (23) complement constraints (20) and (21) and state that if there is no need for training, employees at the market study and operational levels (respectively) should not be trained, regardless of whether or not the employees possess the necessary skills. The total number of employees to allocate to the projects at the market study and operational levels are presented in constraints (24) and (25), respectively. Similarly, constraints (26) and (27) ensure that the total number of trained employees to allocate at the market study and operational levels respectively must be consistent with the required skill of each level. Constraints (28) and (29) ensure that employees are only allocated to projects that have been selected at the market study and operational levels, respectively. Constraints (30) and (31) guarantee that each employee at the market study and operational levels, respectively, is allocated to only one project. Finally, constraint (32) ensures that the available budget is not exceeded.

To solve our bi-objective mathematical model, we propose a new solution method based on methods presented by is it Zimmermann (1978) and Lin (2012). The approach by Zimmermann (1978) maximizes the membership functions through the following model:

$$\begin{aligned}
 & \text{Max } \lambda \\
 & \text{Subject to :} \\
 & \lambda \leq \mu_{z_k}^{min}(x) \\
 & \lambda \leq \mu_{z_r}^{max}(x) \\
 & \lambda \leq \mu_{g_l}(x) \tag{33}
 \end{aligned}$$

These membership functions are defined as follows:

$$\mu_{z_k}^{min}(x) = \begin{cases} 1 & z_k(x) > z_k^{positive} \\ 0 & z_k(x) < z_k^{negative} \\ f_{\mu_{z_k}^{min}} = \frac{z_k^{positive} - z_k(x)}{z_k^{positive} - z_k^{negative}}, & z_k^{negative} \leq z_k(x) \leq z_k^{positive} \end{cases} \tag{34}$$

$$\mu_{z_l}^{max}(x) = \begin{cases} 1 & z_l(x) > z_l^{positive} \\ 0 & z_l(x) < z_l^{negative} \\ f_{z_l}^{max} = \frac{z_l(x) - z_l^{negative}}{z_l^{positive} - z_l^{negative}}, & z_l^{negative} \leq z_l(x) \leq z_l^{positive} \end{cases} \tag{35}$$

$$\mu_{g_l}(x) = \begin{cases} 1 & g_l(x) > b_l \\ 0 & g_l(x) < b_l + d_l \\ f_{z_l}^{max} = \frac{1 - [g_l(x) - b_l]}{d_l}, & b_l \leq g_l(x) \leq b_l + d_l \end{cases} \tag{36}$$

where objective function $z_k(z_l)$ values change from lower bound $z_k^{negative}$ ($z_l^{negative}$) to upper bound $z_k^{positive}$ ($z_l^{positive}$), $\mu_{z_k}^{min}(x)$, $\mu_{z_k}^{min}(x)$, and $\mu_{g_l}(x)$ represent the membership functions of maximum, minimum, and constraints, respectively, and d_l denotes the tolerance value.

Lin (2012) presented an extended approach that first solves the model by Zimmermann (1978) and inserts the values of membership functions (λ) into the following model (Lin, 2012).

$$\begin{aligned}
 & \text{Max } \bar{\lambda} = \frac{1}{r+k+l} \sum_{t=1}^{r+k+l} \lambda_t \\
 & \text{Subject to :} \\
 & \lambda \leq \bar{\lambda} \leq \mu_{z_k}^{min}(x) \\
 & \lambda \leq \bar{\lambda} \leq \mu_{z_r}^{max}(x) \\
 & \lambda \leq \bar{\lambda} \leq \mu_{g_l}(x) \tag{37}
 \end{aligned}$$

The approach by Lin (2012) assumes that the weights of λ_t in the objective function are equal to one another, but this does not hold true in our considered problem as the weights of the criteria are different from one another. Our proposed approach, as shown below, considers the weight of each membership function where θ_t represents the relative importance of each weight of λ_t . It is noteworthy that the weights in the problem we study are determined based on expert opinions.

$$\begin{aligned}
 & \text{Max } \bar{\lambda} = \frac{\sum_{t=1}^{r+k+l} \theta_t \times \lambda_t}{\sum_{t=1}^{r+k+l} \theta_t} \\
 & \text{Subject to :} \\
 & \lambda \leq \bar{\lambda} \leq \mu_{z_k}^{min}(x) \\
 & \lambda \leq \bar{\lambda} \leq \mu_{z_r}^{max}(x) \\
 & \lambda \leq \bar{\lambda} \leq \mu_{g_l}(x) \tag{38}
 \end{aligned}$$

All other constraints are included and remain unchanged.

