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Additional Information

Sustainable bridge design by metamodel-assisted multi-objective optimization and decision-making under uncertainty

Tatiana García-Segura¹, Vicent Penadés-Plà², Víctor Yepes³

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Abstract

Today, bridge design seeks not only to minimize cost, but also to minimize adverse environmental and social impacts. This multi-criteria decision-making problem is subject to variability of the opinions of stakeholders regarding the importance of criteria for sustainability. As a result, this paper proposes a method for designing and selecting optimally sustainable bridges under the uncertainty of criteria comparison. A Pareto set of solutions is obtained using a metamodel-assisted multi-objective optimization. A new decision-making technique introduces the uncertainty of the decision-maker's preference through triangular distributions and thereby ranks the sustainable bridge designs. The method is illustrated by a case study of a three-span post-tensioned concrete box-girder bridge designed according to the embodied energy, overall safety and corrosion initiation time. In this particular case, 211 efficient solutions are reduced to two preferred solutions which have a probability of being selected of 81.6% and 18.4%. In addition, a sensitivity analysis validates the influence of the uncertainty regarding the decision-making. The approach proposed allows actors involved in the bridge design and decision-making to determine the best sustainable design by finding the probability of a given design being chosen.

¹ Assistant Professor, Dept. of Construction Engineering and Civil Engineering Projects, *Universitat Politècnica de València*, 46022 Valencia, Spain. **Corresponding author**. Phone +34963877565; E-mail: tagarse@upv.es

² Graduate Research Assistant, Institute of Concrete Science and Technology (ICITECH), *Universitat Politècnica de València*, 46022 Valencia, Spain. E-mail: vipepl2@cam.upv.es

³ Professor, Institute of Concrete Science and Technology (ICITECH), *Universitat Politècnica de València*, 46022 Valencia, Spain. E-mail: vyepesp@cst.upv.es

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1. Introduction

In the past, construction rules were based on the principle of cost minimization. Since the World Commission on Environment and Development (WCED) proposed a long-term vision to maintain the resources necessary to provide future needs (Butlin, 1989), these rules have been changing, and civil structure projects are attempting to consider sustainable aspects in the selection of structural materials (Castañón et al., 2015), to promote low-carbon construction processes (Chen et al., 2010; Wong et al., 2013) and to select the best design (García-Segura et al., 2014; Yeo and Potra, 2015). This is particularly important in the construction sector, since it is one of the main sectors generating greenhouse gases (Liu et al., 2013) and using natural resources (Lippiatt, 1999). So much so that the United Nations Environment Programme has highlighted that, if existing construction industry patterns do not change, the expansion of construction will destroy or at least disturb natural habitats and wildlife of more than 70% of the Earth's surface by 2032 (United Nations Environment Programme, 2002). Given that sustainable development is mainly based on meeting the three pillar of economic, social and environmental development, each of which has different goals and approaches (Penadés-Plà et al., 2016), the difficulty of optimizing a set of objective functions from non-predefined bridge solutions requires further study.

Bridge design selection for sustainable development represents a multi-criteria decision-making problem (MCDM) (Ardeshir et al., 2014; García-Segura et al., 2017a; Malekly et al., 2010). The MCDM problems can be treated as multi-attribute decision-making (MADM) or multi-objective optimization, depending on whether the alternatives are predefined or defined implicitly through a programming formulation (Singh et al.,

2016). The design of a bridge involves a combinatorial problem of variables which focuses on optimizing the objective functions while guaranteeing the structural constraints. The multi-objective optimization has the advantage of providing the best solutions regarding the objectives studied (Pareto front) while avoiding the previous articulation of preferences (García-Segura and Yepes, 2016). However, two main problems are detected: the multi-objective optimization is time consuming due to the structural analysis and the large number of variables and objectives involved (García-Segura et al., 2017a), and the large number of solutions forces the selection of one solution by an *a posteriori* MADM process (Karimi et al., 2017; Yepes et al., 2015a) whose results might be influenced by the uncertainty of the judgements (Bañuelas and Antony, 2007; Chatterjee et al., 2018; Gervásio and Simões da Silva, 2012). Therefore, there is a need for addressing a research that studies the techniques to design optimum bridges in terms of sustainable criteria and considers the uncertainty associated with the importance of the criteria. This paper aims to answer the following research question: can sustainable bridges be optimally designed under the uncertainty related to the comparison of criteria in the decision-making?,

2. Literature review

Metaheuristics are considered as particularly useful algorithms for the multi-objective optimization of structures, since these techniques allow for problems with non-linear, non-differentiable or noisy objectives to be handled, which types of problems are common in structural engineering (Zavala et al., 2013). Paya et al. (2008) employed a simulated annealing algorithm to optimize reinforced concrete building frames based on constructability, economic cost, environmental impact and overall safety. Chiu and Lin (2014) applied particle swarm optimization to determine the optimum maintenance plan considering life-cycle cost, maintenance times, safety,

serviceability and rationality. García-Segura and Yepes (2016) presented a multi-objective harmony search to study the best designs for a bridge based on cost, CO₂ emissions and the overall safety factor. As the algorithm was successfully used to optimize the bridge design selection, the algorithm was also used to study the cheapest solutions with respect to different safety and durability levels (García-Segura et al., 2017a).

Nevertheless, multi-objective optimization of a bridge problem implies a high computational cost, required to analyze multiple bridges and check their safety and serviceability (García-Segura et al., 2017a). In this sense, metamodels, or surrogate models, provide a relationship between the variables representing the response of the original simulation model. These models are used to effectively simulate processes in the construction sector (García-Segura et al., 2017a; Ozcan-Deniz and Zhu, 2016), especially when a large computational time is needed to solve the problem. Despite the fact that other surrogate models exist, such as polynomial response surfaces, radial basis functions and Kriging models, Artificial Neural Networks (ANN) are considered to be a powerful computation tool for complex structure problems (Caglar et al., 2008; Deb and Nain, 2007; García-Segura et al., 2017a). ANN is a model instrument based on artificial neurons that solves complex and non-linear problems. This instrument learns from training examples and approximates non-linear functions to provide a response or output.

Regarding design criteria, economic structures tend to reduce material consumption, and this also contributes to the minimization of emissions (García-Segura et al., 2015) and energy use (Martí et al., 2016). In this sense, cost optimization is a good approach to achieving an environmentally friendly design (García-Segura and Yepes, 2016). However, as the environmental and economic unit costs of construction

materials do not have a proportional relationship to one another (Yepes et al., 2015b), environmental criteria should be considered to achieve sustainable infrastructures (Barandica et al., 2013; Zastrow et al., 2017; Zhong and Wu, 2015). Both the CO₂ emissions and the embodied energy have also been selected as interesting objectives for environmental optimization (Martí et al., 2016; Yeo and Gabbai, 2011; Yeo and Potra, 2015).

Social aspects relating to the sustainability of infrastructures are studied in depth in several publications since this is an emerging topic (Penadés-Plà et al., 2016; Sierra et al., 2018a; Yu et al., 2017). In bridge planning and design, researchers carry out strategies to improve the aesthetic feel (Ohkubo et al., 1998), cultural heritage and public perception of the bridge (Ugwu et al., 2006), in addition to vehicle operation costs and safety costs (Gervásio and da Silva, 2012), among other factors. Despite authors highlighting the lack of unanimity in the social pillar (Penadés-Plà et al., 2016; Sierra et al., 2018b), it is important to select the criteria based on the characteristics of the case study to achieve the objective sought. Social investments within long-term care include those in improving quality of care and quality of life, increasing capacities to participate in society and the economy and promoting sustainable and efficient resource allocation (Lopes, 2017). In this sense, the design of a bridge must meet the needs for which it has been planned and reduce the long-term use of resources. In order to extend the service life of structures and to optimize maintenance actions, the durability condition and safety criteria should be considered (García-Segura et al., 2017b; Neves and Frangopol, 2005). Additionally, the durability condition also has an influence on the life-cycle cost, since the maintenance of corroded components represents the greater part of the life-cycle costs of long-span coastal bridges (Cheung et al., 2009).

