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A Sugeno ANFIS Model Based on Fuzzy Factor Analysis for IS/IT Project Portfolio Risk Prediction

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ABSTRACT

Risk inherence jeopardises Information System (IS) and Information Technology (IT) Project Portfolio Management (PPM) to realise the strategic objectives. Previous studies have mainly provided Artificial Intelligence (AI) and statistical models to predict the overall risk of IS/IT project portfolio, whereas neuro-fuzzy models were rarely used. This paper proposes a Sugeno Adaptive Neuro-Fuzzy Inference System (ANFIS) model based on Fuzzy Factor Analysis (FFA) named ANFIS-OPR to predict the overall risk of IS/IT project portfolio from historical IS/IT project risk data. The ANFIS-OPR inputs are the relevant factor loadings resulting from the FFA application on the IS/IT projects risks set to cope with the curse of dimensionality. Then, the Sugeno ANFIS model is adopted to give strategic interpretability to the predicted IS/IT project portfolio overall risk by implementing the IS/IT Project Management Office (PMO) expert knowledge, represented by fuzzy rules, on the relationship between IS/IT project portfolio strategic alignment and the IS/IT projects risks. The ANFIS-OPR outputs are the predicted Overall Portfolio Risk (OPR) and Root Mean Square Error (RMSE). The paper also presents an IS/IT PMO case study that shows the proposed ANFIS-OPR efficacy, which predicted the OPR values closely to the OPR estimates with an accepted RMSE of 0.108. The proposed ANFIS-OPR is a novel intelligent decision-making tool that enables the IS/IT PMO to monitor the OPR, considering its linkage with strategic alignment; thus, contingency plans can be carried out appropriately while ensuring that the IS/IT project portfolio is strategically aligned.

Keywords: IS/IT project portfolio Management, Overall Portfolio Risk, Strategic alignment, Fuzzy Factor Analysis, Sugeno ANFIS.

INTRODUCTION

The Information System (IS) and Information Technology (IT) project portfolio overall risk is a key concern of IS/IT Project Management Office (PMO) structures because IS/IT project portfolio management is jeopardised by constraints such as budgeting, time, resource scarcity, and quality. IS/IT PMOs should be endowed with tools to monitor the IS/IT project portfolio's overall risk and appropriately carry out contingency plans. These structures need to harness the historical data generated by the IS/IT project risks throughout the IS/IT portfolio's lifetime to predict the IS/IT project portfolio's overall risk value. This historical data consists of IS/IT project risks that have been assessed by IS/IT project managers concerning their respective projects and have been fed back to the IS/IT PMO, which calculates the up-to-date performance of the IS/IT project portfolio overall risk (Axelos, 2011). Therefore, the IS/IT PMO will be able to monitor the IS/IT project portfolio's overall risk through a unique "version of truth" in the IS/IT project portfolio dashboard and undertake contingency plans appropriately to keep it at an accepted level (Axelos, 2011).

Another issue, which is yet a challenge for IS/IT PMO experts, is to incorporate their knowledge in the quantitative calculation of IS/

IT project portfolio overall risk according to the strategic alignment of IS/IT projects within the IS/IT portfolio. Project portfolio risk was assessed in relation to the project portfolio strategic goals and outcomes, considering the interdependencies of risk factors, which enabled the carrying out of risk response plans (Micán et al., 2023). Apart from forecasting its value from historical data, IS/IT PMO experts may intervene in the calculation process to implement their reasoning logic about the IS/IT project portfolio's overall risk concerning the strategic fit of each IS/IT project portfolio. Therefore, to gain this strategic interpretability of IS/IT project portfolio overall risk, it is worthwhile to enable IS/IT PMO with a predictive model of IS/IT project portfolio overall risk calculation, in which they can incorporate their knowledge of the linkage between IS/IT project portfolio strategic alignment and IS/IT projects risks.

The theory of neuro-fuzzy models has been prominently proven effective in computational intelligence. Within this scientific area, Artificial Neural Networks (ANNs) and Fuzzy Inference Systems (FISs) have been hybridised to bring together their merits. While ANNs are universal approximators adopted for classification and prediction problems (Shalev-Shwartz & Ben-David, 2014). FISs are fuzzy logic-based controllers capable of modelling system non-linearities through a knowledge base provided by experts to convey acquired knowledge decision-making (Du & Swamy, 2014). Meanwhile, using a fuzzy inference system (FIS) model to represent the uncertainty of the system input and output variables using membership functions and incorporating expert knowledge in the fuzzy base is possible. Particularly, the hybridisation between FIS and Artificial Neural Network (ANN) results in a system called Adaptive Neuro-Fuzzy Inference System (ANFIS) based on the Sugeno FIS. This system is perceived as the most effective neuro FIS due to its flexibility, generalisation, utility Back-Propagation (BP), non-linearity, and structured knowledge representation and interpretability capabilities (Jang, 1993). According to Tiruneh et al. (2020), ANFIS is the most popular and successful neuro-fuzzy system. In the Malaysha et al. (2022) study, ANFIS outperformed traditional FIS in classification accuracy.

The curse of dimensionality is a potential issue within the IS/IT project portfolio as long as new incoming IS/IT projects to the IS/IT portfolio will increase the dimension of the IS/IT projects risks dataset. Consequently, applying a dimension reduction technique before an elaborated Sugeno ANFIS model for IS/IT project portfolio overall risk prediction is important. Many feature reduction and extraction techniques are proposed in the literature, such as Factor Analysis (FA) and Principal Component Analysis (PCA) (Du & Swamy, 2014; Kassim et al., 2013). In the case of fuzzy input variables, the Fuzzy Factor Analysis (FFA) of Tzeng et al. (2002) can be adopted to cope with the curse of dimensionality and guarantee the model convergence speed, accuracy, and generalizability.

Several studies have used ANFIS in prediction problems, but none have adopted this model for the overall IS/IT project portfolio risk prediction. Meanwhile, specific issues should substantially be addressed, which are the curse of dimensionality of IS/IT projects risks dataset, fuzziness of variables, interpretability with regard to the linkage between IS/IT project portfolio strategic alignment and IS/IT projects risks, and the prediction accuracy. Therefore, this paper proposes a new Sugeno ANFIS model based on FFA, named ANFIS-OPR, for the Overall Portfolio Risk (OPR) prediction. The key objectives of this paper are two-fold: (1) Devising a mathematical model of ANFIS-OPR for the IS/IT project portfolio overall risk prediction, which integrates IS/IT PMO expert knowledge on strategic alignment of the IS/IT project portfolio within the OPR prediction, and (2) Providing an effective intelligent decision-making tool, whose outcomes are the OPR and the Root Mean Square Error (RMSE), which enables IS/IT PMOs the monitoring of the IS/IT portfolio overall level of risk and the measurement of the model accuracy. Consequently, the IS/IT PMO can undertake contingency plans proactively and appropriately.

LITERATURE REVIEW

This section is dedicated to a thorough discussion and analysis of the main theoretical underpinnings of the new ANFIS-OPR, which are the ANFIS neuro-fuzzy model and FFA. The first part presents risk calculation, prediction techniques, and models. The second part discusses dimensionality reduction techniques, feature descriptions, and extraction techniques.

Risk Calculation and Prediction

According to the Portfolio Management guidances, MoP (Axelos, 2011) and Standard of Portfolio Management (Project Management

Institute, 2017), the portfolio's overall degree of risk should be measured and monitored. Risk calculation and prediction were reported in the literature based on statistical techniques (Micán et al., 2022; Ponsard et al., 2019) and Artificial Intelligence (AI) models (Neumeier et al., 2018; Zhang, 2020). Moreover, neuro-fuzzy models, hybridising ANN and FIS, were also proposed to handle different problems such as the insurance business risk estimation (Hessami, 2018), the overseas construction projects decision prediction (Utama et al., 2019), and stock market segment shocks detection and prediction (Yousofi Tezerjan et al., 2021). However, the latter models were not used to compute the OPR.

