MANAGING UNCERTAINTY IN THE SUSTAINABLE DESIGN OF CONCRETE STRUCTURES

Diego Gómez López

Alfredo del Caño Gochi

M. Pilar de la Cruz López

Roberto Purriños Prieto

Universidad de La Coruña

Ricardo Bendaña Jácome

Universidad de Vigo

Abstract

In 2008 came into force the current version of the Spanish structural concrete Code (EHE), which provides a tool for assessing structural sustainability, using a specific index for that purpose ("Índice de Contribución de la Estructura a la Sostenibilidad": ICES). The EHE does not take into account the uncertainty about the final design and specifications of the structure (and therefore, its potential ICES), existing in the phases of the project prior to structural completion. This paper suggests two mathematical models to manage that uncertainty and summarizes the works currently under development for building the corresponding computer tools. Both are based on the MIVES method (Integrated Value Method for Sustainability Assessment), used in the EHE, which is based in the value analysis technique, and that can use the Analytic Hierarchy Process (AHP) as part of the model. The first new model combines MIVES with Monte Carlo simulation. In this way, the designer, instead of estimating a specific ICES level (A, B, C, D or E), will obtain a cumulative probability curve, to determine the probability of achieving the different ICES levels. The second model combines MIVES with fuzzy mathematics. Here some inputs to the model, and its output, are fuzzy numbers.

Keywords*: structural concrete; sustainability; Spanish EHE Code; uncertainty; Monte Carlo simulation; fuzzy mathematics*

Resumen

En 2008 entró en vigor la nueva norma española EHE que aporta una herramienta para evaluar la sostenibilidad de estructuras de hormigón, mediante el "Índice de Contribución de la Estructura a la Sostenibilidad" (ICES). La EHE no contempla la incertidumbre existente en las fases del proyecto anteriores a la finalización de la estructura, acerca de las características finales de la estructura y, por tanto, de su contribución a la sostenibilidad. En esta comunicación se proponen dos modelos matemáticos para tener en cuenta dicha incertidumbre y se resumen los trabajos que actualmente se están desarrollando para elaborar sus correspondientes herramientas informáticas. Ambos modelos tienen como base el método MIVES (Método Integrado de Valor para Evaluaciones Sostenibles), usado en la EHE, que combina técnicas de análisis de valor y del Proceso Analítico Jerárquico. El primero combina MIVES con la simulación de Monte Carlo. De esta manera el proyectista no obtendrá un nivel concreto de sostenibilidad ICES (A, B, C, D o E), sino una curva de probabilidad acumulada, que le permita determinar la probabilidad de alcanzar los diferentes

niveles de sostenibilidad. El segundo combina MIVES con la matemática difusa, de forma que algunas entradas al modelo y sus salidas son números difusos.

Palabras clave*: estructuras de hormigón; sostenibilidad; Instrucción de Hormigón Estructural EHE; incertidumbre; simulación de Monte Carlo; matemática difusa*

1. Introduction

At the end of 2008, a new Spanish Code for the Design of Concrete Structures (EHE) came into force. For the first time in Spain, this code includes a non compulsory appendix (Appendix 13) for estimating a sustainability index ("Index of Contribution of the Structure to Sustainability"; ICES) of the concrete structure. Two of the authors have also been co-authors of the EHE Appendix 13.

The model is based on the MIVES method (Integrated Value Method for Sustainability Assessment; Ríos, Ríos-Insua, & Ríos-Insua, 1989; Alanne, 2004; Han, 2004; Aguado, Manga, & Ormazábal, 2006; Losada, Rojí, & Cuadrado, 2006; San José, & Josa, 2008), which consists of:

1. Defining the problem to solve, and the decisions to make. In this case, estimating the sustainability index of a structure, and selecting the best alternative for its design, fulfilling a specific set of needs.
2. Building a basic diagram of the decision-support model, establishing all the issues to be taken into account in the assessment. This diagram is a requirements tree one, including the several issues or variables (Aguado, Manga, & Ormazábal, 2006; Losada, Rojí, & Cuadrado, 2006; San José, & Josa, 2008).
3. Defining the mathematical functions that will allow converting the several qualitative and quantitative variables, with different units and scales, into a set of variables expressed with the same units and scale, using the value analysis technique (Miles, 1961; Brugha, 2004).
4. Defining the importance or relative weight of each variable. This can be made directly by subject matter experts (SME). The Analytic Hierarchy Process (AHP) can be used as a help, in case of specific estimation problems (Ahn, & Han 2005; Forman, 1990; Saaty, 1980; Saaty, 2006).
5. Defining the different design alternatives that could satisfy the identified needs.
6. Evaluating those alternatives, using the referred to model.
7. And making the opportune decisions, choosing the adequate alternative.

MIVES has been developed by Spanish researchers of the Technical University of Cataluña (UPC), the Basque Country University (EHU-UPV) and Labein Tecnalia, some of which also formed part of the work team for writing the EHE Appendix 13. The interested reader can find additional information on MIVES and the EHE in Ministerio de la Presidencia (2008), Alavedra and Cuerva (2008), Aguado, Alarcón and Manga (2008), Burón, Carrascón and Carrau (2008), del Caño and de la Cruz (2008), Garrucho and Portas (2008), Losada, Rojí and Cuadrado (2008), Pacios and Martos (2008), San José and Josa (2008), and Vacas and Zornoza (2008).