The multi-objective optimization of sustainable criteria provides a Pareto front of efficient solutions which have conflicting objectives. MADM are used to select these trade-off solutions based on certain information, experience and judgment. In the literature, there are many MADM methods which have been reviewed in a number of publications (De Brito and Evers, 2016; Jato-Espino et al., 2014; Vicent Penadés-Plà et al., 2016). The multi-criteria optimization and compromise solution (VIKOR, derived from the Serbian name *Vise ViseKriterijuska Optimizacija I Komoromisno Resenje*) (Opricovic, 1998) rank the alternatives according to the distance to the ideal point, which is in line with the multi-objective optimization. VIKOR method focuses on ranking and selecting a solution from a finite set of feasible alternatives which are in the presence of conflicting criteria with different units (Chatterjee and Chakraborty, 2016). VIKOR is a helpful tool particularly in a situation where the decision-maker is not able, or does not know to express his/her preference at the beginning of system design (Opricovic and Tzeng, 2004). Therefore, this method can be combined effectively with the multi-objective optimization to select a solution of the Pareto front. As the compromise solution will depend on the value that the decision-maker wants to place to each criterion, the combined use of the Analytical Hierarchy Process (AHP) and VIKOR provides a powerful tool to obtain the closest compromise solution to the ideal point from the verbal judgements of the decision-makers (Chatterjee and Kar, 2017; Pourebrahim et al., 2014; Singh et al., 2016). AHP is a technique used in the decision-making process to help decision-makers set priorities among alternatives and make better decisions by taking into account qualitative and quantitative aspects of the decision (Bañuelas and Antony, 2007). This method has been successfully used in facilitating the judgment of complex problems, as decision-makers are not required to make numerical guesses as subjective judgments are easily included in the process and

the judgments can be made entirely in a verbal mode (Korpela et al., 2001). AHP method is suitable for problems which can be decomposed into a hierarchy (Güngör et al., 2009). In addition, this method can check inconsistencies in the decision-maker's assessments (Saaty, 1987). AHP has been used to select the best bridge construction site (Aghdaie et al., 2012; Ardeshir et al., 2014), the type of bridge (Farkas, 2011) and the bridge construction method (Pan, 2008), among others. A correspondence analysis showed that AHP is centered and located in an intermediate position between the design and planning phase, the construction phase and the operation and maintenance phase (Penadés-Plà et al., 2016). Consequently, this method can be used in these three life-cycle phases.

Despite the fact that AHP facilitates the weight criteria assignment, Abu Dabous and Alkass (2008) stated that the relative importance of two elements is difficult to define using deterministic numbers due to the uncertainty in the behavior of the different elements under consideration. Uncertainty in sustainability can be derived from many sources like data uncertainty, model uncertainty and uncertainty in the decision-making (Baker and Lepech, 2009; Durbach and Stewart, 2012; Lloyd and Ries, 2008; Sierra et al., 2018; Webb and Ayyub, 2017). Data uncertainty and model uncertainty are commonly related to the evaluations of the performance of sustainability criteria. However, uncertainty in the decision-making influences the weighting of the conflicting criteria. This paper focuses on this last type of uncertainty, which is also considered as internal uncertainty (Stewart, 2005). While external uncertainty refers to the lack of knowledge, which may be outside of the control of the decision-maker, the internal uncertainties refer to both the structure of the model adopted and the judgmental inputs (for instance, the introduction of importance weights (Gervásio and Simões da Silva, 2012)). The uncertainty in the decision-making occurs due to

subjective and qualitative judgment of decision-makers (Chatterjee et al., 2018). As researchers like Bañuelas and Antony (2007) claimed, real-world interventions such as the design concept selection, implicate relationships between people and their differential willingness and this affects the capability of reaching consensus and complicates the decision-making. The uncertainty in the criteria weighting can be appreciated even more clearly in the sustainability context, as firstly the contribution of each criterion to the sustainable development is not clear (Yao et al., 2011), and secondly, the stakeholders have different interests and opinions (Delgado and Romero, 2016; Fernández-Sánchez and Rodríguez-López, 2010; Sierra et al., 2018). For this reason, researchers (Gervásio and Simões da Silva, 2012; Umer et al., 2016) pointed out the importance of considering the uncertainty to achieve a good decision-making practice.

The techniques that handle this type of uncertainty can capture the variability of the decision-maker preferences on criteria, which has an impact on the probabilistic ranking of the preferred alternatives (Bañuelas and Antony, 2007). Thus, a methodology that gives a probabilistic interpretation of the preferred solution provides more precise information on the preferred bridge alternative in the context of the sustainable design. In this regard, multi-objective fuzzy decision-making approaches have been developed to select the best bridge construction site (Ardeshir et al., 2014), the bridge construction method (Pan, 2008), the bridge construction project (Chou et al., 2013) and the type of bridge (Jakiel and Fabianowski, 2015; Malekly et al., 2010). Generally, triangular or trapezoidal fuzzy numbers are used to define the uncertainty (Abu Dabous and Alkass, 2008). However, the decision-makers do not take part in the definition of their certainty relating to the sustainable criteria comparison.

3. Research gap and research objectives

Sustainable bridge design requires the consideration of environmental (Yeo and Gabbai, 2011; Zastrow et al., 2017; Zhong and Wu, 2015) and long-term criteria (Cheung et al., 2009; Neves and Frangopol, 2005). Despite researchers claimed the necessity to incorporate the variability of the opinions of stakeholders regarding sustainable criteria importance (Bañuelas and Antony, 2007; Bilbao-Terol et al., 2012; Gervásio and Simões da Silva, 2012; Umer et al., 2016), particularly in bridge selection (Abu Dabous and Alkass, 2008; Ardeshir et al., 2014; Jakiel and Fabianowski, 2015), bridge design optimization has not yet integrated the uncertainty in the selection process (García-Segura et al., 2017a; García-Segura and Yepes, 2016).

Based on the research gap, this paper proposes the following research objectives: (1) to develop a method to design and select sustainable bridges by taking into account the variability of the judgments regarding criteria comparison, (2) to analyze the influence of the variability of the opinions of stakeholders on the selection of the most sustainable bridge.

4. Organization of the paper

The paper is structured as follows: Section 5 presents a method to first define the problem, and then to carry out the multi-objective optimization and finally develop the decision-making technique. Section 6 illustrates the method using a case study of a post-tensioned concrete box-girder bridge and Section 7 carries out a sensitivity analysis to validate the method. Finally, Section 8, 9 and 10 presents respectively the conclusions, implications and limitations and future research.

5. Research framework

In light of the literature analysis, this section proposes a complete method that integrates multi-objective optimization and decision-making that overcomes the

problem of time consumption via the inclusion of the uncertainty relating to the sustainable criteria comparison. The framework of the method is divided into three sequential steps: problem definition, metamodel-assisted multi-objective optimization and decision-making, as shown in Fig. 1.