Statistical Techniques

Literature provided statistical techniques for risk estimation and calculation. Kim et al. (2021) used the modern portfolio theory to construct efficient portfolios for managing risk and uncertainties inherence of the research and development (R&D) project portfolio based on R&D investment past information. Besides, Capelli et al. (2021) designed a metric for forecasting the volatility of financial assets, which integrates financial risk, environmental, social, and governance risk. This metric was intended for investors and fund managers. Furthermore, Mercurio et al. (2020) elaborated an entropy combinatorial risk calculation method, which outperformed significantly, in most cases, the Mean-variance portfolio optimisation of Markowitz (1952). Micán et al. (2022) measured the multidimensional project portfolio risk based on strategic fit, future preparedness, and stakeholder satisfaction.

Meanwhile, Zou et al. (2019) elaborated a Random Walk Method model for project portfolio risk prediction based on project risk dependencies probabilities within the portfolio. Furthermore, Ponsard et al. (2019) combined the Monte-Carlo simulation and analytic hierarchy process (AHP) method in a two-staged Project portfolio risk quantification and management framework. Meanwhile, Serrano-Gomez and Munoz-Hernandez (2019) utilised the Monte-Carlo simulation and the Fuzzy AHP (FAHP) method for risk analysis and assessment, enabling suitable risk response planning to be carried out early. Nevertheless, the statistical techniques did not incorporate expert knowledge, providing interpretability for the risk calculation.

AI Models

When it comes to AI utilisation in risk prediction, Mohanta et al. (2019) stated that machine learning techniques to manage risk factors such as volatility, ambiguity, complexity, and uncertainty enable identifying and defining the contingencies and consequent undertaking actionable plans. Meanwhile, the Bayesian network for overall Project portfolio risk assessment considers IT/IS project dependencies risks within portfolios (Neumeier et al., 2018). Other examples of AI models were also utilised. Support Vector Machine and Long Short Term Memory models were used in financial risk forecasting and outperformed the GARCH model by improving the volatility prediction without bias (Liu, 2019). Moreover, Wang et al. (2020) utilised the Time series autoregressive moving average model based on fuzzy fractional ordinary differential equations for assessing the automatic cyber security risk.

ANNs were also used in risk prediction. In this sense, Li et al. (2020) calculated the changing risk of complex product development projects. Portfolios and neural networks were used to allow mitigation strategies and find effective decision-making. Diaz et al. (2020) set up a normalised radial basis with equal widths and heights ANN architecture to compute the overall digitalisation of the project portfolio risk factor. It enabled managers to cope proactively with riskiness through actionable plans and project cost-benefit analysis for scenario analysis. Meanwhile, a hybrid neural network and runner root algorithm were used to calculate product Portfolio risk (Goli et al., 2019). Zhang (2020) used the logistic regression Feed-forward Neural Networks model to calculate quantitative estimates of credit risk early warning indicators based on historical data, providing policy recommendations. Bai et al. (2022) combined Delphi and social network analysis to consider project portfolio risk interactions in the critical project portfolio risks.

Neuro-Fuzzy Models

Computational Intelligence has evolved with many studies addressing different kinds of problems. Zadeh (1965) devised the fuzzy sets theory in control and expert systems within this area. These systems are called FISs. A FIS is three-stepped: the first step is fuzzification, the second is knowledge base evaluation using a fuzzy rules base and database, and the last is defuzzification. The fuzzification process gathers the inputs and converts them into linguistic values or fuzzy sets. Then, the expert provides the knowledge of the rules base through linguistic or fuzzy rules using linguistic or fuzzy terms or variables linked together by t-norm and t-conorm operators. Afterwards, the decision logic from the input is inferred through the knowledge base until the generation of an output. This is called the fuzzy inference.

Finally, the defuzzification process enables obtaining a crisp output from the fuzzy inferred value. Takagi-Sugeno-Kang (TSK) and Mamdani are two well-known FISs. The TSK model is an additive fuzzy model that aggregates the output of rules using the addition operator, and it has a linear equation in the consequent part (Takagi & Sugeno, 1985). Meanwhile, the Mamdani model adopts the product or the minimum as the t-norm operator and the maximum as the t-conorm operator (Mamdani, 1975). This model is a non-additive fuzzy model that aggregates the output of fuzzy rules using the maximum operator, and a greater interpretability capability characterises it due to its defuzzification layer that uses membership functions in consequent parts (Du & Swamy, 2014).

Neuro-fuzzy models are a hybridisation of both ANNs and FISs, and they have been cited in the literature to address different issues. With the FISs benefits, these models also leverage the ANNs capabilities as efficient data-driven modelling tools to model and identify the dynamics and behaviours of non-linear systems thanks to their universal approximation capabilities and structure flexibility (Shokry & Espuña, 2018). The synergism between the FISs and ANNs is perceived in the neuro-fuzzy models as long as these models harness the ANN learning capability from input data while encompassing expert knowledge, thus giving the neural networks interpretability. ANNs are advocated for their learning capability, computational and algorithmic simplicity, self-organisation, and adaptability (Graupe, 2007).

ANFIS are neuro-fuzzy models that use the combined BP and Least Square Error (LSE) or BP alone as optimisation techniques for minimising the RMSE cost function. The ANFIS model utilises the TSK FIS (Jang, 1993; Soroush et al., 2019). In the review of Mamat et al. (2021), the ANN models' efficacy in embankment stability modelling and prediction with acceptable accuracy underlined the need to extend ANNs to ANFIS models in further research. The ANFIS model was adopted to predict the students' course success with an obtained RMSE equal to 0.36 and represented a decision support system on which students can base to calculate their success on courses (Kaynak et al., 2014). According to the content analysis of Tiruneh et al. (2020), there are 29 percent of the analysed studies have used gradient-based neuro-fuzzy system, 43 percent have used hybrid learning-based neuro-fuzzy system, and 19 percent have used population-based neuro-fuzzy system. In this analysis, ANFIS has been the most popular and successful neuro-fuzzy system used in diverse applications and different research domains, including business, medicine, IS, construction, and engineering.

Omar et al. (2021) compared ANFIS and ANN model accuracies using the RMSE value to forecast the slope stability on soft ground, and it was found that the former model RMSE was higher than the latter RMSE. In that sense, a big data mining-based paddy leaves monitoring system model elaborated on five phases: image acquisition, segmentation, feature extraction, feature selection, and ANFIS classification, showed improved accuracy of 97.28 percent compared to other models accuracies (SVM classifier: 91.2%, KNN: 85.3% and ANN: 88.78%) (Suresh et al., 2020). The dynamic strategy of stock portfolio insurance used ANFIS to forecast the future prices of the selected stocks, which improved the model's prediction accuracy compared to the multilayer neural network (Dehghanpour & Esfahanipour, 2018). To handle uncertainty, Mubarak et al. (2021) used ANFIS prediction models to cope with the fuzzy nature of datasets in real-world problems using data expansion methods. Monteiro et al. (2022) utilised an ANFIS approach for building damage prediction considering input uncertainties. Therewith, the fuzzy C-means clustering and ANFIS-based multi-sensor data fusion application succeeded in reducing by 45.19 percent the imprecision accuracy of current positioning estimation systems for real-time unmanned aerial vehicle (UAV) autonomous navigation in a low computational cost (Paulino et al., 2019).

Dimensionality Reduction

An additional in IS/IT project portfolio risk analysis is the 'curse of dimensionality'. IS/IT PMO has to consolidate the IS/IT project risks, assessed by the IS/IT project managers in the IS/IT project portfolio lifetime, thus maintaining historical mass risk data to accurately calculate the overall degree of IS/IT project portfolio. Many dimensionality reduction and feature extraction techniques were proposed to narrow the discourse space or the set of predictors in the historical dataset to cope with the ‘curse of dimensionality’. The most popular techniques are the Factor Analysis (FA) and the Principal Component Analysis (PCA). FA is a powerful multivariate analysis technique that identifies the common characteristics among a set of variables (Du & Swamy, 2014). This identification goes through finding the correlations or variances from the multidimensional dataset of the input variables to a lower dimensional subspace of latent factors with their factor loadings as closely as possible. FA is a generalisation of PCA, but the factors estimated are not unique, as they depend on rotation (Jöreskog, 1967). FA outperforms the PCA as it explains better the original data in a non-linear prediction problem. While PCA analyses all variances of the dataset, FA analyses only common variances.