Summarizing, calculating the ICES of a concrete structure includes assessing different variables related to the three pillars of sustainability: environmental, social and economic. The environmental one includes twelve criteria, and each environmental criterion is also sub-divided in other variables. Social and economic issues are assessed in a different way, without the use of the already mentioned tree diagram. Altogether, around 60 variables must be assessed to calculate the ICES.

The ICES index is expressed as a number in the [0,1] range, and the ICES level is a conversion of that index to an alphabetical scale similar to the one used in some countries for assessing the energy consumption of electrical appliances (A, B, C, D, E).

The process for designing a sustainable structure normally begins when the client establishes a sustainability objective for the structure (a specific ICES level; for instance, A or B). Then the architect or engineer must design the structure, establishing drawings and specs to achieve that objective (of course, it will exist other project objectives, as can be the related to cost or time). After contracting, the on site works will produce a final product that should have the required ICES level, but not necessarily in the way the designer initially established.

So, it is interesting for the client (owner, promoter, sponsor), designer and construction manager to asses the ICES level in different moments of the project life cycle, to estimate the final ICES level, in order to take corrective actions, if needed. Some of those moments can be, for instance, before beginning the design, in different moments of the design development (to take the needed actions, in an iterative procedure), after the design is finished, in different moments of the construction works (to take actions, if needed) and when the structure is completed.

However, there is uncertainty on the final ICES estimated at moments prior to the one when the structure is finished. There are several reasons for this. Sometimes, the value of specific variables depends on the contracting companies finally contracted (for instance, in relation to the environmental certification of contractors). Additionally, during the building works the client or construction manager could decide to change some parts of the design or specs (for example, percentage of recycled aggregate used to prepare the concrete). Some times simply the design or specs do not include information about an ICES variable, and that is unknown at that moment (for instance, environmental certification of ready mix companies).

All these uncertainty sources may cause important differences among the ICES levels estimated at different moments of the project, and the real one calculated when the structure has been finished; and the stakeholders need to know the likelihood of finally achieving the sustainability objective. Two mathematical models here proposed can help in this. The first one allows the user to represent the uncertainty of the different variables assigning to them probability distributions (a maximum, most likely and minimum values, plus a probability distribution), or probabilistic labels (high, medium, low probability, that will be converted in numerical values), rather than a single deterministic value (“Yes”, “No” or a fixed number). Then the user will obtain, using Monte Carlo simulation, a cumulative curve of probability of achieving each ICES index or level, instead of a single ICES value. Alternatively, using fuzzy numbers for the input variables and fuzzy mathematics for performing the calculations, a fuzzy number of ICES could be obtained, instead of a crisp ICES value. The authors are currently developing two software applications, one for each of these models. The objective of this paper is to present the mentioned models and summarize the works currently under development for building those computer tools.

2. Preliminary works

Before developing the models here mentioned, it has been necessary to carry out the set of preliminary works that will be summarized here.

2.1 Applying the EHE model for better knowing it

First, the EHE model was tested by the assessment of several case studies. For an easier and flexible application, the authors developed a software tool (Gómez, del Caño, & de la Cruz, 2009), based in electronic spreadsheets, as a first step to develop the subsequent software tools that will include the non-deterministic mathematical models here presented.

This phase has been very interesting, because it has allowed the authors to discover several problems and possible improvements of Appendix 13; the reader should remember that this is the first time that an appendix of this kind is included in a code for the design of structures, and it is very difficult to reach a perfect set of code clauses, in these pioneering works. The authors have already informed the Spanish Ministry of Public Works (Ministerio de Fomento) of those problems, and suggested the main potential improvements, and the next EHE version will probably address almost all of them.

2.2 Selection of non-deterministic variables

The next phase has been establishing which model variables should be non-deterministic ones. Allowing the users to assign probabilistic data to all variables makes no sense. Firstly, the user must enter a large amount of data, despite the model is not very sensitive to some of the variables. On the other hand, the results of running the model could include an excessively broad range of possible ICES values.

According to Pareto's Law (80-20 rule), the authors thought that probably a number of variables near to the 20% could be enough relevant to the final ICES assessment, as to be non-deterministic. Anyway, the authors are currently developing a selection process based in assessing the following three criteria:

a. Sensitivity. Maximum influence on the ICES index of the several variables, when their values change.

b. Ignorance by omission in the design. The value of a variable can be unknown because the corresponding information is not included in the design (drawings, specs), or because the decisions about that variable have not been made yet by the client, designer or construction manager. On the other hand, specific issues must be (mandatory) included in the design. The uncertainty is higher in the first case.

c. Risk of modifications. A specification initially established by the design could be modified later, mainly during the construction phase. Besides that, some structural characteristics are more susceptible of changes than others. The first ones will generate more uncertainty than the second ones.