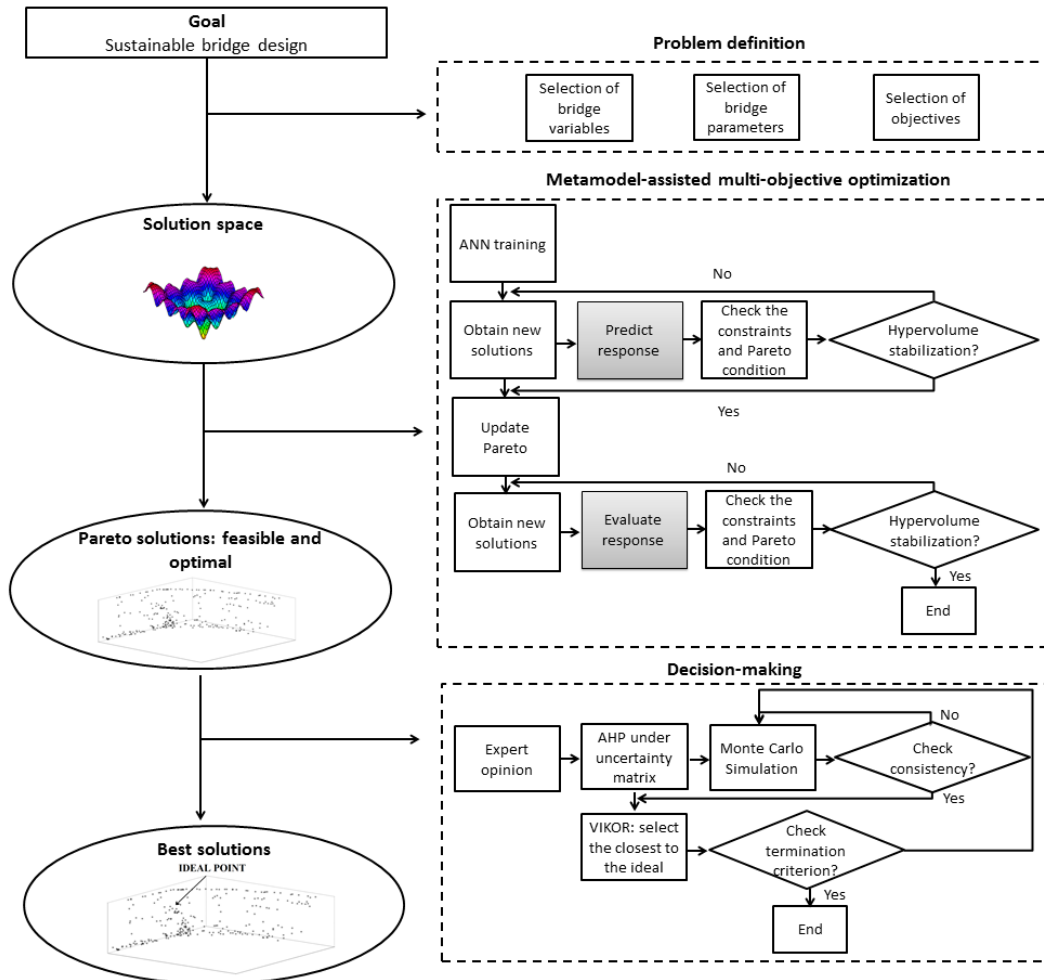


Fig. 1 Flowchart describing the method for designing and selecting a sustainable bridge

5.1. First step: problem definition

Before carrying out the multi-objective optimization, it is important to properly establish the problem definition, which consists of selecting the bridge variables, parameters and objectives to achieve the sustainable goal. This step demarcates a solution space from which the metaheuristic algorithm will find the optimum solutions.

The multi-objective optimization problem aims to minimize or maximize some objective functions F_i while satisfying the constraints G_j . Both the objective functions and structural constraints depend on the design variables x_1, x_2, \dots, x_n and the parameters p_1, p_2, \dots, p_m . Each design variable can adopt discrete values, which range between d_{k1} and d_{kqk} .

$$F_i(x_1, x_2, \dots, x_n; p_1, p_2, \dots, p_m), \quad (1)$$

$$G_j(x_1, x_2, \dots, x_n; p_1, p_2, \dots, p_m) \leq 0, \quad (2)$$

$$x_k \in (d_{k1}, d_{k2}, \dots, d_{kqk}). \quad (3)$$

The parameters, together with the variables, define the complete bridge design. The parameters are all fixed quantities that do not change during the optimization procedure and their choice leads to a particular case study. When varying the parameters, the optimum values of the variables and the objective functions change accordingly. An optimization algorithm explores the search space to find the best values of the variables that optimize the objective functions. These values are discrete in order to guarantee that the bridge can be built. The objective functions are determined with the aim of achieving the pursued goals. Constraints, in the case of bridge design, verify the demands of safety and those relating to the aptitude for service requirement, as well as the geometrical and constructability requirements (García-Segura and Yepes, 2016). Note that the constraints can be transferred to objective functions for further strengthening the solutions that address these objectives.

5.2. Second step: metamodel-assisted multi-objective optimization

The second step aims to reduce the solution space to a feasible and optimal set. To this end, a metamodel-assisted multi-objective optimization is proposed. Multi-

objective optimization (MOO) of bridges requires a large computational time due to the existence of many decision variables and objective functions, as well as the use of finite-element analysis (García-Segura et al., 2017a). For this reason, García-Segura et al. (García-Segura et al., 2017a) proposed an approximate model to reduce the bridge response evaluations. The model uses ANNs to learn from training examples, and then predicts the structural behavior of a bridge design. As mentioned in Section 1.2.1, despite the fact that there are other surrogate models, ANN is considered to be a powerful computational tool for complex structure problems (Caglar et al., 2008; Deb and Nain, 2007; García-Segura et al., 2017a). ANNs are integrated into the constraint module of the multi-objective optimization, which model provides an approximate Pareto front that stabilizes near the true Pareto front. The metamodel-assisted multi-objective optimization is divided into the following four stages (see Fig. 1):

1. ANN training uses a Levenberg-Marquardt backpropagation algorithm to learn from the data and adjusts the weights associated with the neurons. The data are divided into training, validation and test sets with respective percentages of 70%, 15%, 15%. The multilayer feedforward network consists of one hidden layer of sigmoid neurons followed by an output layer of a linear neuron. The input and output variables refer, respectively, to the variables and the safety factors associated with the limit states.
2. The multi-objective optimization is combined with ANN to obtain an approximate Pareto set. As mentioned previously, ANN is used to obtain the safety factors from the design variables and based on these values, nine predictions for each output are carried out and the average value is obtained. The constraints check the bridge response based on the limit states predicted and the objective evaluation verifies the Pareto condition. The multi-objective harmony

search algorithm is employed to find the design variables that optimize the objective functions. The termination criterion of this step is set based on the hypervolume stabilization.

3. The Pareto set is updated through an exact method. Each bridge design is evaluated by a finite-element analysis and a limit state verification. The feasible and optimum solutions constitute the updated Pareto front.

Last stage departs from the updated Pareto front and carries out a finer multi-objective optimization. The multi-objective harmony search generates new solutions that are analyzed through a finite-element analysis and then verified. The optimization process finishes when the difference in the hypervolume value is less than 0.0005.