Solving this model yields the following at both the market study level, and at the operational level under each scenario:

- The projects selected the profit and non-cost value.
- Allocation of employees to projects.
- Usage of employee skills.
- Employee skill training assignments.

A schematic summary of the methodology of this study can be viewed in Fig. 1.

3. Case study

In this section, we present a real-life case study to demonstrate the applicability and efficacy of our proposed method. Northern Cybersecurity Systems¹, is a cybersecurity company in southern Pennsylvania with over 6000 employees that needs to evaluate ten large cybersecurity

¹ The name of the company is changed to protect its anonymity.

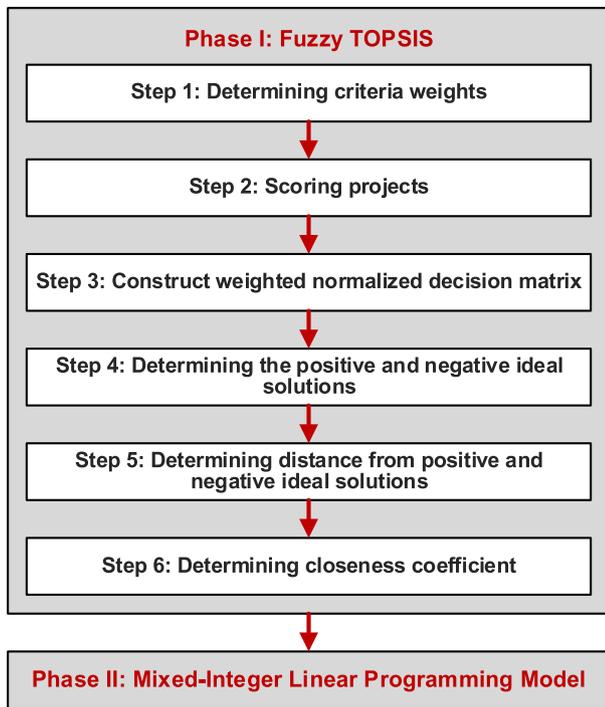


Fig. 1. Proposed framework.

projects. These projects cover a wide range of cybersecurity activities, including assess and plan, detect, and protect, and respond and recover. For the execution of the relevant projects in this organization, the following skills are required: programming, technical support, web development, network management, database management, network security, and project management. For this purpose, the proposed model is implemented in GAMS 24.1.2 and solved using IBM ILOG CPLEX on a machine with the following specifications: Core (TM) i3 1.70 GHz and 4 GB of RAM. The case study consists of data pertaining to 10 projects under three scenarios: optimistic, most likely, and pessimistic. The results obtained from the model execution in the organization is presented below:

Among the ten projects, six are to be selected at the market study level. At the operational level, six, five, and four projects are to be selected for the optimistic, most likely, and pessimistic scenarios, respectively. The implementation procedure of our proposed approach is as follows:

Stage I: Fuzzy TOPSIS

Step 1: Determine criteria weights

Evaluation criteria:

- Criterion 1: Technical and execution capability.
- Criterion 2: Aligning with organizational strategies and objectives.
- Criterion 3: On-time delivery.

- Criterion 4: Organizational experience in the execution of similar projects.

The weight of each criterion is calculated using Table 1 based on the average weighting presented by the five experts. The weights of the four criteria are as follows: Criterion 1 (0.2789), Criterion 2 (0.1963), Criterion 3 (0.2994), and Criterion 4 (0.2254).

Step 2: Score projects

Tables 3 and 4 present the mean score of five expert opinions and the normalized matrix.

Step 3: Construct weighted normalized decision matrix

Table 5 shows the normalized weighted decision matrix.

Step 4: Determine the positive and negative ideal solutions

Table 6 shows the positive ideal solution (A⁺) and negative ideal solution (A⁻).