There are some difficulties for performing a sensitivity analysis of the Appendix 13. Firstly, some environmental criteria have a tiered score system (no linear or other continuous functions). On the other hand, the ICES sensitivity to a variable depends on the specific values that the other variables could have. The last main difficulty is caused by the non-linear characteristics of the value functions. So the sensitivity analysis had to be done semi-automatically, with the help of an electronic spreadsheet, instead of using automated tools (for instance, the ones included in the most frequently used electronic spreadsheet applications). The reader can find additional information and a complete explanation about these difficulties, as well as the way of performing this sensitivity analysis, in (Gómez et al, 2010).

For the other two criteria, taking into account the inherent subjectivity, the authors decided to interview several subject matter experts, using a Delphi analysis, to perform an assessment with semantic labels (high, medium, low, nil). This analysis currently is under development.

Once the previously referred to independent assessments (sensitivity, ignorance by omission, risk of modifications) have been performed, it is necessary to establish a process for selecting the non-deterministic variables. The authors considered two possibilities: the first one is a numerical scoring method and the other is a simple heuristic one.

For the scoring method we can use Equation 1 (suggested by Aguado and Josa, 2009), where the uncertainty of each variable is the weighted sum of the values corresponding to the three previously alluded criteria (sensitivity, ignorance by omission, risk of modifications). Obviously, it is necessary to convert the semantic labels for the latter criteria to numerical values (for example, high = 75%/80%, medium = 50%, low = 25%/20% and nil = 0%).

$$U = \alpha \cdot S + \beta \cdot I + \gamma \cdot C \tag{1}$$

Where:

- U has a value related to the total uncertainty of the variable.
- α is the weight of the sensitivity criterion (for instance, 0’5).
- S is the sensitivity associated to the variable.
- β is the weight of ignorance by omission criterion (for example, 0’25).
- I is the numerical value associated to the ignorance by omission criterion.
- γ is the weighting of “risk of change” (for instance, 0’25).
- C is the numerical value associated to the risk of change criterion.

After that, the total uncertainty U should be estimated for all the variables of Appendix 13, using Equation 1, and those with highest U (above a cutoff Ulim value; U > Ulim) will be selected as non-deterministic variables.

The other alternative is utilizing a heuristic approach, using conceptual criteria to establish a set of rules or conditions based in the previously mentioned selection criteria. Some of them could be:

- Variables with sensitivity higher than a certain value S_a (for instance, 10% of ICES) could be selected as non-deterministic variables if they also have medium or high values for the other two criteria. The motivation is clear, since their influence on the ICES index will be important, and there will be relevant uncertainty about their values.
- Variables with sensitivity higher than a certain value S_a, but with low or nil values for the other two criteria should be taken into account as deterministic variables, because despite their influence in the ICES index is high, their associated uncertainty is irrelevant.
- Variables with sensitivity lesser than a certain value S_b (for example 5% of ICES) should be ruled out as non-deterministic variables, because their influence on the ICES index is very low.
- Variables with sensitivity between two specific values S_a and S_b should be selected as non-deterministic variables if:
    - o Both they have medium values for the other two criteria.
    - o Or, alternatively, one of the values for the other two criteria is high.

- Finally, the variables not satisfying these conditions should be taken into account as deterministic variables.

The authors consider that both selection methods should be tested, to analyze the resulting differences, making a final decision.

2.3 Unknown values

Finally, the last step before building the non-deterministic models is to establish how these models will act when the user does not know the answer to a specific input. The corresponding software tools will allow an “unknown” answer from the user, automatically using specific values. So it is necessary to establish these values.

The authors decided to include this issue in the previously mentioned Delphi analysis. In this part of the analysis the subject matter experts must choose, for each variable, one of the following possibilities:

1. Deterministic and conservative. To assign the value that will result in a lower level of sustainability. This is an option applicable to non-frequent or innovative issues, when there is not an important uncertainty about the final variable value.
2. Deterministic and most likely. To assign the most likely value that the variable could have, according to the real circumstances of the Spanish construction sector. This is a “less prudent” but more realistic option than the previous one, applicable to conditions frequently fulfilled, when there is not an important uncertainty.
3. Non-deterministic. Depending on the model, to assign a fuzzy number or alternatively, a probabilistic label (high, medium or low probability) or a three point estimate (maximum, most likely and minimum value). This could be adequate when the variable is non-deterministic and it is difficult to assign a single value to it.
4. Not allowed. The last option is not allowing the users an “unknown” answer, normally because it is compulsory to establish that kind of data in the structural design, or because for applying Appendix 13 it is essential to know that information.

After generating all the information here mentioned, the next step will be building the software applications for both models.

3. The probabilistic MIVES model

3.1 The Monte Carlo method.

Monte Carlo is a stochastic method (Ayyub, & McCuen, 2003; Duby, 2000; Gentle, 2005; López Agüí, 2008) used to obtain approximate solutions to a wide variety of real problems which analytical, exact solution is difficult or impossible. It is based on simulation, calculating a high amount (normally thousands of iterations) of potential final results of a model; in this case, the EHE model (that is, the ICES index). In each iteration the several model variables will have random values generated according to specific distribution functions. Simplifying, the main stages of the Monte Carlo method are the following ones:

A. To establish the model to be simulated.
B. To associate each probabilistic variable of the model to a distribution function (normal, binomial, triangular, etc.) describing the potential future scenarios for that variable.
C. To generate a random value for each model variable, using those distribution functions.

