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Dependence relationships modelling in financial appraisal under uncertainty

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Abstract

The modelling of dependence relationships is one of the most difficult processes in simulation models. Dependence relationships are especially important in financial problems under uncertainty conditions. Unfortunately, in complex situations we cannot easily assume mathematical functions –technical relationships- for relating cash flow components, like revenues or costs. In an attempt to approach this problem, fuzzy logic is used for designing and modelling "fuzzy" relationships between selected financial parameters. A fuzzy inference engine has now been included in the PRAPPIS v2.0 software for project appraisal under risky and uncertainty conditions. This engine can assess relationships using a set of basic fuzzy rules that control their behaviour in a given context. Fuzzy relationships are easily defined by the user or decision maker guided by a natural language system. Mizumoto's approach is used to obtain fuzzy relationship results and standard Monte Carlo simulation is applied to assess the financial project. Statistical distributions of many financial parameters are available in PRAPPIS with or without dependence relationships.
In this paper, different results are shown corresponding to different statistical distributions of financial parameters using a first set of fuzzy inference rules called here "neutral" in comparison to standard Monte Carlo simulation assuming independent statistical distributions. In an agricultural environment, which is uncertain, we have chosen some controlled relations between two selected parameters such as, for example, part-time hand labour in harvesting and production. Results show that the variance of the statistical distributions in the project results is reduced if fuzzy relationships are used.

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In conclusion, a fuzzy inference engine has been designed and developed for modelling dependence relationships and this methodology offers a more realistic assessment of financial risk in uncertainty environments.

1 Introduction

The financial appraisal of investment projects is one of the most appropriate fields for simulation (Goodwin [1]). This is because decision analysis is based on a cash flow table that needs to determine future revenues, costs and investments. These financial parameters depend on unknown future human decisions and the environment behaviour in the business. In a financial appraisal context, there are three main practical problems related to a simulation process in an initial phase: to estimate the correct statistical distribution for each parameter, the number of computer iterations needed to simulate the process and, finally, the almost infinite relations between financial parameters. The first item needs deep analysis or knowledge of the project evolution. It is a decision maker problem. The second point can be solved using convergence algorithms (Ross [2]) based on the standard error of, for example, the Net Present Value (NPV) of the project. But, finally, the dependence relationships between financial parameters are not ease to manage. In a complex project there are almost infinite ways for them to interrelate. Therefore, parameters are usually aggregated to avoid difficulties in the analysis of technical and non-technical (almost always unknown) relationships. Decision makers and financial analysts can make some intuitive approaches to these relationships with the sole support of their own knowledge but such simplification makes it difficult to determine mathematical functions, or to elicit a specific statistical distribution of a parameter conditioned by another parameter value, or to assume that the statistical distributions of related parameters are the same and so on (Goodwin [1]). Dependence relationship management in a financial appraisal context is also difficult because decision makers have not enough previous data for a statistical analysis and the number of iterations needed is very high measured in terms of computer time and costs. In conclusion, decision makers know that dependence relationships exist and, in some contexts, they need to manage them for greater precision in their financial appraisal so that, finally, they can relate financial parameters in a semantic way based on their knowledge. This paper shows our vision of this real problem.

2 The PRAPPIS v2.0 system

In order to facilitate software use for financial project appraisal in uncertain environments, PRAPPIS v2.0 is now being tested (García [5]). This tool is a general purpose application that will also cover economic and social analysis in the future. The standard Monte Carlo method (Ross [2]) is used to control the simulation process. Users can choose between different statistical distributions to adjust any financial parameter of the project that needs to be analysed.

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Certainty is also considered an option, if necessary. Finally, simulation results are studied using nonparametric statistical procedures (Sheskin [4]) and standard financial analysis.
The difference between versions 1.X and version 2.0 is a proposal for managing dependence relationships of project parameters. Relations between financial parameters must be represented in as similar as possible to a decision maker's semantic explanation of them. The PRAPPIS system manages each relationship and users can also introduce a certain level of uncertainty in the application of the rules in the management process. This last utility allows the appearance of very strange results in some special but real circumstances.

3 Dependence relationship modelling

First it was necessary to establish different structural types of dependence relationships in financial models. Two basic structures (Figure 1) were found for modelling: "simple" and "inverse multiple". There are also mixed structures combining these basic ones such as "simple linked up" ones and "direct multiple" ones (Figure 1). The PRAPPIS v2.0 system is now testing the behaviour of simulation results using "simple" dependence relationships. The parameter on the left hand side of the relation was called "dominant" while that on the right hand side was called "dominated".