5.3. Third step: decision-making

The final step conducts a decision-making process using a hybrid MADM method that reduces the large number of solutions of the multi-objective optimization and makes the preferences between sustainable criteria more flexible. AHP is employed to provide the weights for the criteria and VIKOR to rank the alternatives according to their proximity to the ideal solution (Chatterjee and Kar, 2017; Pourebrahim et al., 2014; Singh et al., 2016). This method extends the AHP method by proposing probabilistic distributions to represent the uncertainty in the decision-maker's preferences.

AHP is a decision analysis technique that incorporates expert preferences through pairwise comparisons using Saaty's fundamental scale (Saaty, 1987). This is an appropriate method to study sustainability of bridge design as it uses a hierarchical model. The elements are compared based on their degree of contribution to the next higher level. In this regard, criteria are compared based on their importance in order to achieve a sustainable bridge design. Table 1 shows the numerical scale assignment

associated with each verbal scale of importance. These values are transferred to a reciprocal matrix of the order of (m,m) , where m is the number of criteria. This matrix is considered to be of acceptable consistency when the consistency ratio (CR) is less than 0.1. In this case, the criteria weights (w_j) are obtained by the eigenvector method, so that this method guarantees consistency of judgments.

Table 1. Saaty's fundamental scale (Saaty, 1987)

Numerical scale (P)	Verbal scale	Explanation
1	Same importance	The two elements make a similar contribution to the criterion
3	One item moderately more important than another	Judgment and earlier experience favor one element over another
5	One item significantly more important than another	Judgment and earlier experience strongly favor one element over another
7	One item much more important than another	One element dominates strongly. Its domination is proven in practice
9	One item very much more important than another	One element dominates the other with the greatest order or magnitude possible

As the relative importance between two elements is difficult to define with deterministic numbers due to the uncertainty in their behavior (Abu Dabous and Alkass,

2008), this paper proposes a modified AHP that takes into account the uncertainty associated with the criteria comparison. A triangular distribution is defined for each pairwise comparison value of the AHP matrix. The distribution is then defined by the most likely value (P) and the low and high limits (A , B). The conventional AHP provides the P value (see Table 1) and the A and B values symbolize the range of variability of the relative importance of each pair of criteria. These values are determined through the uncertainty value (UV), which represents one side of the symmetric triangular distribution. Table 2 defines the UV according to each verbal scale of uncertainty. Note that the scale of values should be consistent with the reciprocal comparison matrix. In this sense, A and B follow the scale of values ($1/9, 1/8, 1/7, 1/6, 1/5, 1/4, 1/3, 1/2, 1, 2, 3, 4, 5, 6, 7, 8, 9$). As an example, Fig. 2 shows the triangular distribution of the random variables that correspond to an extreme case of judgment “Experts are very uncertain that Criterion 1 has the same importance as Criterion 2”. In this case, the high limit considers that Criterion 1 is very much more important than Criterion 2 ($B=9$) and the low limit considers that Criterion 2 is very much more important than Criterion 1 ($A=1/9$). The UV (equal to 8) determines the steps between the high limit B and the most likely value (P) (equal to 1). However, the random variables that lie within the A - P range should be transformed to the scale of values previously mentioned following these equations:

Table 2. Uncertainty values

Numerical scale (UV)	Verbal scale	Explanation
$\frac{0}{4}(9 - P)$	Very certain	The expert is very certain that the assessment is correct

$\frac{1}{4}(9 - P)$	Certain	The expert is certain that the assessment is correct
$\frac{2}{4}(9 - P)$	Fairly certain	The expert is fairly certain that the assessment is correct
$\frac{3}{4}(9 - P)$	Uncertain	The expert is uncertain that the assessment is correct
$\frac{4}{4}(9 - P)$	Very uncertain	The expert is very uncertain that AHP assessment is correct

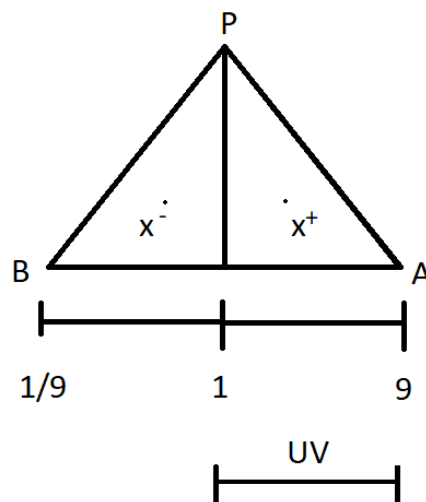


Fig. 2 Example of triangular probability distribution

$$x = \begin{cases} x^+, & \text{with probability } 0.5 \\ x^-, & \text{with probability } 0.5 \end{cases}, \quad (4)$$

$$x^- = P - (x^+ - P) \text{ if } x^- > 1, \quad (5)$$

$$x^- = (2 + x^+ - 2P)^{-1} \text{ if } x^- < 1. \quad (6)$$

Once the triangular distributions are defined, the values are obtained through Monte Carlo simulations. The simulation selects random values from the triangular distribution and uses these values to complete the reciprocal matrix. Next, the weights corresponding to consistent matrices are saved and applied to each criterion. The VIKOR method (Opricovic, 1998) is then used to select the closest alternative to the ideal point. The ideal solution contains the best values of each criterion from the set of solutions. In contrast, the negative-ideal solution is obtained as the worst values for each criterion. This method evaluates the *L_p-metric* distance from any point to the ideal vector in the *p* norm as:

$$\lambda_j = w_j / \delta_j = \frac{w_j}{(z_j^* - z_j^-)} \quad , \quad (7)$$

$$L_p = [\sum_{j=1}^q \lambda_j^p |z_j^* - z_j(x)|^p]^{1/p} \quad p=1,2,\dots, \quad (8)$$

$$L_\infty = \lim_{p \rightarrow \infty} L_p = \max_{j=1,\dots,q} \lambda_j |z_j^* - z_j(x)|, \quad (9)$$

where $z_j(x)$, $j = 1, \dots, q$ are the criteria considered in the problem, $z^* = (z_1^*, \dots, z_q^*)$ is the ideal solution, $z^- = (z_1^-, \dots, z_q^-)$ is the negative-ideal solution, λ_j ($j = 1, \dots, q$) are the normalized weights associated with the criteria and w_j ($j = 1, \dots, q$) are the weights obtained from the AHP method. This method considers the Manhattan (L_1) and Chebyshev (L_∞) metrics, also called the *S* and *R* metric, respectively. Finally, the values Q_j associated with each solution j are obtained as:

$$Q_j = v \frac{S_j - S^*}{S^- - S^*} + (1 - v) \frac{R_j - R^*}{R^- - R^*}, \quad (10)$$

where ν is introduced as the weight of the strategy of the maximum group utility, S^* and R^* are the best values and S^- and R^- are the worst values of the Manhattan and Chebyshev metrics. This paper considers $\nu = 0.5$.

6. Case study

6.1. Problem definition

The case study involves a three-span post-tensioned concrete box-girder bridge located in a coastal region. The width of the deck (11.8 m) and the length (114.4 m) are parameters of the problem. The bridge design uses 34 variables that define the concrete strength, the cross-sectional dimensions, passive and post-tensioning steel. Nine variables define the geometry and the reinforcing steel is specified by 21 variables, which describe the diameter of the longitudinal and the transverse reinforcing steel, the number of bars per meter of the longitudinal reinforcing and the spacing of all of the transverse reinforcing. The amount of post-tensioning steel and the parabolic layout are determined by three variables: the eccentricity in the external span, the point of inflection and the number of strands.