D. To use these values for running the model, to calculate one of the possible future scenarios of the model, using both deterministic and probabilistic variables.

E. To repeat steps C and D many times, until the results converge, to generate a distribution function for the future scenarios of the model.

F. To build the corresponding outputs of the Monte Carlo method (moments, distribution histogram, cumulative probability curve).

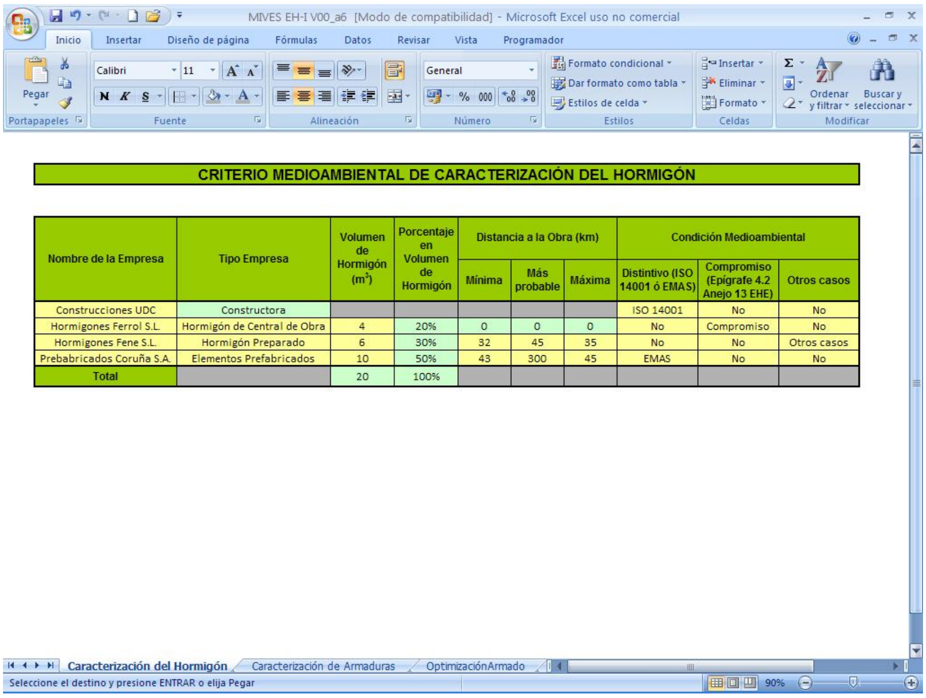
G. Testing and validating the model, performing the needed modifications, and using it.

H. Contrasting the model with reality, in this case after construction projects are finished, to detect problems and fine-tuning the model.

MIVES is a method that can make use of the Analytic Hierarchy Process for defining the weight of each variable. The literature includes references related to stochastic AHP (for instance, Saaty, & Vargas, 1987; Paulson, & Zahir, 1995; Stam, & Silva, 1997; Triantaphyllou, 2000; Hahn, 2003; Manassero, Semeraro, & Tolio, 2004; Banuelas, & Antony, 2004; Tavana, 2004; Bojórquez-Tapia, Sánchez-Colón, & Martínez, 2005; or Chan, Chung, & Choy, 2006). But the works found are mainly focused in using simulation to calculate the variables' weight. This approach can not be used here, since the weights of the Appendix 13 variables are established by the EHE, and the designer can not modify them. The authors did not found references dealing with the use of probabilistic simulation for dealing with the uncertainty of the MIVES entry data, and then for running calculations and establishing non-deterministic output values.

On the one hand, applying probabilistic simulation for calculating the variables' weight has a limited interest here, mainly for comparing its results with the deterministic EHE weights. On the other hand, the literature does not found important differences. The authors consider that the approach here presented is much more interesting.