The FA guarantees the model convergence speed, accuracy, and generalizability. According to the survey of Sorzano et al. (2014), dimensionality reduction techniques based on projections and dictionaries are considered rapidly evolving techniques. Their survey stated the utilisation of the FA technique before the ANN model in order to eliminate data redundancy by decorrelating input data, simplify neural network architecture, speed up training, and improve the whole model prediction. Li et al. (2018) elaborated a PCA and BP neural network for air quality evaluation. Besides, it is stated the FA-based ANFIS that improved sock prediction performance (Huang et al., 2021) and the FA-based proportional integral derivative model applied on high dimensional and sparse matrix, where FA outperforms PCA with better convergence speed (Li et al., 2021).

When the input variables are fuzzy numbers, the Fuzzy Factor Analysis (FFA) of Tzeng et al. (2002) can be adopted to cope with the curse of dimensionality and guarantee the model convergence speed, accuracy, and generalizability. The FFA was used to assess the quality of an e-learning service from different perspectives by reducing 44 input variables to 13 assessment factors and using triangular fuzzy data to model interviewee perceptions (Baradaran & Ghorbani, 2020).

Step 1: Creating a fuzzy data matrix
A fuzzy data matrix $\tilde{X}_{n\times p} = (\tilde{x}_{ij})$, where $i = 1..n,\ j = 1..p$ is created by collecting fuzzy data for each observed variable, which is the project risk PR_i. Each triangular fuzzy number $\tilde{x}_{ij}$ is the rating of ith observation for $the\, j$th variable as $\tilde{x}_{ij} = (x_{ij}, x_{ij}^L, x_{ij}^R)$, where n observed variables, n is the sample size.

Step 2: Calculating fuzzy correlation matrix
In this step, it is calculated the fuzzy correlation matrix $(\tilde{R}_{ij}) = (r_{ij}, r_{ij}^L, r_{ij}^R),\ i,j = 1..n$ from the observed fuzzy data matrix $\tilde{X}_{n\times p}$ Each element shows the correlation coefficient or linear interdependence between two variables calculated from the observed data matrix.

Using the model of Tzeng et al. (2002), the fuzzy correlation coefficient between two triangular fuzzy variables $\tilde{X}_i = (\bar{x}_i, \bar{x}_i^L, \bar{x}_i^R)$ and $\tilde{X}_j = (\bar{x}_j, \bar{x}_j^L, \bar{x}_j^R)$, where the mean of the ith variable $\bar{\tilde{X}}_i = \left(\frac{\sum_{j=1}^{n} x_{ji}}{n}, \frac{\sum_{i=1}^{n} x_{ji}^L}{n}, \frac{\sum_{i=1}^{n} x_{ji}^R}{n}\right)$, can be calculated using the Equation 1.

$$\tilde{R}_{ij} = \frac{\sum_{k=1}^{n} (\tilde{X}_{ik} - \bar{\tilde{X}}_i)(\tilde{X}_{jk} - \bar{\tilde{X}}_j)}{\sqrt{\sum_{k=1}^{n} (\tilde{X}_{ik} - \bar{\tilde{X}}_i)^2 \sum_{k=1}^{n} (\tilde{X}_{jk} - \bar{\tilde{X}}_j)^2}} \tag{1}$$

As the fuzzy operations may increase the range of the fuzzy correlation coefficient, a correction is applied to the correlation coefficients r_{ij}, r_{ij}^L, and r_{ij}^R according to Equation 2.

$$\hat{r}_{ij} = \left(r_{ij}, r_{ij} - \frac{r_{ij}^L}{n}, \begin{cases} r_{ij} - \frac{r_{ij}^R}{n} & where\ r_{ij} - \frac{r_{ij}^R}{n} < 1 \\ 1 & where\ r_{ij} - \frac{r_{ij}^R}{n} \geq 1 \end{cases} \right) \tag{2}$$

Step 3: Determining the number of latent factors and calculating their loadings
It is assumed that the vector $F_{m\times 1}$ is a set of m latent variables or common factors for the vector of fuzzy variables $\tilde{X}_{n\times 1}$, which is related to the fuzzy data matrix $\tilde{X}_{n\times p}$. The relationship between the latent factors and the observed variables can be modelled using Equation 3.

$$\tilde{X}_{n\times 1} = \widetilde{W}_{n\times m} \times F_{m\times 1} \tag{3}$$

Where,

$\widetilde{W}_{n\times m}$ is a fuzzy coefficient or loading factors matrix extracted from the correlation coefficients matrix $\tilde{R}_{n\times n}$.
$\widetilde{W}_{n\times m}$ contains the correlation coefficients between the observed and latent variables.

Through the calculation of eigenvalues and eigenvectors of $\tilde{R}_{n\times n}$, the common factors' number and their coefficients or loadings can be determined. That is, each square fuzzy matrix $\tilde{R}_{n\times n}$ will have a maximum n fuzzy eigenvalue $\tilde{E}_k = \left(\lambda_{k,}\ \lambda^L_{k,}\lambda^R_k\right)$ where $\tilde{E}_1 \geq \tilde{E}_2 \geq \ldots \geq \tilde{E}_n$. The centre value of eigenvalues λ_k, calculated by solving the equations $|R-\lambda I| = 0$, where R is a crisp matrix including the central elements of the fuzzy correlation coefficients $\left(r_{ij}\right)$. Besides, the eigenvectors (e_k) are obtained by solving the $Re_k = \lambda_k e_k$. According to the mathematical models of Nakamori et al. (1997), acceptable left and right values of the triangular eigenvalue fuzzy numbers of $\tilde{R}_{n\times n}$ are given in Equations 4 and 5.

$$Max\ \sum_{k=1}^{n} \lambda_k^L \tag{4}$$

Where,

$$0 \leq \lambda_k^L \leq \lambda_k\ \forall k = 1..n, \quad \text{and} \quad \left|\lambda_k^L e_{ik}\right| \leq \max\left\{\left|\sum_{j=1}^{n} r_{ij}^L\, e_{jk}\right|, \left|\sum_{j=1}^{n} r_{ij}^R\, e_{jk}\right|\right\} k = 1..n$$

$$Min \sum_{k=1}^{n} \lambda_k^R \tag{5}$$

Where,

$$\lambda_k^L \geq \lambda_k\ \forall k = 1..n, \quad \text{and} \quad \left|\lambda_k^R e_{ik}\right| \geq \min\left\{\left|\sum_{j=1}^{n} r_{ij}^L\, e_{jk}\right|, \left|\sum_{j=1}^{n} r_{ij}^R\, e_{jk}\right|\right\}, k = 1..n$$

λ_k, r_{ij}^L, r_{ij}^R, and e_{jk} are respectively centre eigenvalues, left correlation coefficients, right correlation coefficients, and centre eigenvectors. λ_k, r_{ij}^L, r_{ij}^R, and e_{jk} are known, whereas λ_k^L and λ_k^R are decision variables of the model to be obtained.

Then, the fuzzy loading factors are calculated based on the fuzzy eigenvalues using Equation 6.

$$\widetilde{W} = (\widetilde{w}_{kl}) = \left(\left[w_{kl}^L, w_{kl}^R\right]\right) \tag{6}$$

Where,

$$(\widetilde{w_{kl}}) = \begin{cases} \left[\sqrt{\lambda_l^L}\, e_{kl}, \sqrt{\lambda_l^R} e_{kl}\right], e_{ik} \geq 0 \\ \left[\sqrt{\lambda_l^R}\, e_{kl}, \sqrt{\lambda_l^L} e_{kl}\right], e_{ik} < 0 \end{cases}$$

As a rule of thumb, the number of the latent factors for the observed variable is the number of eigenvalues larger than 1. In the present FFA, the used criterion for common factors extraction is the centre value greater than , as the calculated eigenvalues are triangular fuzzy numbers. The scree plot is the chart that depicts the variation of latent factors' eigenvalues to determine the number of factors to be retained in the FFA covering the most variance.