The criteria are selected to be consistent with the sustainable approach from the design perspective. In this regard, this paper proposes the embodied energy, the overall safety and the corrosion initiation time as objective functions. In view of the discussion of Section 1.2.2, the embodied energy can be selected as an interesting objective for the environmental optimization (Martí et al., 2016; Yeo and Gabbai, 2011). The corrosion initiation time and safety objective functions are considered with the aim of designing for longevity and reduced long-term impacts (García-Segura et al., 2017b; Neves and Frangopol, 2005). The multi-objective optimization will allow for the discovery of useful knowledge regarding the best bridge designs to reduce the embodied energy and increase bridge durability and safety.

The embodied energy is evaluated as the energy of material production, transport and placement where construction units considered are concrete, post-tensioning steel, reinforcing steel and formwork. Each construction unit includes raw material extraction, manufacture, transportation and placement. The embodied energy (E) is calculated according to the unit energy of concrete (E_{co}), the volume of concrete (V_{co}), the unit energy of reinforcing steel (E_{rs}), the weight of reinforcement steel (W_{rs}), the unit energy of prestressed steel (E_{ps}), the weight of prestressed steel (W_{ps}), the unit energy of formwork (E_f) and the area of the formwork (A_f). Unit energies, shown in Table 3, are obtained from the Institute of Construction Technology of Catalonia (ITEC) database (BEDEC).

$$E = E_{co} \cdot V_{co} + E_{rs} \cdot W_{rs} + E_{ps} \cdot W_{ps} + E_f \cdot A_f \quad (11)$$

Table 3. Embodied energy related to construction units

Unit measurements	Energy
Square meter of formwork	8.7
Kilogram of steel (B-500-S)	10.44
Kilogram of prestressed steel (Y1860-S7)	12.99
Cubic meter of concrete 35 MPa	612.22
Cubic meter of concrete 40 MPa	646.61
Cubic meter of concrete 45 MPa	681.00
Cubic meter of concrete 50 MPa	715.39
Cubic meter of concrete 55 MPa	749.77
Cubic meter of concrete 60 MPa	784.16
Cubic meter of concrete 70 MPa	852.94
Cubic meter of concrete 80 MPa	921.72
Cubic meter of concrete 90 MPa	990.49
Cubic meter of concrete 100 MPa	1059.27

The overall safety factor (S) is evaluated as the minimum overall safety factor for the torsion, flexure, transverse flexure and shear limit states. The overall safety factor corresponds to the ratio between the ultimate resistance of the structural response

and the ultimate load effect of actions for each limit state. These limit states are based on the safety approach proposed in the structural codes (European Committee for Standardisation, 2005; Fomento, 2008) which consider partial safety factors for loads and material strengths to guarantee a reliable structure. It is worth noting that an overall safety factor of one implies strict compliance.

The corrosion initiation time (t_{corr}) is the time required to achieve a critical threshold value (C_r) on the surface of the reinforcing steel due to chloride attack. The model used to evaluate this period is based on Fick's second law, which depends on the surface content (C_o), the apparent diffusion coefficient (D) and the error function (erf). The apparent diffusion coefficient model, suggested by Vu and Stewart (2000) and also proposed by Papadakis et al. (1996), depends on the chloride diffusion coefficient in an infinite solution ($D_{H2O} = 1.6 \times 10^{-5} \text{ cm}^2/\text{s}$ for NaCl), the mass density of cement (ρ_c is considered to be 3.16 g/cm^3), the mass density of the aggregates (ρ_a is considered to be 2.6 g/cm^3), the aggregate-cement ratio (a/c) and the water-cement ratio (w/c). The model considers the uncertainties in the apparent diffusion coefficient (normal function, $\mu = 1$, $\text{COV} = 0.2$), chloride concentration on the surface (log-normal function, $\mu = 2.95$, $\text{COV} = 0.3$), concrete cover (normal function, $\mu = c_c$, $\text{COV} = 0.25$) and the critical threshold value (uniform function, $\text{min}=0.6$, $\text{max}=1.2$). These values were proposed by Vu and Stewart (2000). The corrosion initiation time distribution is obtained by Monte Carlo simulation. The mean value of the lognormal distribution is given as the representative value (García-Segura et al., 2017a).

$$C(x, t) = C_o \left[1 - \text{erf} \left(\frac{x}{2\sqrt{tD}} \right) \right] \quad (12)$$

$$D = D_{H_2O} 0.15 \cdot \frac{1 + \rho_c \frac{w}{c}}{1 + \rho_c \frac{w}{c} + \frac{\rho_c \alpha}{\rho_a c}} \left(\frac{\rho_c \frac{w}{c} - 0.85}{1 + \rho_c \frac{w}{c}} \right)^3 \quad (13)$$

6.2. Metamodel-assisted multi-objective optimization

This multi-objective optimization considers the embodied energy, the overall safety factor and the corrosion initiation time as objectives to achieve the sustainability goal. The constraints check all the serviceability limit states (SLSs) and the ultimate limit states (ULSs) that the structure must satisfy. These limit states are specified in the Spanish code (Fomento, 2011, 2008), based on the Eurocode (European Committee for Standardisation, 2005, 2003). The constructability requirements are also checked.

The neural network is trained using 4500 data points. Each datum comprises 34 input variables and one output variable. The input variables are those mentioned in Section 3.1 and the output variables correspond to the safety factors associated with the limit states. To predict the 17 limit states, the process is carried out 17 times and the number of neurons is adjusted to provide the best performance, avoiding overfitting and poor generalization ability for other data. In this case, the ANN was calibrated with 10 neurons. More details regarding the multi-objective optimization problem can be found in the study of García-Segura et al. (2017a). Figure 3 illustrates the results of the multi-objective optimization problem.

The Pareto front provides a set of optimum bridge solutions taking account of the embodied energy, the overall safety factor and the corrosion initiation time. Results show the increment in the embodied energy as the demands on durability and safety increase. While a safety improvement leads to a high increment in embodied energy, this is not so for durability improvement. Figure 3 shows the parabolic relationship between the embodied energy and the overall safety factor. A similar trend was obtained

by Paya et al. (2008) when comparing the cost versus overall safety. The Pareto front provides a set of trade-off solutions from which the designer must select the most desirable one. Solutions with higher safety and durability require higher amounts of materials and concrete of a higher strength, but the lifetime extension would also reduce future maintenance requirements.

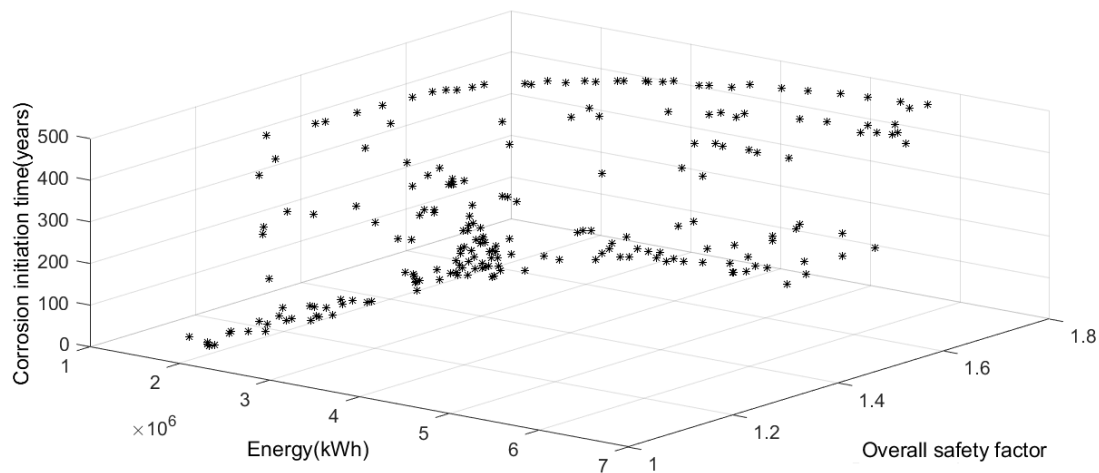


Fig. 3. Pareto front of solutions

6.3. Decision-making

For this case study, the AHP under uncertainty method is used to obtain the weights for the energy, corrosion initiation and overall safety criteria. Experts provide their judgments regarding the relative importance of the criteria and the uncertainty related to these opinions. Note that an overall safety factor of one implies a strict compliance with the code. As all of the solutions have an overall safety factor greater than one, the minimum safety level required by the code is guaranteed. Based on this, the overall safety and the other criteria are compared.