Figure 1: Main spreadsheet of the MIVES Monte Carlo software tool



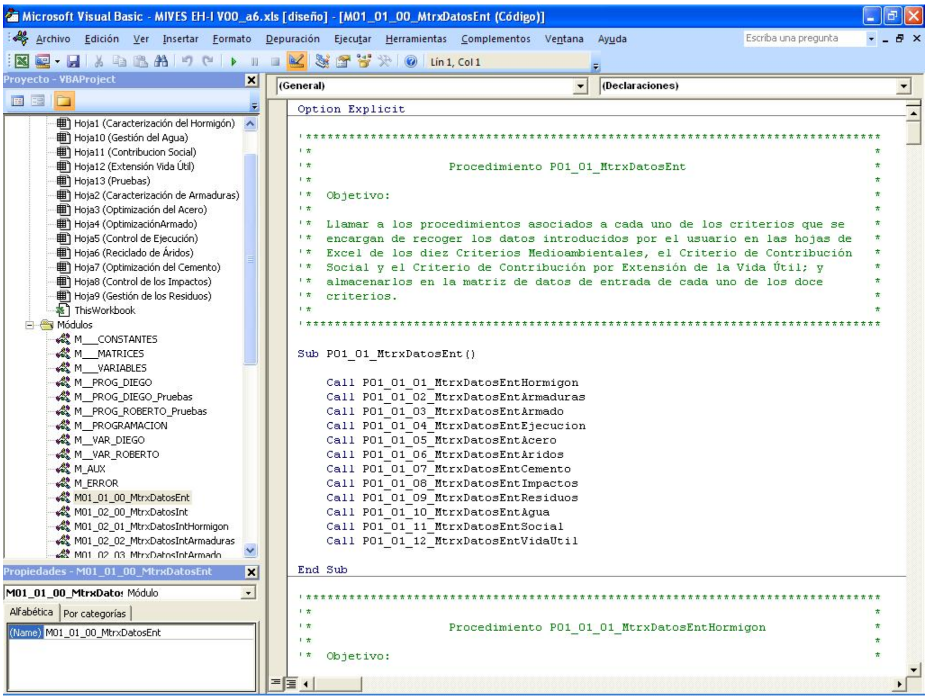
CRITERIO MEDIOAMBIENTAL DE CARACTERIZACIÓN DEL HORMIGÓN

Nombre de la Empresa	Tipo Empresa	Volumen de Hormigón (m^3)	Porcentaje en Volumen de Hormigón	Distancia a la Obra (km)			Condición Medioambiental		
				Mínima	Más probable	Máxima	Distintivo (ISO 14001 ó EMAS)	Compromiso (Epígrafe 4.2 Anejo 13 EHE)	Otros casos
Construcciones UDC	Constructora						ISO 14001	No	No
Hormigones Ferrol S.L.	Hormigón de Central de Obra	4	20%	0	0	0	No	Compromiso	No
Hormigones Fene S.L.	Hormigón Preparado	6	30%	32	45	35	No	No	Otros casos
Prebabricados Coruña S.A.	Elementos Prefabricados	10	50%	43	300	45	EMAS	No	No
Total		20	100%						

3.2 Applying Monte Carlo to Appendix 13

Monte Carlo means the need of using computer tools. In this case the authors have selected the versatility and simplicity of an electronic spreadsheet (Microsoft Excel; Figure 1), combined with the programming language VBA (Visual Basic for Applications; Figure 2) to develop the software tool. The tool will be used by clients, designers and construction managers, and this originates the need for a widely used software application. At the moment of writing this paper a first basic prototype of this tool is finished and has passed several partial and global tests, successfully. Additional works are currently under development to build a friendly user interface, including additional output information and configuring the input modules in the way we will explain later here.

Figure 2: Visual Basic for Applications Screen, showing a part of the software coding



Besides the fact that the selection of the non-deterministic variables is currently under development, since the EHE model could be modified in the future (and so, its sensitivity), and the uncertainty characteristics of the several Appendix 13 variables could also change, the authors decided programming the MIVES Monte Carlo software tool with the possibility of considering probabilistic all the model variables. Nevertheless, the user will not be allowed to do that; the authors will limit the set of probabilistic variables to the one selected in the previously alluded Delphi analysis, because of the reasons given earlier in this paper. In this way the final software tool will have a high flexibility to be adapted to changing circumstances, by means of very short and simple reprogramming operations made by the authors or, perhaps, of a specific configuration menu (configuration open or closed to the user).

As for the stage A (establishing the model) of the Monte Carlo method, the basic model to be simulated is the one defined by Appendix 13 (Ministerio de la Presidencia, 2008). Depending on the nature of the variable, different data will be requested by the software tool:

- For deterministic variables:
    - Numerical ones, as the percentage of recycled aggregate. The user must enter the corresponding deterministic value (for instance, 10%).
    - Discrete variables that take non-numerical values. Among other, Yes / No when the user must answer simple questions as can be the ones related to whether the site approaches are adequately paved, or have specific systems for cleaning the truck tires. Other times there are several possible answers, as can be the ones related to the environmental commitment of the contractor: (Environmental certification; Complying with company environmental commitment requirements; No environmental commitment).
- For probabilistic variables:
    - Numerical ones, as the variable related to the percentage of steel with quality mark. The user has two possibilities:
        - Entering a point value (for instance, 80%), considering it a deterministic one.
        - Entering a three point estimation (for instance, 70%, 80%, 100%), respectively for the minimum, most likely and maximum values.
    - Discrete variables that take non-numerical values, as can be the ones related to the environmental circumstances of cement production, or the use of water sprinklers to prevent dust production on site. The user has also two possibilities:
        - Entering a single value, considering the variable a deterministic one; for instance: (EMAS certification; ISO 14001 certification; No certification), or (Yes; No).
        - Using likelihood labels (high, medium or low likelihood) for establishing an approximate probability range for a specific non-numerical value (for instance, EMAS certification).

In specific cases of all kind of variables (deterministic, probabilistic, numerical or non-numerical), the user could choose the “Unknown” option, when the tool allows for it.

In relation to the stage B (associating each probabilistic variable to a distribution function), since the user will not have enough information for establishing the opportune distribution function, the computer tool establish it automatically. Discrete functions as binomial or trinomial (Ayyub, & McCuen, 2003; Duby, 2000; Gentle, 2005; López Agüí, 2008; Ogunnaike, 2010) have been selected to discrete variables.