Step 4: Interpreting latent factors

To determine the number of common factors , the scree plot and the rule of eigenvalues greater than one are analysed. It can be said that previous studies disparately addressed the two interrelated perspectives, which are project portfolio risk calculation and prediction and strategic alignment. However, none of them has specifically focused on elaborating an IS/IT project portfolio overall risk prediction model, which combines a feature extraction technique for fuzzy input variables to cope with 'the curse of dimensionality' and the Sugeno ANFIS for strategic interpretability of the linkage between OPR and IS/IT project portfolio strategic alignment. While statistical techniques and AI models can effectively predict the risk score, neuro-fuzzy models, particularly the ANFIS model, are more effective in addressing the underlying question of OPR prediction in linkage with IS/IT project portfolio strategic fit. It is due to their ability to incorporate experts' knowledge, reduce computational time, and improve prediction accuracy while providing interpretability.

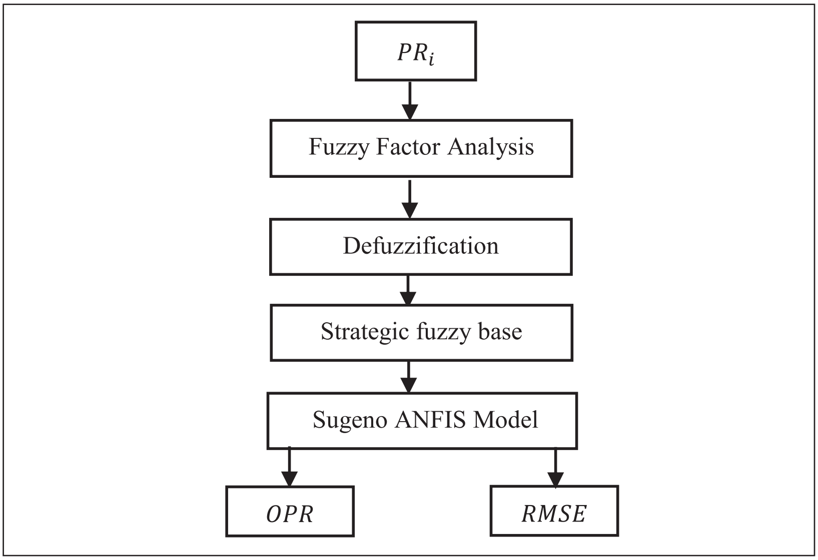
Notably, the IS/IT PMO ought to address the OPR in compromise with the IS/IT project portfolio strategic attractiveness. The OPR should be calculated to inform decision-making on the IS/IT project portfolio level of risk. Furthermore, it is recommended that the IS/IT PMO experts' knowledge of IS/IT project portfolio strategic alignment be considered in the OPR calculation. The new decision-making tool will provide the IS/IT PMO with informed and strategic decision-making by monitoring the overall risk from a strategic perspective. Consequently, the IS/IT PMO can design contingency plans and execute managerial actions efficiently and effectively. The new ANFIS-OPR proposed in this study aims to address this gap in the literature.

MATERIALS AND METHODS

The devised ANFIS-OPR has four main steps, as outlined in Figure 1.

Figure 1

The Steps of ANFIS-OPR.



Fuzzy Factor Analysis

First, the FFA is applied to the input variables , which are the IS/IT project risks. Each IS/IT project has risks estimated by a corresponding IS/IT project manager during the IS/IT project phases. The number of IS/IT project risks can be different for different IS/IT projects within the IS/IT project portfolio timeframe. The FFA outputs are the latent factors with their fuzzy factor loadings. Second, the relevant latent factors are selected based on defined criteria. Third, a defuzzication is performed on the selected fuzzy factor loadings to compute their crisp values. Fourth, the IS/IT PMO experts carry out a strategic analysis to represent their knowledge of the relationship between the IS/IT projects strategic fit and the risk inherence, thus elaborating a strategic fuzzy base for the Sugeno ANFIS model. Fifth, the deffuzified fuzzy factor loadings are given as inputs to the Sugeno ANFIS model, which performs the prediction. Finally, the outcomes of the new model are the predicted OPR and the RMSE.

Defuzzification

A defuzzication is performed on the selected fuzzy factor loadings to obtain their crisp values. Due to the fuzzy nature of the FFA outputs, this intermediate step enables to have crisp risk factors to be assessed in the next step according to the strategic fit. Thus, defuzzifying the relevant fuzzy risk factors that most materialise the IS/IT projects risks.

Strategic Fuzzy Base

In this step, the IS/IT PMO experts carry out a strategic analysis to incorporate their knowledge about the strategic fit of IS/IT projects to their riskiness level. The IS/IT PMO experts assess the performance of the crisp values of the relevant factor loadings resulting from step 3 using the Strengths, Weaknesses, Opportunities, Threats (SWOT) technique, which is effective in assessing internal and external factors relative to a change in the organisation (Axelos, 2011). The assessment scale is a three-point Likert scale.

The sub-steps of the strategic analysis of IS/IT PMO experts are as follows:

1. List the selected relevant factor loadings;
2. Rate them according to their probabilities and impacts;
3. Calculate their strategic fit as the product of their probabilities and impacts;
4. Rank them with respect to their strategic fit;
5. Formulate the new strategic fuzzy rules;
6. Elaborate the strategic fuzzy base for the Sugeno ANFIS model

Sugeno ANFIS Model

The Sugeno ANFIS model layers, as shown in Figure 2 below, are:

Input Layer

Let the vector $X = (x_i), i = 1..n$ where each input variable is fuzzy. The input variables x_i are the IS/IT project risks.

This layer contains n nodes where each node corresponds to the IS/IT project risk. In this layer, the connections of each input variable are performed with its fuzzy sets.

Fuzzification Layer

There are nK nodes in this layer, where each input variable has K fuzzy rules. Each node exhibits the membership function of ith antecedent of the jth rule as in Equation 7.

$$o_{ij}^{(2)} = \mu_{A_j^i}(x_i) \tag{7}$$

Where,

A_j^i is the space partition of x_i given as input to the jth rule, and

$\mu_{A_j^i}(x_i)$ is the membership function of $x_i, j = 1, \dots, K$.

Rule Layer

This layer uses the product aggregation operator to perform the t-norm operation on the input variables. A node in this layer represents a fuzzy rule's antecedent or premise part. When the jth rule is fulfilled, the output of the jth node is given in Equation 8.

$$o_j^{(3)} = \bigwedge\nolimits_{i=1}^{n} \mu_{A_j^i}(x_i) \tag{8}$$

Where,

$j = 1, \dots, K$.

Thus, the output of the jth node is as in Equation 9.

$$o_j^{(3)} = \prod\nolimits_{i=1}^{n} \mu_{A_j^i}(x_i) \tag{9}$$

Normalisation Layer

This layer computes outputs through normalisation, which are the normalised firing strengths.

The number of nodes at the layer is the same as the number of nodes at the rule layer LR. The output of the jth node is calculated as in Equation 10.

$$o_j^{(4)} = \frac{o_j^{(3)}}{\sum_{i=1}^{n} o_i^{(3)}} \tag{10}$$

Where,

$j = 1, \ldots, K$.

Consequent Layer

The nodes in this layer compute the consequent part of a rule. Each node applies a function, which is the Sugeno FIS function. This function is a linear relation of input variables x_i as shown in Equation 11.

$$y = f_j(x) = \sum_{i=1}^{n} a_{j,i}\, x_i + a_{j,0} \tag{11}$$

Where,

$a_{j,i}$ are the consequent part parameters of f_j.

The number of nodes at this layer is the same as those at the rule and normalisation layers. For the inputs $(x_1, \ldots, x_n)$, the $o_j^{(5)}$ output of this layer for the jth rule is calculated as in Equation 12.

$$o_j^{(5)} = o_j^{(4)} f_j(x) \tag{12}$$

Where,

$j = 1, \ldots, K$.

The fuzzy rules are outlined in Equation 13.

$$R_j\!: IF\ x_1\ is\ A_j^1\ AND\ x_2\ is\ A_j^2\ AND \ldots AND\ x_n\ is\ A_j^n$$
$$THEN\ y = f_j(x) \tag{13}$$

Where,

n is the input variables number or input space dimension, $j = 1, \ldots, K$, and $K$is the rules number.

Output Layer

This layer contains one node. The output of the Sugeno ANFIS model is outlined in Equation 14.