This case study proposes the following judgments:

- Experts are certain that the energy is much more important than the overall safety factor. This leads to $P_1=7$, $UV_1=1/2$, $A_1=6.5$, $B_1=7.5$.

- Experts are certain that the initiation of corrosion is significantly more important than the overall safety factor. This leads to $P_2=5$, $UV_2=1$, $A_2=4$, $B_2=6$.

- Experts are fairly certain that the energy is equally as important as the initiation of corrosion. This leads to $P_3=1$, $UV_3=4$, $A_3=1/5$, $B_3=5$.

The following matrix contains the values of the triangular function [A,P,B]. Random values are obtained based on each distribution by applying the Monte Carlo method. It is worth noting that 10,000 consistent matrices are obtained to generate a histogram of the weight of each criterion. AHP matrices which are not consistent are not considered. Note that some ranges of values may lead to inconsistent matrices. Therefore, it may be that increasing the uncertainty range does not change the results.

	Energy	Overall safety	Corrosion initiation
Energy	1	[6.5,7,7.5]	[1/5,1,5]
Overall safety	[1/7.5,1/7,1/6.5]	1	[1/6,1/5,1/4]
Corrosion initiation	[1/5,1,5]	[4,5,6]	1

Figures 4, 5 and 6 show the histograms of energy, corrosion initiation and overall safety weights. The histograms show a good approximation to a normal distribution function. Both energy and corrosion initiation have higher AHP values with respect to the overall safety. Consequently, the energy and corrosion initiation weights are much higher than the weight for the overall safety. The histogram of the energy weight (Fig. 4) has minimum and maximum values of 0.45 and 0.641, where the median is 0.548. The histogram of initiation corrosion weight (Fig. 5) has minimum and

maximum values of 0.285 and 0.477, where the median is 0.375. Figure 6 shows the overall safety weight histogram. In this case, the minimum and maximum values are 0.068 and 0.085, and the median is 0.076. As experts consider overall safety factor to be less important than the other criteria, the weight associated with this criterion is smaller.

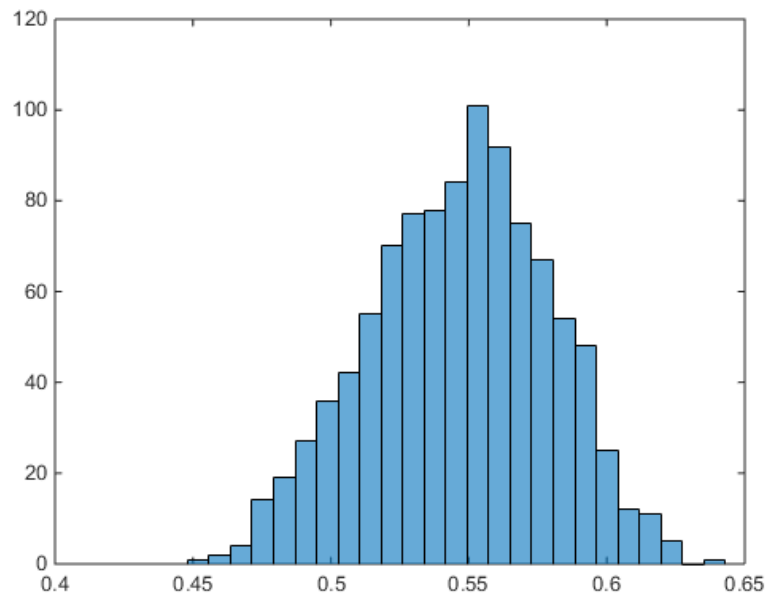


Fig. 4. Histogram of energy weight

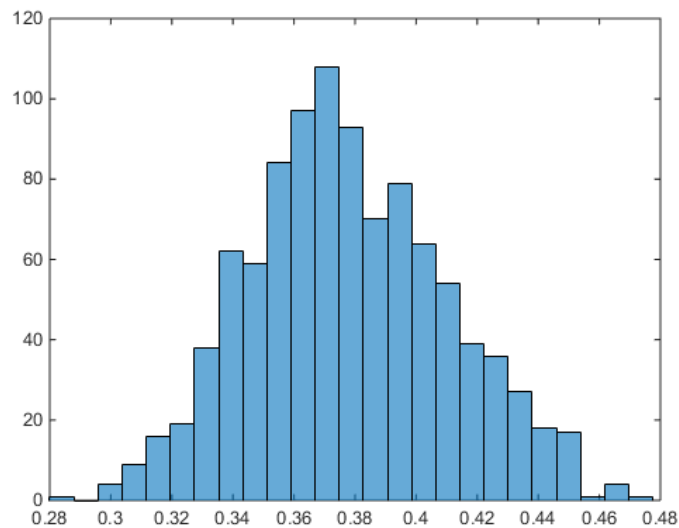


Fig. 5. Histogram of corrosion initiation weight

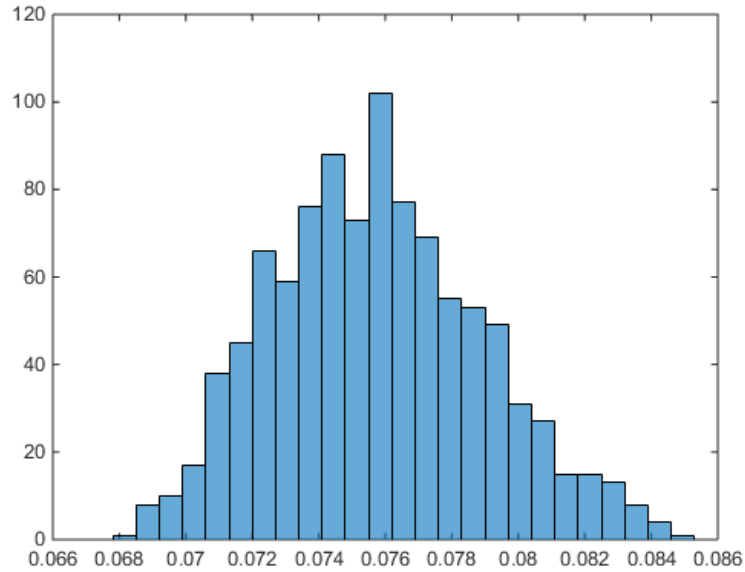


Fig. 6. Histogram of overall safety factor weight

The histograms provide decision-makers with a range of weights that can be assigned to the criteria according to their preferences, ensuring consistency between the criteria. In this case study, 211 bridge alternatives form a set of solutions of the Pareto front obtained by the multi-objective optimization (see Fig. 3). These alternatives are feasible and optimal. The experts must select one alternative from this set to obtain the best bridge design. As the set of solutions is very large, it is necessary to reduce the number of solutions, which is achieved by prioritization with a distance-based method called VIKOR that uses the weights obtained by the AHP under uncertainty method.