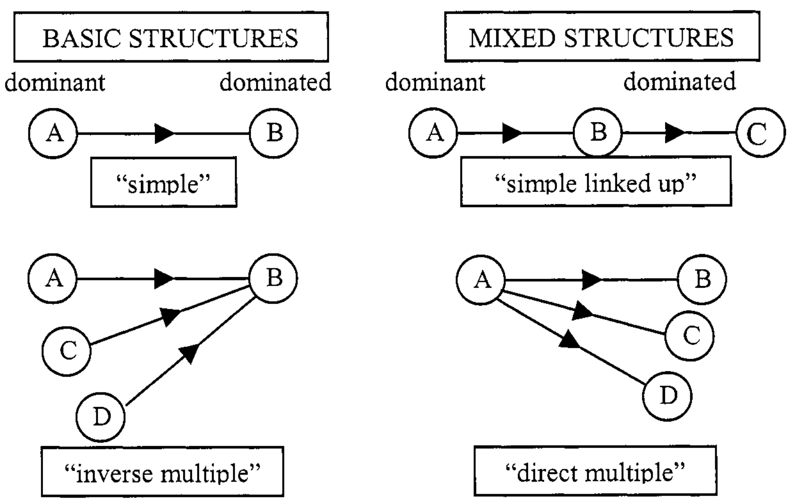

Figure 1. Structural types of dependence relationships.

Once the value of the dominant parameter was calculated by a simulation process depending on the statistical distribution chosen, the PRAPPIS system automatically assumes five membership functions for it, Figure 2. Initially a triangular structure was chosen for each membership function. This is the easiest way to manage the inference method later because it simplifies the integration

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routines needed. The membership functions were called: "high decrease" (A, Figure2), "slight decrease" (B, Figure 2), "average" (C, Figure 2), "slight increase" (D) and "great increase" (E). The physical position of each of them depends on the extreme (max-min) values of the parameter, its average and the statistical distribution chosen for it. In conclusion, when the value of the dominant financial parameter is calculated by the simulation process, the PRAPPIS system also automatically determines if this value has a "high decrease", "slight decreases", is close to the "average", "slight increases" or, finally, has a "greater increase". Of course, the "grade" or the "degree" of membership to each function is evaluated and used in the inference process.

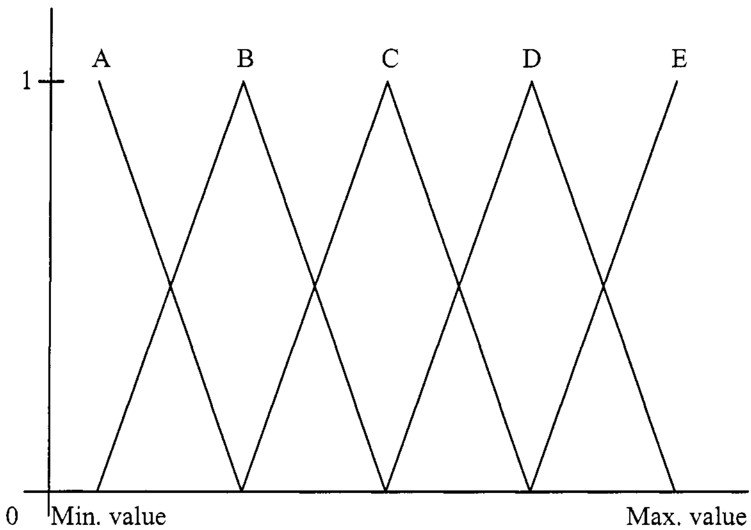

Figure 2. Membership functions.

Another five membership functions are assumed for the dominated financial parameter in the dependence relationship. Their structure is determined in exactly the same way as the dominant ones and it is used to obtain the conclusions of the fuzzy rules application.
Five "intensity" options were assumed for every dependence relationship between financial parameters: "very positive", "positive", "neutral", "negative" and "very negative" relationships. Each intensity option has five fuzzy rules, in this stage of development for the PRAPPIS system. These fuzzy rules create a fuzzy inference engine that controls the fuzzy reasoning process. The inference method chosen was Mizumoto′s product-sum-gravity method (Mizumoto [3]) that is derived from the Min-Max gravity method. This method requires a very complicated software routine for determining the center of gravity of the combined inference results. Finally, the value of the center of gravity is assumed as the dominated financial parameter value.