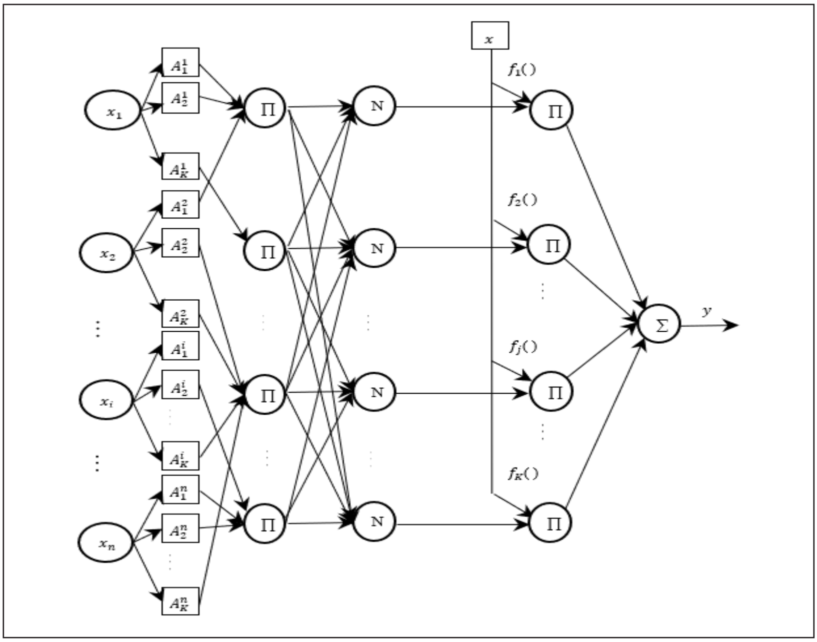
$$o_j^{(6)} = \sum_{j=1}^{K} o_j^{(5)} \tag{14}$$

Thus, the output becomes as in Equation 15.

$$y = \frac{\sum_{j=1}^{K} \mu_{A_j^i}(x_i) f_j(x)}{\sum_{j=1}^{K} \mu_{A_j^i}(x_i)} \tag{15}$$

Figure 2

Sugeno ANFIS Model Architecture



Case Study

In order to demonstrate the applicability of the proposed ANFIS-OPR, an experiment was carried out in an IS/IT PMO case study.

Data Collection

First, the Risk Breakdown Structure (RBS), as depicted in Figure 3, was used to break down the identified risks of IS/IT projects within the IS/IT portfolio by the IS/IT PMO. IS/IT PMO experts are identified as follows: an IS/IT PMO committee chief, 3 IS/IT PMO committee members, and 14 IS/IT project managers (Table 1). IS/IT project managers provided their IS/IT project risk estimates using the Risk Potential Assessment (RPA) instrument of Axelos (2011) by filling the related IS/IT project risks according to the RBS hierarchy, then the IS/IT PMO committee members consolidate these estimates. IS/IT project managers adopted a novel IS/IT project risk assessment based on the definition of project risk as the product of three risk factors: Probability, Impact, and Proximity, which is the timing of the risk to occur if no action was undertaken (Axelos, 2017). The IS/IT project risk is outlined in Equation 16.

$$PR = P_r \times I_m \times P_x \tag{16}$$

Where,

PR is the IS/IT project risk, P_r its probability, I_m impact, and P_x proximity.

To assess uncertainty most conveniently, the IS/IT project risk factors were assessed by the IS/IT project managers with respect to their IS/IT projects using a 3-point Likert scale. Each scale value for probability, impact, and proximity is a linguistic variable as shown respectively in Tables 2 to 4.

Figure 3

RBS of IS/IT Project Portfolio Overall Risk.

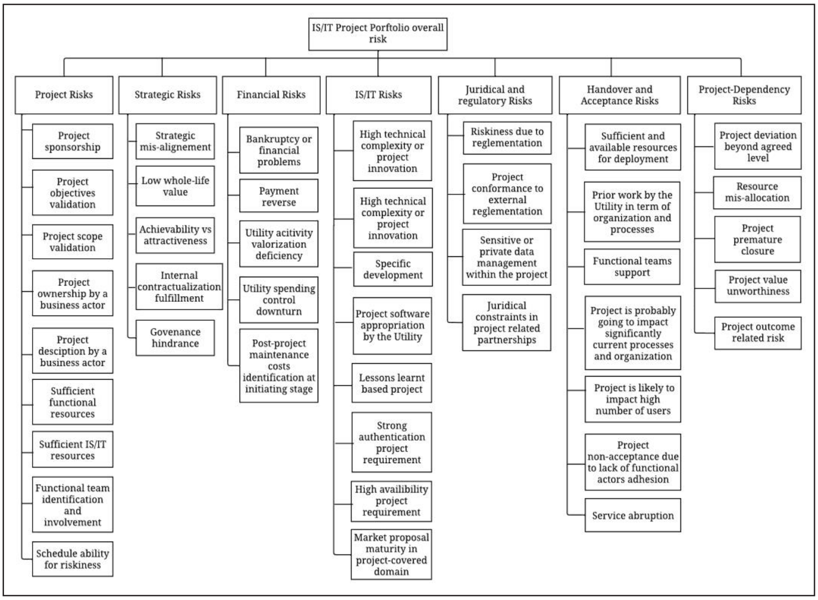


Table 1

IS/IT PMO Experts Characteristics

Code	Gender	Age	Experience (Years)	Job Title
Expert 1	M	49	20	IS/IT PMO committee chief
Expert 2	F	42	10	IS/IT PMO committee member
Expert 3	M	41	11	IS/IT PMO committee member
Expert 4	F	47	15	IS/IT PMO committee member
Expert 5	M	37	18	IS/IT project manager
Expert 6	M	45	14	IS/IT project manager
Expert 7	M	39	15	IS/IT project manager
Expert 8	M	43	17	IS/IT project manager
Expert 9	M	45	15	IS/IT project manager
Expert 10	M	48	15	IS/IT project manager

(continued)

Code	Gender	Age	Experience (Years)	Job Title
Expert 11	F	42	10	IS/IT project manager
Expert 12	M	32	5	IS/IT project manager
Expert 13	M	40	15	IS/IT project manager
Expert 14	M	42	8	IS/IT project manager
Expert 15	M	43	11	IS/IT project manager
Expert 16	F	45	15	IS/IT project manager
Expert 17	M	40	12	IS/IT project manager
Expert 18	M	39	10	IS/IT project manager

Table 2

Three-Point Likert Scale for

$\tilde{1}$: Low	$\tilde{2}$: $Medium$	$\tilde{3}$: $High$
(0;0.5;1)	(0.5;1;1.5)	(1;1.5;2)

Table 3

Three-Point Likert Scale

$\tilde{1}$: $Minor$	$\tilde{2}$: $Moderate$	$\tilde{3}$: $Serious$
(0;0.5;1)	(0.5;1;1.5)	(1;1.5;2)

Table 4

Three-Point Likert Scale for P_x

$\tilde{1}$: $Remote$	$\tilde{2}$: $Moderate$	$\tilde{3}$: $Imminent$
(0;0.5;1)	(0.5;1;1.5)	(1;1.5;2)

The result of this data collection step is a training dataset of 15 attributes, which are the 14 IS/IT projects risk and the output variable to be predicted. Each attribute is a linguistic variable calculated using Equation 16 after the defuzzification and fuzzification phases by the ANFIS-OPR program and follows a 3-point Likert scale (Table 5). The is also a linguistic variable predicted by the ANFIS-OPR program following a 3-point Likert scale (Table 6) to represent the overall level of risk of the IS/IT project portfolio. The IS/IT PMO experts give the initial values after carrying out interviews with the IS/IT Project Managers about their respective IS/IT projects and estimating the overall degree of the IS/IT project portfolio in the different cases of the dataset. Finally, the training dataset is composed of 80 observations collected in a 14-month frame of IS/IT project risk assessment to inform IS/IT project portfolio risk performance. An overview of the training dataset is provided in Figure 4.