Converting likelihood labels to numerical probabilities can be performed establishing probability ranges for each label (for example, high likelihood: 75%-85%; medium-high likelihood: 50%-75%; medium-low likelihood: 25%-50%; and low likelihood: 15%-25%). At the moment of writing this paper the final, definitive values are not still defined. It is important to take into account that these kinds of conversions suffer of important subjectivity, and the system should include tools for reducing it.

Another problem here is choosing the type of probabilistic distribution function for each non-deterministic continuous numerical variable. There are a lot of distribution functions that could be used (normal, log-normal, beta, uniform, triangular, trigen, among others; see Ayyub, & McCuen, 2003; Duby, 2000; Gentle, 2005; López Agüí, 2008; Ogunnaike, 2010), but currently there is not enough information on the Appendix 13 variables for choosing a specific function. So, for the moment, the authors decided to use the triangular and trigen (general triangular) functions (see Figure 3 and 4). On the one hand, this allows for using open (trigen) and close (triangular) functions, unbiased and biased distributions (symmetric and asymmetric; both functions can be used for both purposes).

Finally, it is important to take into account the usual excessive biases suffered even by experts when estimating probabilistic variables, reported by several authors; for instance, see Hubbard (2009). The software users can suffer of this problem, which can be minimized by the calibrating processes described by Hubbard.

Figure 3: Example of general triangular function (trigen)

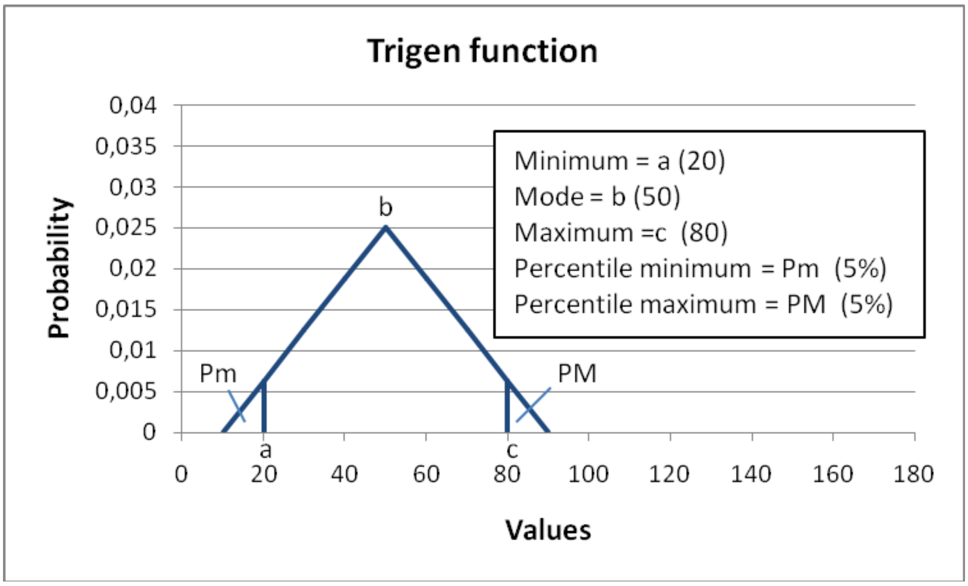
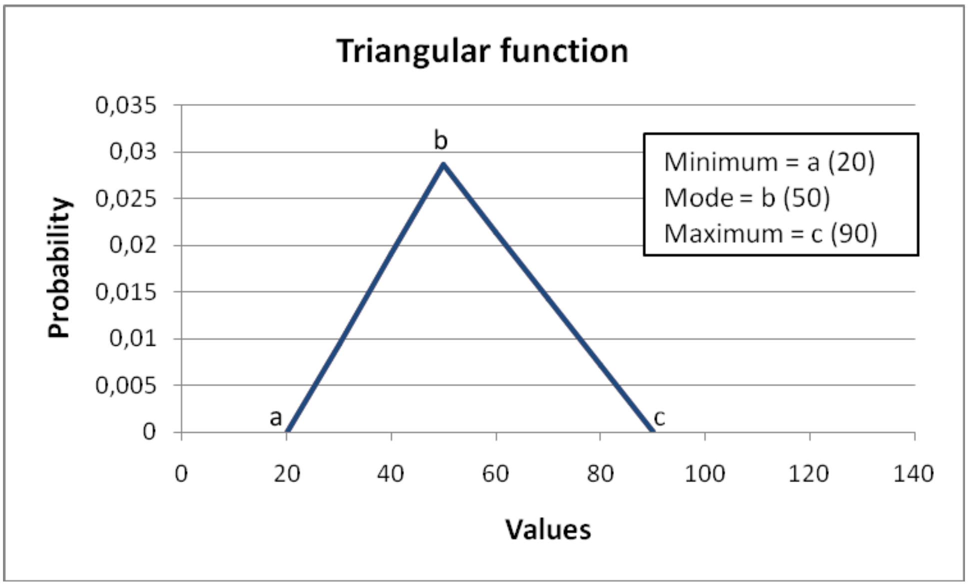


Figure 4: Example of triangular function



As for the stage C of the Monte Carlo method (generating a random value for each variable), at this moment the Monte Carlo simulation will start. A value is obtained for each probabilistic variable, by generating a random number using the previously established distribution functions. In case of the user answering “Unknown”, the software tool will work as previously mentioned in this paper. On the other hand, the several interrelations and correlations among the Appendix 13 variables have been carefully studied, and then taken into account when programming the software application.