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Obviously, the dominated financial parameter is not determined by an independent simulation process except if the decision maker wants to introduce an uncertainty level in the application of the fuzzy inference engine. In this situation, the inference method is controlled by a random parameter that decides if the inference method is applicable or not.
In all cases, a standard financial appraisal method was selected according to European Union methodologies (Fabre [6]).

4 Tests and results

A five years project is selected to analyse the differences between standard Monte Carlo simulation technique with and without dependence relationships. Table 1 shows the basic parameters for financial appraisal. All these parameters are uncertain so a minimum-maximum interval is established. The discount rate is also uncertain and varies from 7.0% to 8.5%. Cost and revenue inflation is also uncertain and varies respectively from 2.5% to 4.0% and from 3.0% to 4.5%.

Table 1. Project financial parameters.

	Investments (x1000 euros)		Costs (x1000 euros)				Revenues (x1000 euros)	
			A		B			
Year	Min	Max	Min	Max	Min	Max	Min	Max
1	120	175	45	55	25	35	100	145
2			45	65	30	45	110	175
3	45	85	30	60	15	35	95	165
4			35	75	35	50	120	180
5	-50	-30	45	65	25	60	120	175

In a with-dependence-relationship, five relations were established between revenues as the dominant parameter and costs B as the dominated parameter. "Simple" direct relationships were fixed each project year as follows: year one revenues are related to year one costs B, year two revenues are related to year two costs B, and so on. A "neutral" intensity was selected for controlling the inference engine. Finally, a 2.5% Net Present Value (NPV) standard error was selected to limit the iteration number.
A sensitivity analysis was carried out repeating each analysis three times, with and without dependence relationships. Main results, in terms of iteration number and Net Present Value, are shown in Table 2 (with-dependence-relationships) and in Table 3 (without-dependence-relationships). Figure 3 and 4 show the cumulative probability distribution for every analysed situation.
The number of iterations needed to achieve an standard error lower than 2.5% of the NPV average decreases up to 29.14% in a with-dependence-relationship situation. This fact is because of a variability reduction due to the dependence

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relationships. The variability reduction is also evident in a significant decrease of the standard deviation, Table 2 and 3.
A standard statistical analysis was carried on using NPV parameter. A Kolmogorov-Smirnov-Lilliefors goodness-of-fit test was used to verify if the NPV statistical distributions could be considered as normal ones. Results are shown in Table 4. In the with-dependence-relationship situation every statistical distribution could be considered as normal ones. On the contrary, in the without-dependence-relationship situation the analysis 2 shows a statistical distribution that cannot be considered as a normal one.
The NPV average is identical in both analysed situations (Table 2 and 3), but its standard deviation is not. In a with-dependence-relationship situation this statistical parameter, that is a measure of the financial risk, is up to 17.77% lower than the without-dependence-relationship one.

Table 2. With dependence relationships results.

Analysis	Iterations nº	NPV (euros)			
		Average	Std deviation	Minimum	Maximum
1	2208	32424.19	37849.87	-75416.82	145164.29
2	2436	31440.19	38482.20	-81913.32	172100.75
3	2282	32052.54	37980.33	-97035.78	161526.30

Table 3 Without dependence relationships results.

Analysis	Iterations nº	NPV (euros)			
		Average	Std deviation	Minimum	Maximum
1	3226	32068.97	45235.21	-121880.50	168881.70
2	3459	31394.13	46027.29	-129058.34	193929.13
3	3116	32854.31	45706.14	-116255.38	184440.40

Table 4. Kolmogorov-Smirnov-Lilliefors test of normality.

	With dependence relationships		Without dependence relationships	
Analysis	Test statistic	Significance	Test statistic	Significance
1	0.016	0.200	0.010	0.200
2	0.014	0.200	0.020	0.004*
3	0.013	0.200	0.012	0.200

(*) The null hypothesis can be rejected.

The statistical range of NPV distribution is, of course, lower in the with-dependence-relationship situation (Table 2 and 3, Figure 3 and 4). This means that its cumulative probability function slope is greater and fits better with a normal distribution. The probability of a negative NPV also decreases in the analysed situation up to 0.206, from 0.24 in a without-dependence-relationship situation, Figure 3 and 4. The real financial risk of the project is lower than standard Monte Carlo method shows. Therefore, both lower and greater NPVs

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have a lower probability in a with-dependence-relationship situation. Both statistical distributions cut themselves in 29360-29370 NPV euros and a probability of 0.485.