The VIKOR method obtains the closest alternative to the ideal point. This solution depends on the weights assigned to each criterion and the set of solutions studied. In this case, 10,000 random AHP matrices are obtained based on the triangular distributions. Each matrix leads to one set of weights. These weights modify the distances from the Pareto solutions to the ideal one and the VIKOR method ranks these solutions based on Eq. (10) to select the best one. After 10,000 iterations, the set of the Pareto front is reduced to a set of preferred solutions.

In this case, the 211 solutions that represented the Pareto front have been reduced to two alternatives (Alternatives A and B). Table 4 shows the criteria values of these preferred solutions. The percentage of times in which these solutions have been selected is 81.6% and 18.4% for Alternatives A and B, respectively. Thus, Alternative A is more likely to be selected. Results of the conventional AHP-VIKOR also give Alternative A as the preferred solution. Therefore, results show that even where there is uncertainty regarding the importance of the different criteria, the probability of selecting this preferred solution is very large.

Table 4. Preferred alternatives obtained after applying AHP-VIKOR under uncertainty method

Alternative	Energy (kWh)	Overall safety	Corrosion initiation (years)
A	21,52,404	1.139	500
B	2,214,495	1.221	500
C	2,246,406	1.295	500
D	2,260,262	1.340	500

The values for the energy, overall safety factor and corrosion initiation time of the Pareto front range between 1,910,862 and 6,015,223 kWh, 1.03 and 1.73 and 9.9 and 500 years, respectively. Both of the preferred alternatives have the highest value of corrosion initiation time. The results suggest that the increment in durability, evaluated as the initiation of corrosion, does not entail large energy differences and therefore, the solutions with higher durability are preferred. Comparing Alternative A and the solution

with the lowest embodied energy, Alternative A consumes 13% more energy but increases the safety and the corrosion time by 10% and 4,935%. The Alternative B consumes 16% more energy, but improves the safety by 18%. These results are compared to those of García-Segura et al. (2017b) in which study a lifetime maintenance optimization was carried out for the bridge Pareto solutions regarding cost, corrosion initiation time and overall safety. The results coincidentally showed that alternatives that maximize the corrosion initiation time have the lowest life-cycle impacts. Thus, it is of fundamental importance to take into account the durability criterion for the sustainable approach.

This tool provides a rational technique to help engineers and decision-makers to design and select preferred solutions based on conflicting criteria. This methodology facilitates the design of trade-off solutions and the complex decision-making in the context of sustainability by providing judgments with a degree of uncertainty.

7. Sensitivity analysis

A sensitivity analysis is carried out to validate the method and this section aims to analyze the influence of the inherent uncertainty in the criteria comparison on the decision-making results. To this end, the uncertainty value is varied while the most likely value is kept constant. In the previous case study, experts were fairly certain about the energy and initiation of corrosion comparison, certain about the energy and the overall safety factor comparison and certain about the overall safety factor and the initiation of corrosion comparison. To examine the effect of the level of uncertainty on the solution selection, 27 experiments are analyzed for the sensitivity analysis. These experiments cover all of the combinations of uncertainty values related to very certain (VC), fairly certain (FC) and very uncertain (VU) comparisons. Results of the sensitivity analysis are summarized in Tables 4 and 5. Table 4 shows the criteria values

for the four preferred alternatives (Alt. A-D) obtained in all of the experiments. Table 5 shows the level of uncertainty for each criteria comparison and the percentage of times each alternative has been selected.

Table 5. Experiments for the sensitivity analysis

	Uncertainty	Uncertainty	Uncertainty	Alt.	Alt.	Alt.	Alt.
	energy vs.	initiation of	energy vs.	A	B	C	D
	overall	corrosion vs.	initiation of	(%)	(%)	(%)	(%)
	safety factor	overall safety	corrosion				
Exp 1	VC	VC	VC	100.0	0.0	0.0	0.0
Exp 2	VC	VC	FC	82.8	17.2	0.0	0.0
Exp 3	VC	VC	VU	83.1	16.9	0.0	0.0
Exp 4	VC	FC	VC	70.8	29.2	0.0	0.0
Exp 5	VC	FC	FC	84.5	15.5	0.0	0.0
Exp 6	VC	FC	VU	85.4	14.6	0.0	0.0
Exp 7	VC	VU	VC	71.3	28.7	0.0	0.0
Exp 8	VC	VU	FC	82.0	18.0	0.0	0.0
Exp 9	VC	VU	VU	85.8	14.2	0.0	0.0
Exp 10	FC	VC	VC	60.5	39.5	0.0	0.0
Exp 11	FC	VC	FC	77.8	22.2	0.0	0.0
Exp 12	FC	VC	VU	82.7	17.3	0.0	0.0
Exp 13	FC	FC	VC	56.2	43.8	0.0	0.0
Exp 14	FC	FC	FC	78.9	21.1	0.0	0.0
Exp 15	FC	FC	VU	79.1	20.9	0.0	0.0
Exp 16	FC	VU	VC	64.0	35.8	0.2	0.0
Exp 17	FC	VU	FC	79.5	20.3	0.2	0.0
Exp 18	FC	VU	VU	81.2	18.5	0.3	0.0
Exp 19	VU	VC	VC	56.8	39.6	3.6	0.0
Exp 20	VU	VC	FC	69.0	27.0	4.0	0.0
Exp 21	VU	VC	VU	70.9	25.3	3.8	0.0
Exp 22	VU	FC	VC	52.5	43.8	3.7	0.0
Exp 23	VU	FC	FC	67.4	29.4	3.2	0.0
Exp 24	VU	FC	VU	72.2	24.0	3.8	0.0
Exp 25	VU	VU	VC	55.0	38.6	6.3	0.1
Exp 26	VU	VU	FC	65.2	29.9	4.8	0.1
Exp 27	VU	VU	VU	72.8	22.6	4.5	0.1