In stage D (running the model to calculate one of the possible future scenarios), now we have a deterministic value for each EHE variable, independently of the real type of variable (deterministic, probabilistic, unknown answer, etc). Therefore, this stage consists of applying Appendix 13 to these values, for obtaining an ICES index; this will be a potential final scenario.

Stage E will consist in repeating steps C and D many times (thousands) to generate a distribution function for the potential ICES scenarios. There are several ways for deciding when stop the simulation. One is applying statistical theory to calculate the necessary size of the sample. Another way is to carry out a number of iterations so high (for instance, 20.000) that we will ensure that the corresponding sample is representative; despite this will slow down the software application, with the current computers the difference will be very reduced, in this case. The third one is to stop when the results converge. A set of ICES parameters (as mean, standard deviation and some percentiles; for instance, the 5%, 25%, 50%, 75% and 95 % ones) are calculated after, for example, iteration 100. Then, the same parameters are calculated 100 iterations later (including the 200 data sets), and compared with those previously calculated. If the (absolute or relative) differences between them are lesser than a tolerance value (for instance, 0’1, 0’01, 1% or 0’1%) we can say that the results are converging. The simulation will continue and comparisons will be made after other 100 iterations, comparing now the parameters calculated with the current 300 data sets and the previous 200 ones. To ensure that the real convergence is achieved, the tool should not stop until convergence conditions are satisfied in a specific number of consecutive comparisons. Depending on the model to be simulated, this technique could need a stopping maximum number of iterations, to prevent problems when convergence is not achieved within a normal range of iterations. Convergence has been the way chosen by the authors to stop the simulation; the current prototype stops after five positive comparisons, being a positive comparison when all the differences of all the alluded parameters are lesser than 0’01 (taking into account that the ICES index is a number between 0 and 1). In this way, the simulation uses to stop before 5.000 iterations.

Finally, in stage F the corresponding Monte Carlo outputs must be built. Previous stages have generated thousands of possible ICES for the structure under study, and now it is necessary to arrange and synthesize them. The maximum, minimum, mean and modal values will be calculated, as well as the variance and standard deviation, and the percentiles, among other statistical moments. It is also common to build two types of graphs. The first one is the ICES distribution histogram (Figure 5), showing the frequency for each ICES level. Nevertheless, the most useful graph is the cumulative probability curve (Figure 6), representing the probability of achieving a certain ICES level. This graph is very useful for the designer or builder, because knowing the likelihood of achieving the wanted level of ICES can help to make decisions for ensuring a minimum sustainability index.

Figure 5: Example of simulation histogram

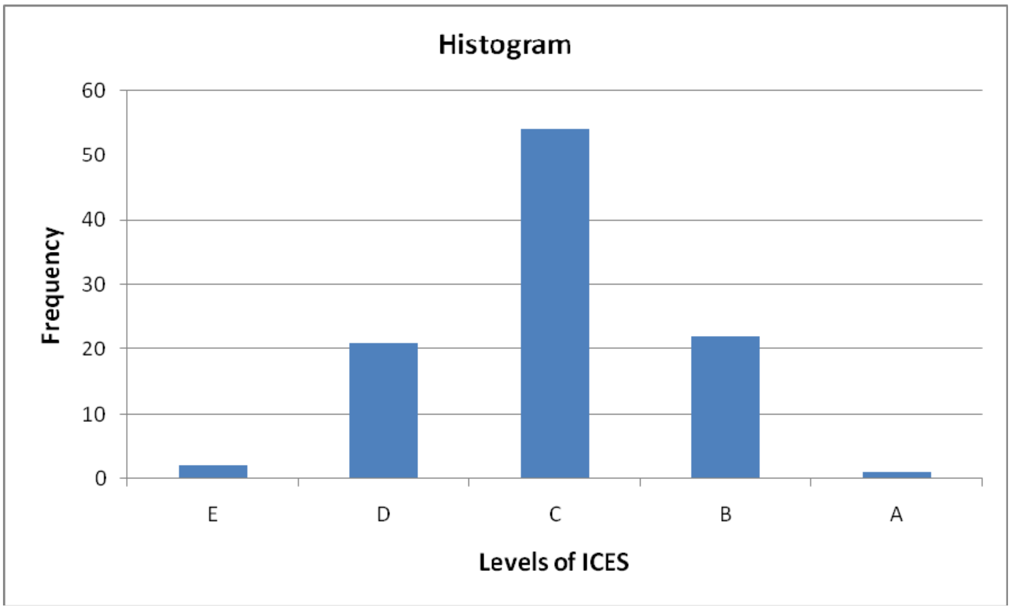
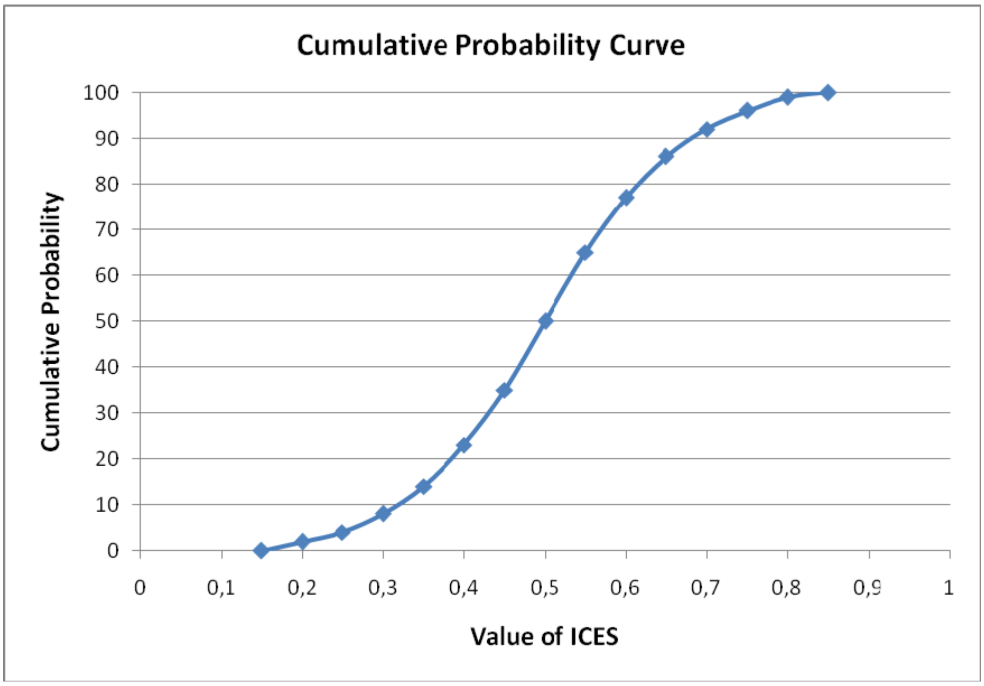