The results presented in Tables 5 and 6, can be used to visualize the normalized weighted performance for each project at each criterion, where the values are between the positive ideal solution and the negative ideal solution. In Figs. 2–4, we present the performance of each project based on the proposed four criteria using three fuzzy numbers. A project with good performance is one where the centroid is closer to the positive ideal solution and farther away from the negative ideal solution (see Fig. 5).

Step 5: Determine distance from the positive and negative ideal solutions

Table 7 shows the distance between the positive and negative ideal solutions for each project.

Step 6: Determine closeness coefficients

Table 8 represents the closeness coefficients for each project, which are used in Stage II of our proposed method.

Stage II: MILP model

Estimating the upper and lower bounds of the objective functions, the membership functions are defined as follows:

$$\mu_{Z^{benefit}} = \frac{Z^{benefit} - 39,404,000}{143,671,000 - 39,404,000}$$

$$\mu_{Z^{Total\ value\ of\ project\ portfolio}} = \frac{Z^{Total\ value\ of\ project\ portfolio} - 1.781}{5.979 - 1.781}$$

We first obtain $\lambda = 0.49$ using the approach by Zimmermann (1987). Based on expert opinions, the weight of the (first) objective function that maximizes profit is 0.7, while the weight of the (second) objective function that maximizes the non-cost values is 0.3. We use this information as input for our proposed approach:

$$Max \bar{\lambda} = 0.7 \times \lambda_1 + 0.3 \times \lambda_2$$

Subject to :

$$0.49 \leq \bar{\lambda} \leq \frac{Z^{benefit} - 39,404,000}{143,671,000 - 39,404,000}$$

$$0.49 \leq \bar{\lambda} \leq \frac{Z^{Total\ value\ of\ project\ portfolio} - 1.781}{5.979 - 1.781}$$

Table 3

Each project score based on experts' opinion each criterion.

Project	Project Name	Criterion 1			Criterion 2			Criterion 3			Criterion 4		
		a	b	c	A	B	c	A	B	c	a	B	C
1	VPS	7	8.6	9.4	4.4	6	7.6	2.8	4.4	6	2	2.8	4
2	Hub-Spoke	6.6	8.2	9.2	4	5.6	7	3	4.4	5.8	3	4.2	5.6
3	QR-Code Payment	6.6	8.2	9.4	5	7	8.6	4.4	6	7.4	4	5.6	7
4	Advanced Communication Services	5	6.8	8.4	3.8	5.6	7.2	1.4	2.8	4.6	2	3	4
5	HDSL	5.4	7	8.2	5.4	7.4	8.8	1.8	3.2	4.8	2.4	3.4	4.2
6	Video Conference Infrastructure for Customers	5.4	7	8.2	2.2	4.2	6.2	1.6	3.2	5	3	4.4	5.4
7	Online Educational Networks	5.4	7.4	9.2	2.4	4.2	6.2	2.4	4	5.8	3.4	4.4	5.4
8	National Health Network	6.6	8	8.8	6.6	8	8.8	3.2	5	6.8	1.6	3.2	4.2
9	AAA systems (Authentication, Accounting & Authorization)	3.8	5.6	7	2.8	4.6	6.6	1.8	3.4	5.4	1.4	2.8	4
10	VIOP	6.6	8.4	9.6	3.4	5.4	7.4	0.6	2.2	4.2	3.2	5	6.2

Table 4
Normalized score of each project based on experts' opinion on each criterion.