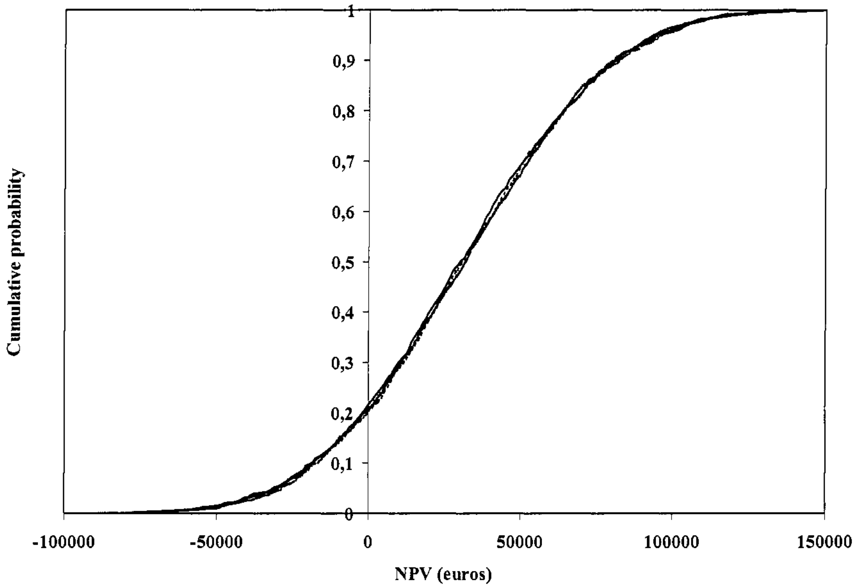

Figure 3. Net Present Value cumulative probability distribution with dependence relationships.

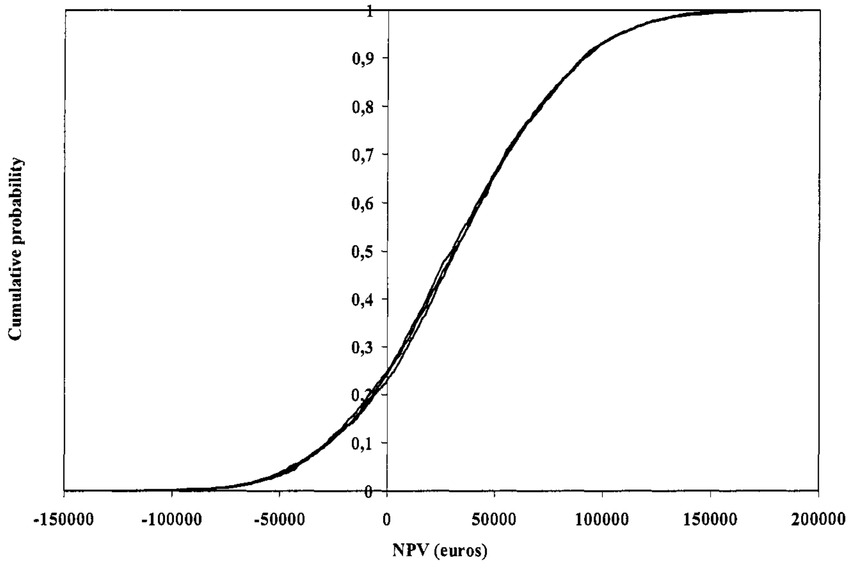

Figure 4. Net Present Value cumulative probability distribution without dependence relationships.

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5 Conclusions

The standard Monte Carlo simulation method is very appropriate for project financial appraisal in risky and uncertainty environments but assumes that any statistical distribution of the financial parameters used are independent. This assumption artificially increases the financial statistical risk (standard deviation). Therefore, the financial analysis can be inexact and its conclusions wrong. The reason of this situation is so clear, financial appraisal is based on future predictions that depend on human decisions and environment evolution. To many financial parameters should be considered and also to many dependence relationships between them exist and cannot be ignored.

A new approach to dependence relationship modelling is analysed in this paper. Fuzzy logic can be used to represent the structure of imprecise relationships between different financial parameters. Decision makers almost always can determine and describe dependence relationships in an semantic way, but it is very difficult for them to calculate technical relationships as mathematical equations.

The financial appraisal considering dependence relationships reduces the iteration number, the statistical range and the standard deviation of any financial results, for example: Net Present Value. These results are more precise and realistic because extreme and very strange situations are eliminated.

The “simple” relationship structure and the “neutral” intensity option are now being tested but other different combinations are also under consideration.

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