Table 5

Three-Point Likert Scale for PR

$\tilde{1}$: *Low*	$\tilde{2}$: *Medium*	$\tilde{3}$: *High*
-(0;0.5;1)	(0.5;1;1.5)	(1;1.5;2)

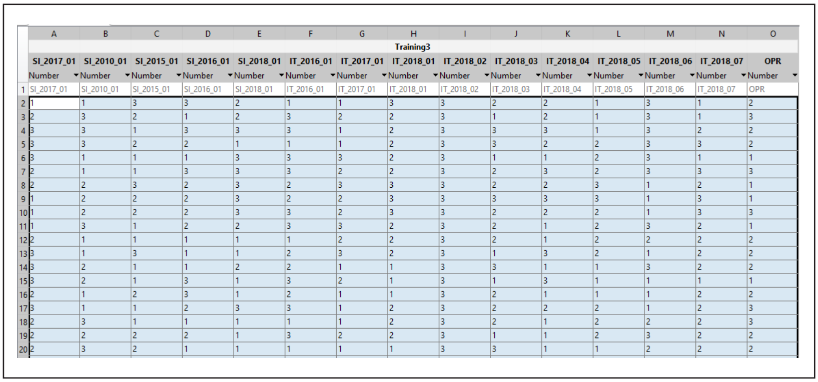
Table 6

Three-Point Likert Scale for OPR

$\tilde{1}$: *Low*	$\tilde{2}$: *Medium*	$\tilde{3}$: *High*
(0;0.5;1)	(0.5;1;1.5)	(1;1.5;2)

Figure 4

Training Dataset



Training3

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
	SI_2017_01	SI_2010_01	SI_2015_01	SI_2016_01	SI_2018_01	IT_2016_01	IT_2017_01	IT_2018_01	IT_2018_02	IT_2018_03	IT_2018_04	IT_2018_05	IT_2018_06	IT_2018_07	OPR
	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number	Number
1	SI_2017_01	SI_2010_01	SI_2015_01	SI_2016_01	SI_2018_01	IT_2016_01	IT_2017_01	IT_2018_01	IT_2018_02	IT_2018_03	IT_2018_04	IT_2018_05	IT_2018_06	IT_2018_07	OPR
2	1	1	3	3	2	1	1	3	3	2	2	1	3	1	2
3	2	3	2	1	2	3	2	2	3	1	2	1	3	1	3
4	3	3	1	3	3	3	1	2	3	3	3	1	3	2	2
5	3	3	2	2	1	1	1	2	3	3	2	2	3	3	2
6	3	1	1	1	3	3	3	2	3	1	1	2	3	1	1
7	2	1	1	3	3	3	2	2	3	2	3	2	3	3	3
8	2	2	3	2	3	2	3	3	3	2	2	3	1	2	1
9	1	2	2	2	3	2	2	3	3	3	3	3	1	3	1
10	1	2	2	2	3	3	2	3	3	2	2	2	1	3	3
11	1	3	1	2	2	3	3	2	3	2	1	2	3	2	1
12	2	1	1	1	1	1	2	2	3	2	1	2	2	2	2
13	3	1	3	1	1	2	3	2	3	1	3	2	1	2	2
14	3	2	1	1	2	2	1	1	3	3	1	1	3	2	2
15	3	2	1	3	1	3	2	1	3	1	3	1	1	1	1
16	2	1	2	3	1	2	1	1	3	2	1	1	1	2	2
17	3	1	1	2	3	3	1	2	3	2	2	2	1	2	3
18	2	3	1	1	1	1	1	2	3	2	1	2	2	2	3
19	2	2	2	2	1	3	2	2	3	1	1	2	3	2	2
20	2	3	2	1	1	1	1	1	3	3	1	1	2	2	2

Data Processing

Using the MATLAB R2020a software, the ANFIS-OPR program was implemented, taking the previous dataset as input. MATLAB R2020a software was preferred for its suitability and integration of the Sugeno ANFIS functions and the neural fuzzy logic designer. According to the new model flow chart (Figure 1), the steps in the ANFIS-OPR program proceed as follows:

Step 1: The fuzzy factor loadings resulting from the FFA are computed.
Step 2: A defuzzication is performed on the selected five fuzzy factor loadings to obtain their crisp values.
Step 3: The latent factors are included as new risk factors in the SWOT technique by the IS/IT PMO experts. This step is performed following the sub-steps of the strategic analysis within the ANFIS-OPR as follows:

1. The selected relevant latent factors with their loading are identified;
2. IS/IT PMO experts rate their probabilities and impacts using the respective scales as depicted in Table 7;

Table 7

Scales of Risk Factors Probabilities and Impacts

Probability scale			**Impact scale**		
Low	Medium	High	Low	Medium	High
Less than 40%	Between 40% and 70%	Between 70% and 100%	0 < impact <= 0.3	0.3< impact <= 0.6	0.6 < impact <= 1

3. IS/IT PMO experts calculate their strategic fit as the product of their probabilities and impacts;
4. IS/IT PMO experts rank them with respect to their strategic fit;
5. Next, as the latent factors are the inputs of the Sugeno ANFIS model, the IS/IT PMO experts formulate the new strategic fuzzy rule PMO experts to implement their reasoning logic using logical operators AND and OR and the linguistic values, , and ;
6. Finally, the Sugeno ANFIS model rule base updates the strategic fuzzy rules.

Step 4: In the ANFIS-OPR program, the crisp values of the fuzzy factor loadings are fuzzified and then given as inputs to the Sugeno

ANFIS model. The strategic fuzzy rules are incorporated into the fuzzy base of the Sugeno ANFIS model. Finally, the ANFIS-OPR computes its two outcomes: OPR crisp value and RMSE.

Results

In each step of the proposed ANFIS-OPR, the following results were provided:

Step 1: According to the criterion of FFA, the FFA scree plot in Figure 5 depicts five fuzzy factor loadings to be selected whose centre eigenvalues are greater than 1. They explain the total variability of the project risks data, where the remaining factors represent a very small proportion of the variability; thus, they are irrelevant factors. The five relevant fuzzy factor loadings are given in Table 8.

Figure 5

FFA Scree Plot

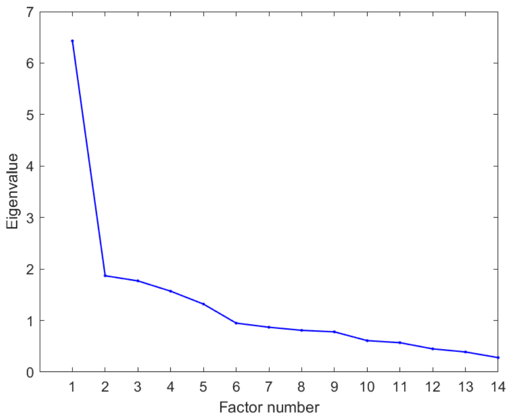


Table 8

Fuzzy Factors Eigenvalues

Factor number	Eigenvalues		
	Left	Center	Right
1	2.25	6.58	2.69
2	0.93	1.9	1.02
3	1.14	1.8	1.68
4	0.19	1.7	0.23
5	1.02	1.4	1.23

Step 2: The crisp values of the selected fuzzy factor loadings were calculated.

Step 3: Using the strategic analysis, the selected relevant latent factors with their loadings were identified as Factor 1, Factor 2, Factor 3, Factor 4, and Factor 5, and their strategic fits were calculated as depicted in Table 9.

Table 9

Strategic Analysis

Factor loadings	Probability	Impact	Strategic fit
Factor 1	Low (10%)	Medium (0.4)	0.04
Factor 2	Medium (50%)	High (0.9)	0.45
Factor 3	High (80%)	Low (0.3)	0.24
Factor 4	Low (10%)	Medium (0.4)	0.04
Factor 5	Medium (50%)	High (0.9)	0.45

Then, the IS/IT PMO experts ranked the five latent factors from the least to the most strategically important: Factor 5, Factor 2, Factor 3, Factor 1, and then Factor 4. Table 10 provides the Sugeno ANFIS model parameters for their execution.

Table 10

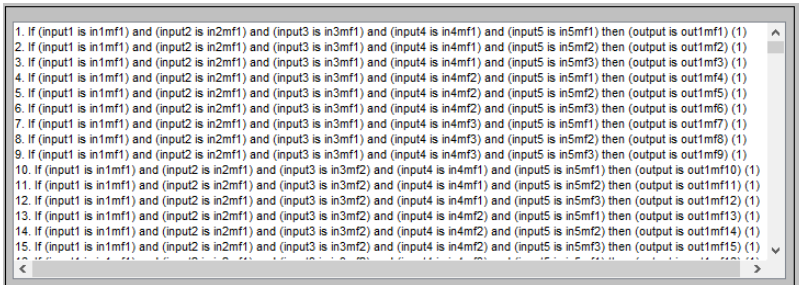
Sugeno ANFIS Models Parameters

Parameter	Value
Epoch number	10
Optimisation method	Hybrid: BP and LSE

It should be noted that, at first execution, the Sugeno ANFIS model generates 243 strategic fuzzy rules as depicted by Figure 6; however, the IS/IT PMO experts can update the model fuzzy rule base with strategic fuzzy rules, representing their knowledge identified in the strategic analysis.