Project	Criterion 1			Criterion 2			Criterion 3			Criterion 4		
	a	b	c	a	b	C	a	b	c	a	b	C
1	0.72917	0.89583	0.97917	0.50000	0.68182	0.86364	0.37838	0.59459	0.81081	0.28571	0.40000	0.57143
2	0.68750	0.85417	0.95833	0.45455	0.63636	0.79545	0.40541	0.59459	0.78378	0.42857	0.60000	0.80000
3	0.68750	0.85417	0.97917	0.56818	0.79545	0.97727	0.59459	0.81081	1.00000	0.57143	0.80000	1.00000
4	0.52083	0.70833	0.87500	0.43182	0.63636	0.81818	0.18919	0.37838	0.62162	0.28571	0.42857	0.57143
5	0.56250	0.72917	0.85417	0.61364	0.84091	1.00000	0.24324	0.43243	0.64865	0.34286	0.48571	0.60000
6	0.56250	0.72917	0.85417	0.25000	0.47727	0.70455	0.21622	0.43243	0.67568	0.42857	0.62857	0.77143
7	0.56250	0.77083	0.95833	0.27273	0.47727	0.70455	0.32432	0.54054	0.78378	0.48571	0.62857	0.77143
8	0.68750	0.83333	0.91667	0.75000	0.90909	1.00000	0.43243	0.67568	0.91892	0.22857	0.45714	0.60000
9	0.39583	0.58333	0.72917	0.31818	0.52273	0.75000	0.24324	0.45946	0.72973	0.20000	0.40000	0.57143
10	0.68750	0.87500	1.00000	0.38636	0.61364	0.84091	0.08108	0.29730	0.56757	0.45714	0.71429	0.88571

Table 5
Normalized weighted matrix.

Project	Criterion 1			Criterion 2			Criterion 3			Criterion 4		
	a	b	c	a	b	C	a	b	c	a	b	C
1	0.20337	0.24985	0.27309	0.09815	0.13384	0.16953	0.11329	0.17802	0.24276	0.06440	0.09016	0.12880
2	0.19174	0.23823	0.26728	0.08923	0.12492	0.15615	0.12138	0.17802	0.23466	0.09660	0.13524	0.18032
3	0.19174	0.23823	0.27309	0.11153	0.15615	0.19184	0.17802	0.24276	0.29940	0.12880	0.18032	0.22540
4	0.14526	0.19755	0.24404	0.08477	0.12492	0.16061	0.05664	0.11329	0.18611	0.06440	0.09660	0.12880
5	0.15688	0.20337	0.23823	0.12046	0.16507	0.19630	0.07283	0.12947	0.19421	0.07728	0.10948	0.13524
6	0.15688	0.20337	0.23823	0.04908	0.09369	0.13830	0.06474	0.12947	0.20230	0.09660	0.14168	0.17388
7	0.15688	0.21498	0.26728	0.05354	0.09369	0.13830	0.09710	0.16184	0.23466	0.10948	0.14168	0.17388
8	0.19174	0.23242	0.25566	0.14723	0.17845	0.19630	0.12947	0.20230	0.27512	0.05152	0.10304	0.13524
9	0.11040	0.16269	0.20337	0.06246	0.10261	0.14723	0.07283	0.13756	0.21848	0.04508	0.09016	0.12880
10	0.19174	0.24404	0.27890	0.07584	0.12046	0.16507	0.02428	0.08901	0.16993	0.10304	0.16100	0.19964

Table 6
Positive and negative ideal solutions.

Negative ideal solution	Positive ideal solution	Criterion
(0.1104, 0.1104, 0.1104)	(0.2789, 0.2789, 0.2789)	1
(0.04908, 0.04908, 0.04908)	(0.1963, 0.1963, 0.1963)	2
(0.02428, 0.02428, 0.02428)	(0.2994, 0.2994, 0.2994)	3
(0.04508, 0.04508, 0.04508)	(0.2254, 0.2254, 0.2254)	4

All other constraints are included without any changes. Solving the model yields the result of projects 3, 4, 6, 7, 9 and 10 being selected at the market study level. The portfolios selected in the operational level are shown in Table 9. Notice that all of the aforementioned projects were selected under the optimistic scenario, while project 9 was omitted under the most likely scenario and projects 7 and 9 were omitted under the pessimistic scenario.

We analyze the results obtained by focusing on the operational level and looking into the differences between the three scenarios. Recall that there are 4, 5, and 6 projects selected to be in the portfolios of the pessimistic, most likely, and optimistic scenarios, respectively. Table 10 shows the number of employees to be trained in at least one skill and the total number of employees assigned to projects in each scenario.