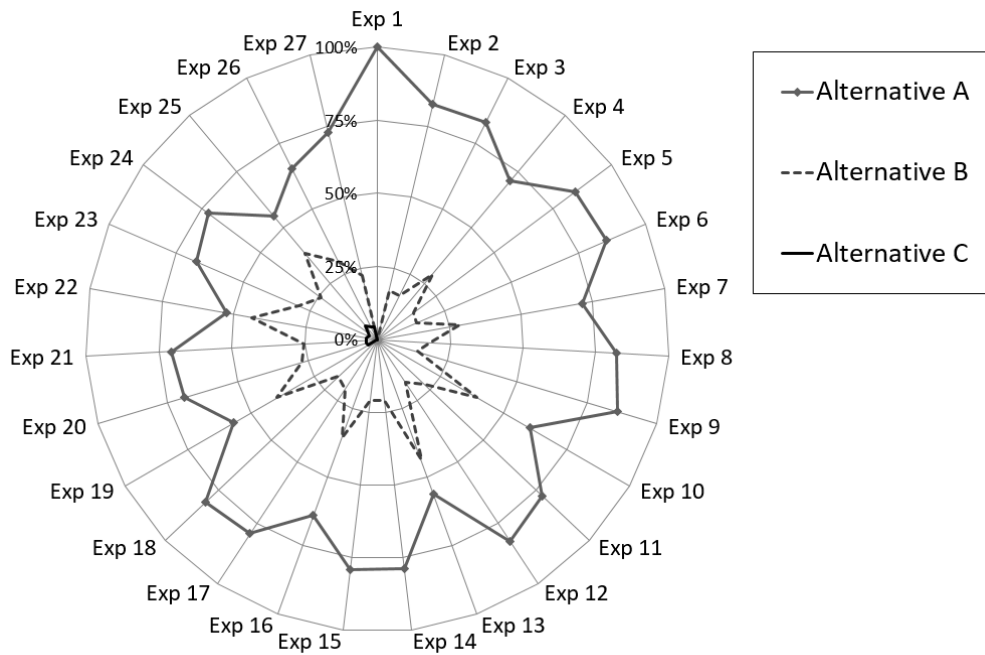


Fig.7. Results of sensitivity analysis

The outcomes reveal that the higher probability remains Alternative A. Alternative B acquires a higher percentage in some experiments compared to the case study analyzed in Section 3; however, the probability of selecting Alternative A is higher than the probability of selecting Alternative B in all of the experiments. The maximum selection rates of Alternatives B, C and D are 43.8%, 6.3% and 0.1%, respectively. Figure 7 clearly illustrates the percentage of Alternatives A, B and C. Results show a tendency to decrease the percentage of selecting Alternative A as the uncertainty of the relative importance between the energy and overall safety factor increases. Alternative A has the lowest embodied energy compared to Alternatives B, C and D. Thus, when this uncertainty increases, the decision-maker selects solutions which have higher energy but are safer. This indicates that the uncertainty of this criteria comparison influences the results.

Looking at the experiments which have the same uncertainty between the energy and overall safety factor, results also reveal that for cases in which there is high

certainty that energy has the same importance as the corrosion initiation time, Alternative B acquires greater importance and Alternative A obtains the lowest values. Experiment 27, which corresponds to the case of high uncertainty for every comparison, has been analyzed in order to examine this question in more detail (see Fig. 8). In this case, the relative importance of energy and corrosion initiation cannot take values between $1/3$ and $1/9$, since this would lead to inconsistent matrices. Thus, corrosion initiation cannot have significantly more importance than energy to be consistent with other judgements and, consequently, only when there is great certainty regarding this comparison, can the decision-making process accept solutions with higher energy as preferred solutions.

Therefore, the sensitivity analysis shows that the inherent uncertainty of the criteria comparison has an influence on the decision-making results. The method proposed is robust as it coincides with the conventional AHP-VIKOR approach to the preferred alternative. However, other alternatives are selected with lower percentages. The percentage associated with a given design depends on the degree of uncertainty and the criterion dominance. A high level of dominance of one criterion reduces the probability of selecting an alternative to the one preferred. Besides, results show that an optimized solution that improves greatly one criterion without worsening the other criteria significantly is more likely to be selected even when there is uncertainty in the criteria comparison. Therefore, the multi-objective optimization phase provides an effective prior selection that reduces the variability of the preferred solution.

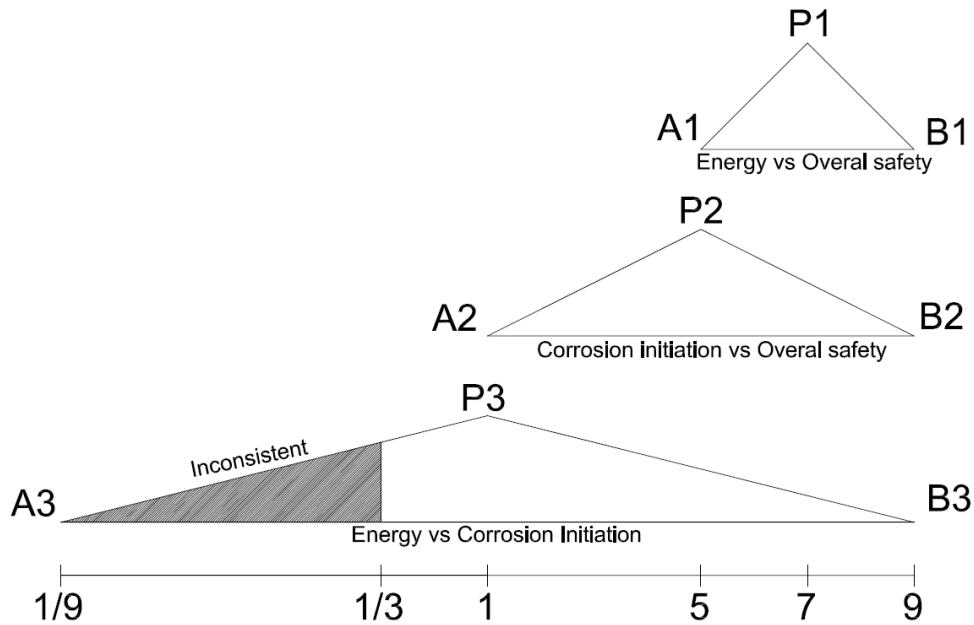


Fig. 8. Triangular distributions of Experiment 27

8. Conclusions

This paper proposes a metamodel-assisted multi-objective optimization for designing optimum trade-off solutions and a new decision-making technique under uncertainty. Artificial neural networks are integrated into the multi-objective optimization to predict the structural response. This metamodel reduces the solution space to a feasible and optimal set. From this point, a decision-making method integrates AHP and VIKOR and considers the uncertainty in the pairwise comparisons. This method modifies AHP by including triangular distributions to represent the variability in the perspective of the decision-makers. The methodology gives a probabilistic interpretation of the preferred solution. This method has been applied to a post-tensioned concrete box-girder bridge regarding energy, corrosion initiation time and the overall safety factor. The objective functions are selected for further identifying the solutions that reduce the embodied energy and guarantee a long service life through durability and safety improvement. In this case study, solutions with higher durability are preferred, as durable bridges are also sustainable in terms of embodied energy and

safety. The sensitivity analysis shows that the variability of the opinions of stakeholders has an influence on the decision-making results. However, a high level of dominance of one criterion reduces the probability of selecting an alternative to the one preferred. Besides, the multi-objective optimization phase provides an effective prior selection that reduces the variability of the preferred solution even when there is uncertainty in the criteria comparison.

9. Academic and managerial implications

The methodology proposed facilitates the design of trade-off solutions and complex decision-making in the context of sustainability by providing judgments with a degree of uncertainty. This implies that decision-makers will not have to reach consensus regarding the importance of each criterion for the sustainable selection. Instead, the decision-making technique captures this variability to find the probability of a given design being chosen. This approach overcomes a barrier to sustainable development as it gives flexibility by considering different perspectives simultaneously. Besides, the multi-objective optimization provides the optimal trade-off solutions, guaranteeing an effective prior selection from a solution space. The methodology proposed can be applied to other decision-making processes in the context of sustainability when alternatives can be defined implicitly through an optimization problem formulation. In this case, the problem characteristics (variables, parameters and objectives) and the judgments with a degree of uncertainty should be defined to achieve a sustainable selection. Results will inform about the characteristic of the sustainable alternative. It is worth mentioning that the method is open to any constraint that the decision-maker considers important. For example, a threshold can be proposed to any criterion in order to avoid high or low values.

10. Limitations and future research

There is a significant number of criteria that can be studied for sustainability. This study is limited to the embodied energy, corrosion initiation time and the overall safety factor. However, future research is needed to study other sustainability criteria and to analyze how these criteria influence sustainable bridge design.

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