Figure 6

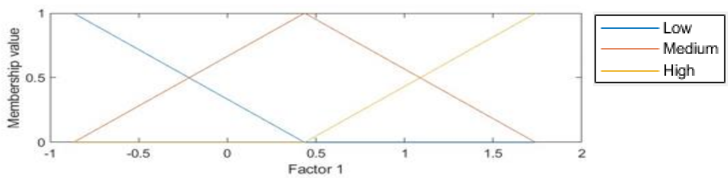
Part of Strategic Fuzzy Rules of the Training Model


1. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) then (output is out1mf1) (1)
2. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf2) then (output is out1mf2) (1)
3. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf3) then (output is out1mf3) (1)
4. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf1) then (output is out1mf4) (1)
5. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf2) then (output is out1mf5) (1)
6. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf3) then (output is out1mf6) (1)
7. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf3) and (input5 is in5mf1) then (output is out1mf7) (1)
8. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf3) and (input5 is in5mf2) then (output is out1mf8) (1)
9. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf3) and (input5 is in5mf3) then (output is out1mf9) (1)
10. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) and (input4 is in4mf1) and (input5 is in5mf1) then (output is out1mf10) (1)
11. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) and (input4 is in4mf1) and (input5 is in5mf2) then (output is out1mf11) (1)
12. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) and (input4 is in4mf1) and (input5 is in5mf3) then (output is out1mf12) (1)
13. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) and (input4 is in4mf2) and (input5 is in5mf1) then (output is out1mf13) (1)
14. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) and (input4 is in4mf2) and (input5 is in5mf2) then (output is out1mf14) (1)
15. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) and (input4 is in4mf2) and (input5 is in5mf3) then (output is out1mf15) (1)

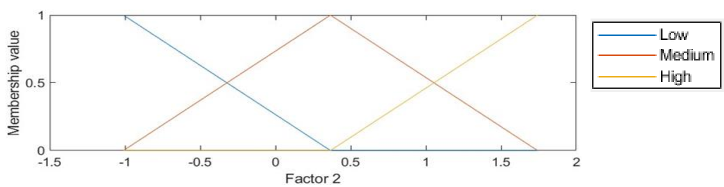
Step 4: After fuzzification by the ANFIS-OPR program, the five latent factors' crisp values are given as inputs to the Sugeno ANFIS model. Figure 7 conveys the membership functions of the five latent factors (Factor 1, Factor 2, Factor 3, Factor 4, Factor 5)

Figure 7

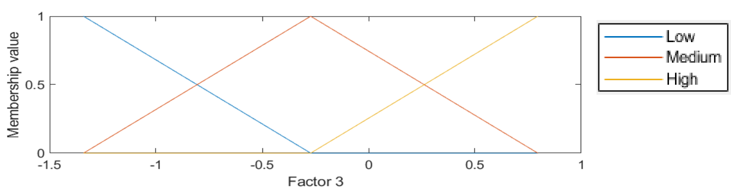
Five Latent Factors Membership Functions



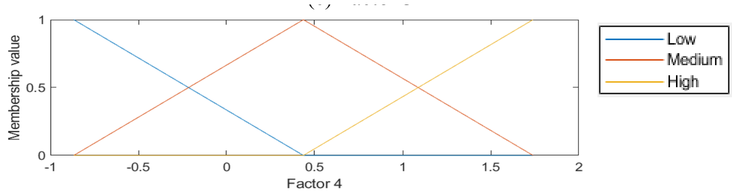
(a) Factor 1



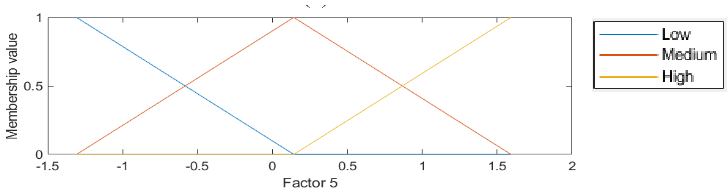
(b) Factor 2



(c) Factor 3



(d) Factor 4



(e) Factor 5

In this step, the IS/IT PMO experts can incorporate new strategic fuzzy rules according to their strategic concerns by updating the fuzzy base of the Sugeno ANFIS model according to their strategic analysis. This experiment's 243 strategic fuzzy rules generated at first execution were kept unchanged. The generated Sugeno ANFIS model structure is depicted in Figure 8. Finally, the ANFIS-OPR provided its two outcomes, the predicted OPR and the RMSE, as shown in Figure 9 and Table 11.

Figure 8

Generated Sugeno ANFIS Model Structure

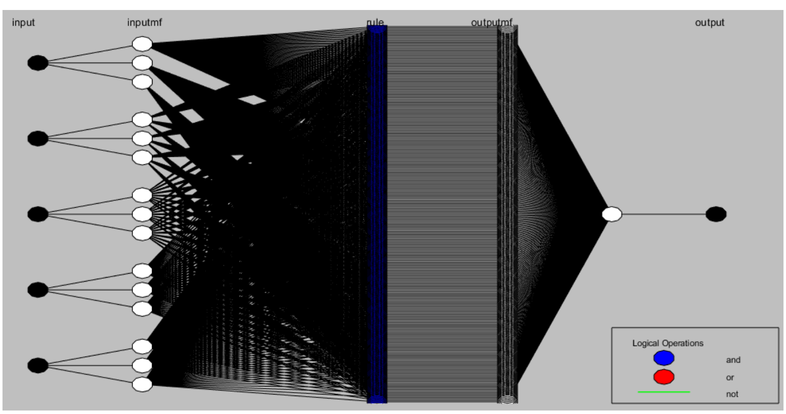


Figure 9

Predicted and Actual OPR

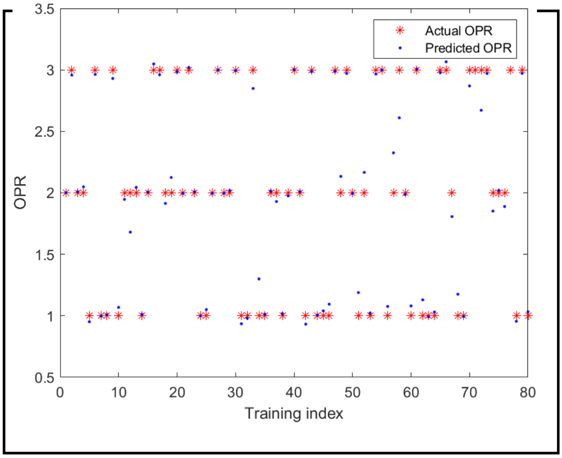


Table 11

Performance Metrics

Metric	Training
RMSE	0.108

Figure 9 reveals that the predicted OPR values are relatively close to the estimated OPR values in the dataset, which indicates the ANFIS-OPR adequacy of modelling the estimated data, dealing with potential non-linearities in IS/IT project portfolio risk data. The highest predicted OPR crisp value, 3.25, is less than the estimated OPR crisp value, 3.4. First, due to ANFIS-OPR's ability to reduce the set of IS/IT project risks using the FFA to relevant features covering the most variance based on the most variance and to its strategic interpretability, it could be possible to obtain a good RMSE.

As depicted by the scree plot and based on the selection criterion of the rule of eigenvalues greater than 1, the ANFIS-OPR reduced the set of IS/IT project risks to five relevant risk features covering the most variance of risk data. These relevant fuzzy factor loadings having centre eigenvalues 6.58, 1.9, 1.8, 1.7, and 1.4 were subject to strategic analysis in which IS/IT PMO experts evaluated the linkage with the strategic fit. This enabled the IS/IT PMO experts to rank them from the most to the least risky or the least to the most strategically important, as Factor 5, Factor 2, Factor 3, Factor 1, then Factor 4. Meanwhile, as each of the five-factor loadings materialises an amount of risk, IS/IT PMO experts evaluate from a SWOT-based strategic perspective, calculate their strategic scores, and then rank them from the most strategic to the least. Afterwards, they formulate their reasoning logic, through the strategic analysis, on the linkage between the degree of risk and strategic fit to finally elaborate strategic fuzzy rules. The strategic fuzzy rules generated at the training phase enhanced the RMSE at ten epochs.