Note that while both the pessimistic and most likely scenarios need less than 38% of their assigned employees to be trained, almost half of the assigned employees in the optimistic scenario require training. Also, notice that the increase of total employees between the most likely and optimistic scenarios is fewer than the increase between the pessimistic and most likely scenarios. However, the increase in employees needing training between the most likely and optimistic scenarios is double over the increase between the pessimistic and most likely scenarios. This implies that as the number of projects in a portfolio increases, it is not necessarily the case that many more employees are needed. However, it

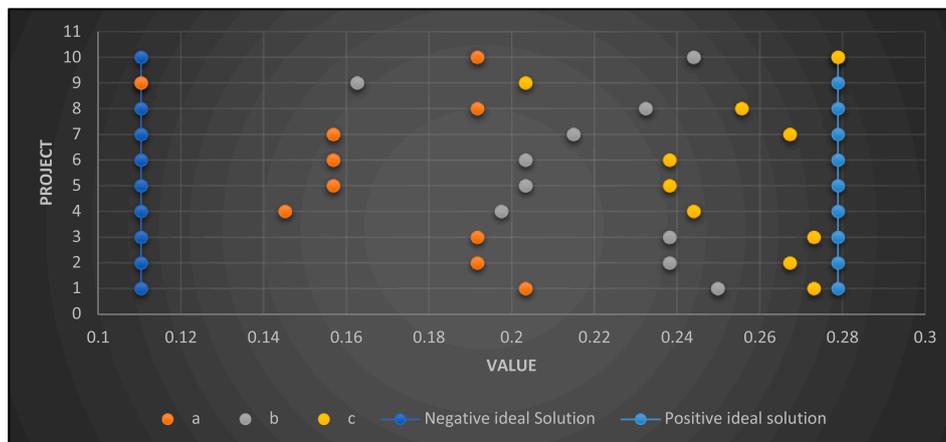


Fig. 2. Normalized weighted performance value for each project at Criterion 1.

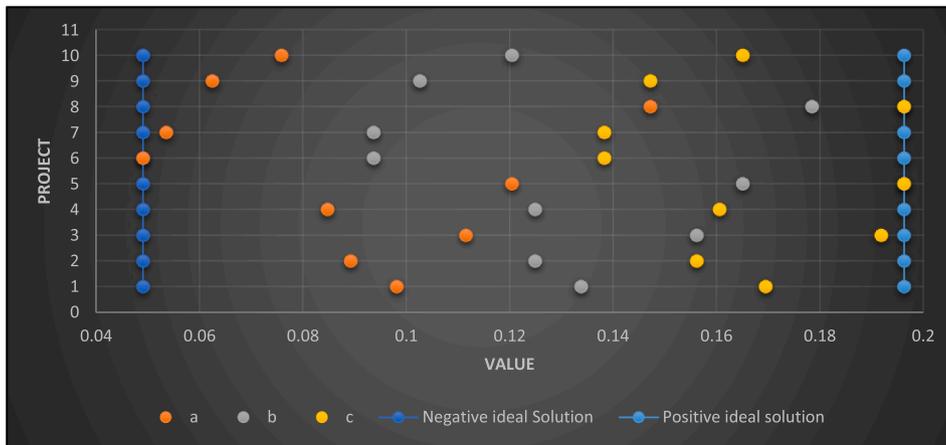


Fig. 3. Normalized weighted performance value for each project at Criterion 2.

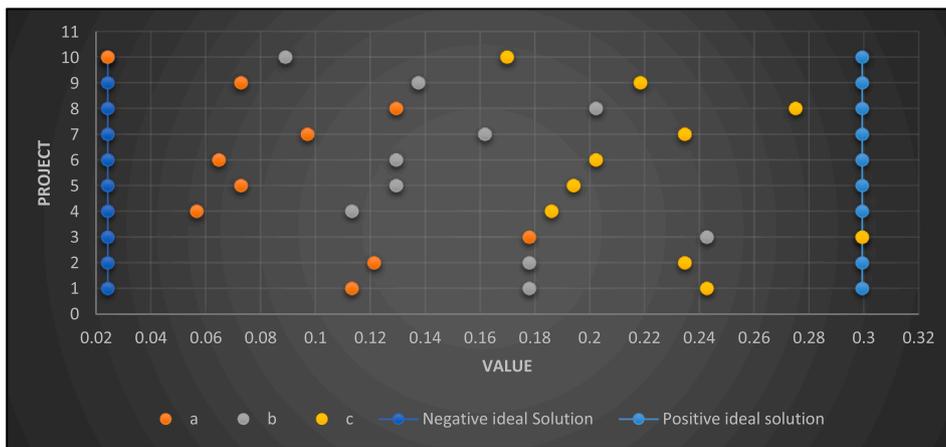


Fig. 4. Normalized weighted performance value for each project at Criterion 3.