Figure 6: Example of cumulative probability curve of a simulation



4. The fuzzy MIVES model

Fuzzy sets, fuzzy mathematics and fuzzy logic have been used for supporting decision making since many years (Zadeh, 1965; Hipel, 1982; Nguyen, 1985; Ward, 1985; Trillas, & Gutiérrez, 1992; Aranda, Morilla, & Fernández, 1993; Trillas, 1994; Bendaña, del Caño, & de la Cruz, 2008; for instance). Fuzzy sets and fuzzy algebra allows, on the one hand, for a complete representation of uncertainty; on the other hand, they serve for managing qualitative, vague or ambiguous concepts commonly used in natural language.

As already seen, MIVES can make use of AHP for defining the variables' weight. The literature includes references related to fuzzy AHP (Arslan, & Khisty, 2006; and Wang, & Wang, 2006; for instance). Again, the works found are exclusively focused in using fuzzy mathematics to calculate those weights. As previously explained for the probabilistic MIVES model, this approach can not be used here. Once more the authors did not found references dealing with the use of fuzzy mathematics for dealing with the uncertainty of the MIVES entry data and output values. Yet again, applying fuzzy mathematics to calculating the variables' weight has a limited interest here, for the reasons previously explained.

Otherwise, the basic structure of the probabilistic MIVES model before defined in this paper will serve for building the fuzzy MIVES model. This time, instead of using distribution functions to define the possible values of an Appendix 13 variable, fuzzy numbers will be used. After that, the Appendix 13 model must be applied to calculate the ICES index that now will be a fuzzy number, reflecting the possible future scenarios. The operations will not be now the crisp algebraic ones established by the EHE, but the corresponding fuzzy algebraic ones. Performing this type of calculations is not excessively complicated (for instance, see Kaufmann and Gupta, 1988), and the corresponding tool will probably be based in MATLAB or, once more, in the combination of Excel and VBA.

5. Conclusions

Appendix 13 is a good tool to assess the contribution to sustainability of a concrete structure and the pioneering way of doing it in a structural code environment. To apply it before the structural completion can be difficult, because an important part of the necessary information about the structure can be unknown in those moments, or may change during construction. This paper suggests a general way of managing that uncertainty, and two potential mathematical models (probabilistic and fuzzy MIVES) for performing the corresponding uncertainty analysis. When necessary, the users can enter non-deterministic values to the system, and can even choose an "unknown" answer. On the other hand, they do not get a single result, obtaining outputs reflecting the probabilities or possibilities of achieving the sustainability objective (ICES level). This will facilitate making decisions for a better achievement of this objective. Finally, in relation to the two types of mathematical models and their associated tools, the main goal will be to use both systems, to establish comparisons, to decide which one is more useful, and to develop the one finally chosen. The use of the final system will be completely free, in order to promoting the design of sustainable structures.

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Correspondencia (Para más información contacte con):

Diego Gómez López
Phone: +34-981-33-74-00 ext: 3867
Fax: +34-981-33-74-10
E-mail: diegogomezlopez@gmail.com
URL: www.ii.udc.es/gridp