As mentioned below, ANFIS prediction models did not leverage the FFA as a dimensionality reduction technique for fuzzy variables to cope with ‘the curse of dimensionality’ and ensure generalizability. Bui et al. (2018) elaborated the ANFIS-ICA and ANFIS-FA hybrid models for flood spatial prediction, achieving RMSEs respectively equal to 0.35 and 0.129, but without figuring out models overfitting because optimisation was applied within the ANFIS model and not before the prediction model. Besides, the ANFIS model of Barlybayev et al. (2023) predicted the stock prices of companies in the EV sector and obtained an RMSE which equals 5.906 at 2000 epochs. However, their model did not integrate a dimensionality reduction to ensure model generalizability. Asemi et al. (2023) utilised the ANFIS approach to discover managerial traits on investor decision prediction and achieved an RMSE of 0.837, but it failed to handle the dataset dimensionality, thus the generalizability issue. Keneni et al. (2019) tuned an ANFIS-based explainable AI model for UAV and obtained an RMSE of 0.05. Nevertheless, their model did not integrate a dimensionality reduction technique to address the potential increase of autonomous vehicle data.

Our model obtained an acceptable RMSE value of 0.108 due to its following particularities:

- It reduces the dimensionality of the set of IS/IT project risks by considering these risks as input fuzzy variables to produce fuzzy latent factors using FFA to ensure the Sugeno ANFIS model generalizability;
- It provides strategic interpretability of IS/IT PMO experts by incorporating their knowledge on the linkage between OPR and IS/

IT project portfolio strategic fit, thus improving adaptive learning and overall model accuracy.

However, we project to undertake a study to compare, based on RMSE, the performance of our Sugeno ANFIS model based on FFA with the performance of other ANFIS models using the same historical dataset.

DISCUSSION AND CONTRIBUTIONS

The empirical study aimed to experiment with the effectiveness of the new ANFIS-OPR, providing a first finding, which is the predicted OPR (Figure 9) from the IS/IT projects risks historical data while incorporating IS/IT PMO experts' logical representation of how strategically attractive are IS/IT projects from a risk perspective. The second finding is that the computed RMSE (Table 11) was considered satisfactory by the IS/IT PMO experts.

First, the predicted OPR values were close to the initial OPR values provided by the IS/IT PMO in the dataset. It shows a positive prediction trend as predicted values stay close to the estimated ones and implies the effectiveness of the ANFIS-OPR despite potential IS/IT project portfolio risk non-linearities and risk data dimensionality. For instance, to illustrate the learning capability of the proposed ANFIS-OPR, the highest predicted OPR crisp value, 3.25 at the 60^{th} set, was less than the estimated OPR crisp value, which is 3.4. Specifically, the FFA before the ANFIS model enables the model to have the most variance in risk data, which equals the sum of the selected five factors centre eigenvalues 13.38. According to the rule of thumbs, in which each selected factor has a centre eigenvalue greater than 1, five factors are selected and then scored strategically concerning the risk they materialise. At the training phase, the fuzzy rules are generated without modifying the fuzzy base, and the ANFIS-OPR is obtained in 10 epochs with a satisfactory RMSE of 0.108 for IS/IT PMO experts. In the IS/IT PMO context, the computed RMSE demonstrated good accuracy as the measured difference between all estimated and predicted values of OPR is small, which again emphasises the effectiveness of ANFIS-OPR in adaptive learning and interpretability.

In the proposed ANFIS-OPR, from one part, the FFA technique gives generalizability and copes with model overfitting, and from the second part, the Sugeno ANFIS model provides adaptive learning and interpretability. Babu et al. (2018) combined PCA and ANFIS for satellite image fusion and improved the RMSE to 10.38, but it is known that the PCA technique provides less generalizability than FFA. Abdul Mokhtar et al. (2016) modelled the reservoir water release decision through two ANFIS models using the BP and hybrid optimisation methods and obtained RMSEs respectively equal to 0.656 and 0.712, without addressing the ANFIS model generalizability.

In one part, a neuro-fuzzy system incorporates expert knowledge, increases learning speed, and enhances accuracy (Du & Swamy, 2014). That was demonstrated through the case study where the strategic fuzzy rules were generated by the Sugeno ANFIS model, leading to a reduced RMSE. Moreover, our new ANFIS-OPR enables IS/IT PMO experts each time to update the Sugeno ANFIS rule base with new strategic fuzzy rules, implementing their knowledge of the relationship between strategic fit and riskiness while ascertaining an improved accuracy at each execution.

In the second part, the new ANFIS-OPR supports managerially decision-making in IS/IT PMOs by enabling the IS/IT PMO to incorporate their reasoning logic on the relationship between IS/IT project portfolio strategic alignment with OPR flexibly and dynamically while predicting the overall level of risk under high dimensionality of IS/IT projects risks. This is in line with the duality that should exist between IS/IT project portfolio attractiveness or strategic alignment and risk or achievability (Axelos, 2011). Consequently, the new ANFIS-OPR enables the IS/IT PMO to monitor the IS/IT project portfolio risk inherence and carry out appropriate contingency plans according to the overall level of the IS/IT project portfolio from a strategic perspective. In the realm of Project Portfolio performance, risk, and strategic alignment are key areas to be monitored by the IS/IT PMO. In that sense, our proposed ANFIS-OPR is in accordance with the decision-support system of Bilgin et al. (2023), which assesses portfolio risk and strategic fit based on previous, ongoing, and potential project knowledge, providing recommendations about Project Portfolio performance features and strategies. Moreover, the relevance of the proposed ANFIS-OPR in supporting managerial risk decision-making is confirmed by a previous study that addresses risk-based soft sensors for failure rate monitoring in water distribution networks through an ANFIS prediction model (Gheibi et al., 2023).

In the third part, the new ANFIS-OPR is an effective intelligent decision-making tool to predict the IS/IT project portfolio overall risk from IS/IT projects risks based on a novel three-factor IS/IT project risk assessment, where the IS/IT project risk proximity is the third factor. This benefited IS/IT project managers in evaluating the IS/IT project risk more accurately in a predefined IS/IT project portfolio timeframe.

CONCLUSION

The present study elaborated a Sugeno ANFIS model based on FFA for the risk prediction of IS/IT project portfolio. The new ANFIS-OPR enabled, at first training, the prediction of the overall degree of IS/IT project portfolio to be closely related to IS/IT PMO estimates of the overall level of risk and accurately using a lower RMSE. This was performed by extracting five relevant risk factors from 14 IS/IT project risks, narrowing the set of IS/IT project risks, and incorporating IS/IT PMO experts' knowledge about the relationship between Portfolio strategic fit and risk, thus achieving a better RMSE accuracy which equals 0.108. The benefits of this intelligent decision-making tool are dimensionality reduction for the IS/IT project risks fuzzy variables, interpretability of IS/IT project portfolio strategic alignment with relation to IS/IT project portfolio riskiness, accuracy, and automation. This will allow IS/IT PMO to carry out managerial actions appropriately according to the overall risk level in relation to strategic alignment. Therefore, this new intelligent decision-making tool can be generalised to other prediction problems characterised by the curse of dimensionality, fuzziness, and representation of expert knowledge.

As a future direction, it is aimed to integrate the predicted KPI within an IS/IT project portfolio dashboard by improving the current version of the ANFIS-OPR program to include data visualisation and leveraging risk data intelligence and automation to support decision-making accurately. Meanwhile, tuning of the Sugeno ANFIS model hyper-parameters can be applied to guarantee convergence speed in case of ANFIS-OPR performance issues. Therefore, IS/IT PMO will be equipped with an effective, holistic, intelligent, and automated tool that provides the unique 'version of the truth' about IS/IT project portfolio performance from the risk perspective and enables to take risk mitigation action plans effectively and managerial actions appropriately.

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