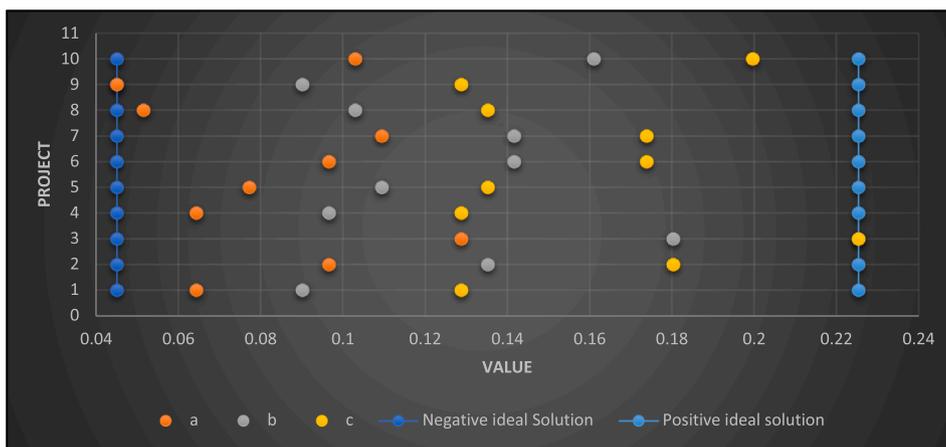


Fig. 5. Normalized weighted performance value for each project at Criterion 4.

might be the case that many of those assigned employees will need training in at least one skill.

The total number of employees assigned under each scenario has a direct impact on wages as follows: pessimistic scenario wages totaling 2.88 million dollars, most likely scenario wages totaling 3.48 million dollars, and optimistic scenario wages totaling 3.84 million dollars. The wages under the most likely scenario are 20.83% higher than those under the pessimistic scenario. In comparison, the wages under the

optimistic scenario is only 10.34% higher than the wages under the most likely scenario. The wage increase from the pessimistic scenario to the most likely scenario is about double the wage increase from the most likely scenario to the optimistic scenario. This tallies with the increase in the number of employees where five additional employees needed for most likely scenario compared to for pessimistic scenario, and three additional employees needed for optimistic scenario compared to the most likely scenario.

Table 7
The distance between positive and negative solutions for each project.

Project	Positive distance	Negative distance
1	0.046818	0.134788
2	0.055906	0.125858
3	0.055604	0.12829
4	0.092497	0.09424
5	0.086073	0.095074
6	0.086073	0.095074
7	0.079772	0.112058
8	0.058558	0.119112
9	0.125902	0.061553
10	0.05417	0.132684

Table 8
Closeness coefficient of projects.

Project	Closeness coefficient
1	0.742199
2	0.692424
3	0.697631
4	0.504666
5	0.524846
6	0.524846
7	0.584154
8	0.670412
9	0.328361
10	0.710093

Table 9
The selected projects for each scenario at the operational level.

Scenario	Project					
	3	4	6	7	9	10
Pessimistic	Yes	Yes	Yes	No	No	Yes
Most Likely	Yes	Yes	Yes	Yes	No	Yes
Optimistic	Yes	Yes	Yes	Yes	Yes	Yes

Table 10
The number of trained and total employees.

Optimistic scenario	Most likely scenario	Pessimistic scenario	Employee type
15	11	9	Trained employee
32	29	24	All employee

The number of employees needing training under each scenario has a direct impact on the training costs as follows: pessimistic scenario training costs totaling 1.623 million dollars, most likely scenario training costs totaling 2.15 million dollars, and optimistic scenario training costs totaling 2.841 million dollars. The percentage of employees needing training increases by a similar amount for each increase in the optimism level, with 32.37% increase for the first increase in in the optimism level (pessimistic to most likely), and 32.14% increase for the second increase in the optimism level (most likely to optimistic). These results imply that while not many additional employees are needed in the optimistic scenario (compared to the most likely scenario), there is a higher necessity for employee training.

The benefit (first objective value) under each scenario is shown in

Table 11
Objective function value.

Benefit (Optimistic)	Benefit (Most Likely)	Benefit (Pessimistic)
43,675,000	38,450,000	29,562,000

Table 11, while the non-cost value (second objective value) is calculated to be 3.438.

As expected, the optimistic scenario yields the largest benefit, while the pessimistic scenario yields the smallest benefit. The increase in benefit is (at 30.07%) higher between the pessimistic and most likely scenarios than it is (at 13.59%) between the most likely and optimistic scenarios. This is due to the optimistic scenario needing more employees to be trained compared to the most likely scenario.

Based on the obtained results, it can be argued that the number of projects selected at the operational level will increase by enhancing the optimism level (the projects selected in the optimistic scenario outnumber those in the most likely scenario, and the projects selected in the most likely scenario outnumber those in the pessimistic scenario). As the number of projects increases, the need for employees and employee training increases. We found that the need for additional employees reduces with each increase in the level of optimism. The optimistic scenario (with six projects) requires only three more employees than the most likely scenario (with five projects), which requires five more employees than the pessimistic scenario (with four projects). However, the need for trained employees increases with each increase in the level of optimism. The optimistic scenario (with six projects) requires four more trained employees than the most likely scenario (with five projects), which requires only two more trained employees than the pessimistic scenario (with four projects). Thus, we can conclude that in this context, the higher the number of projects, the need for employee training becomes more important than the need for additional employees. The need for additional employees and employee training is, of course, associated with an increase in costs. On the other hand, increasing the number of projects leads to an increase in revenues. In this case study, the increase in the slope of the revenue function is greater than that of the cost function, which means an increase in the overall profitabilities. However, the increase in the number of projects will also increase the risks; thus, a trade-off is made between profit maximization and risk minimization. An organization that takes high-risk expects high profits, and the one that is risk-averse (takes little risk) should not expect high profits.

4. Conclusion and future research directions

This study proposed a two-stage hybrid approach to evaluate and select the optimum portfolio of projects with interdependencies under uncertainty. The projects were first ranked at the market study level using fuzzy TOPSIS and given scores. A bi-objective mixed-integer linear program was formulated to select the projects considering their synergy, employee skill, and the optimization of employee development. The objectives at once optimized the monetary-based benefit derived from selecting the projects, and the non-cost value derived from the project scores previously obtained. In the proposed model, the projects were analyzed at the market study level. Then, each project would be implemented at the operational level if it reached satisfactory outcomes. This model was solved using a two-step process that we specifically developed for this purpose. We demonstrated the applicability and efficacy of the proposed model through a real-world case study at a cybersecurity company by evaluating three possible scenarios: optimistic, most likely, and pessimistic. The proposed bi-objective model was converted into a single objective model using a new fuzzy multi-objective approach, which was implemented in GAMS software using the Cplex solver. Our approach was able to determine the portfolios at the market study level and the operational levels under all three scenarios, along with the associated costs, benefits, and employee utilization and development. We showed that the increase in the scenario optimism level increases the number of employees and employee training, which themselves increase costs. Nevertheless, these cost increases were overshadowed by the increase in revenues as a result of taking on more projects.

Along with its benefits, every research naturally suffers from some

limitations, which ultimately lead to future research. For instance, a multitude of MCDM methods exists in the literature for calculating the weights of criteria (i.e., AHP, analytic network process, and best-worst method, among others). One of these methods could be employed within fuzzy TOPSIS for an integrated project evaluation and selection framework. Moreover, the GAMS software that was used in this study to solve the proposed model is only suited to solve smaller sized problems in a reasonable amount of time. However, the GAMS software is not able to do so if the number of projects is increased significantly. A reasonable approach for tackling larger-scale project selection problems would be to make use of heuristic or meta-heuristic algorithms.

CRedit authorship contribution statement

Madjid Tavana: Conceptualization, Formal analysis, Methodology, Writing - review & editing, Visualization. **Ghasem Khosrojerdi:** Investigation, Resources, Software, Project administration. **Hassan Mina:** Conceptualization, Investigation, Formal analysis, Validation, Data curation, Software. **Amirah Rahman:** Writing - review & editing.

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