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Benchmark portfolio selection and efficient diversification of Congolese Bank

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Abstract

The study, based on available data on the Congolese banking sector has succeeded in establishing a benchmark of the ideal distribution of a bank's credit portfolio by sector in order to improve its profitability while reducing the risk of default.
This benchmark has been established on an exclusively quantitative basis on the results of three distinct methods of multi-criteria decision aid: AHP and TOPSIS. It can help banks to assess of the quality of their credit portfolio (or, at least, their sectorial allocation) relative to the latter, which is derived from the aggregates of the entire banking sector. It would benefit from being usefully combined with a more qualitative analysis that escapes the spectrum of this study taking into account the quality and availability of the guarantee, track record, etc.
The Student t-test, as the correlation coefficient has shown that the results of our different methods are in perfect correlation with the data of the bank, and the difference of the discrepancies between our methods and the data of the bank are random, that is to say not significant.

Keywords: *Bank, Portfolio Management; AHP; TOPSIS; Multi-Criteria Decision Aiding; Multi-Criteria Analysis; Credit; Risk; Profitability; Joint Analysis; Student Test.*

1. Introduction

The financial decisions of an organization (company, bank, etc.) are part of an optimization context. Financial theory always analyzes these short and long term financial decisions, but always with an optimal perspective [1]. The optimal nature of these financial decisions has led a large number of researchers to propose operational research techniques to resolve the problems inherent in these decisions [2]. The operational research is a discipline whose objective is to help managers and decision-makers to make good decisions in complex situations through the use of mathematical models [3 - 5].
For fifteen years, the banking sector has greatly developed in the Democratic Republic of Congo, with an average of about twenty financial credit institutions, and the Congolese are becoming more and more familiar with the bank, compared to the years before 2000.
In the era of advanced technology, risk management has undoubtedly become one of the most important areas for financial institutions, in order to maintain confidence and ensure its sustainability [6 - 8]. Credit is the sensitive element of a financial institution or our banks. Its importance comes from the fact that, it generates most of the income through interest paid by borrowers. These revenues are used to cover most of the operating costs of a financial institution.
The credit will enable the institution to generate a profit that will ensure its viability, growth and the maintenance of adequate capitalization. As a result, the assets of the institution are dispersed in the hands of a multitude of borrowers. This situation makes the management of the credit function very complex and sometimes dangerous. This is why it is necessary to have recourse to methods and tools that reduce the risk, associated with credit and that make this activity profitable [8 - 12].
In general, the real problem of the banker is related to liquidity. However, the Congolese banker has an average of 80% of current accounts and a maximum of 18% of savings accounts. This amounts to saying that the bank collects short term deposits but must make short and long term credits!
The majority of our banks have customers as individuals and the government. However, to save, you must first cover your primary expenses and needs in order to fund your savings account, which are not obvious in view of the socio-economic situation of the country. Despite this situation, the banker has a duty to find profitable areas for the viability of his bank.
The choice of lending sectors is relative to each bank, according to its investment policy after a prior market study, and the mechanisms put in place for collections. It should be noted that, a prolific sector for one bank is not a fortiori interesting for another bank.
So, not being sure to find a similar portfolio in two or three banks with the same sectors, this articl e proposes to work on the data of a single bank, but using two different methods to compare the final results.

With regard to the mismatching between short-term deposits and long-term loans, we will use multicriteria decision support methods to analyze profitable sectors with the lowest risks to find the ideal distribution of our loan portfolio.

To do this, we have organized the article as follows: Introduction, Modelization, Application and analysis and Conclusion and perspective:

2. Modeling

Portfolio management appears to be a multi-criteria problem and multi-criteria analysis, provides the methodological framework necessary for the resolution of such problems [12 - 16]. It then seemed, opportune to study the problem from this angle, by proposing a multi-criteria methodology for the management of loan portfolios, in a bank with the support of expert credit analysts.
The portfolio concept involves distributing credits, so as to capitalize on the diversification effect. The first step towards diversification is to avoid concentration. Also, banks define maximum limits sometimes in sectorial terms, sometimes in terms of business or even in geographic terms. These limits can be set in dollars, as a percentage of the credit portfolio, or as a percentage of capital.
Originally proposed by Markowitz [17], the medium-variance model for the portfolio selection problem was the benchmark formulation in the field and has served as the basis for the development of modern financial theory over the past 70 years.
In his model, Markowitz considers the mathematical expectation of the portfolio, as return on investment and the variance as risk of investment.

2.1. Classical mathematical formulation

Consider a portfolio P for which the expected performance $E(R_P)$ and risk σ_P^2 are known [17]. The classical management portfolio problem is formulated as follows:

$$(\mathrm{PS})\begin{cases}\max\,(1-w)\sum_{i=1}^{n} r_i x_i - w\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij}x_i x_j \\ \text{such that} \\ \sum_{i=1}^{n} x_i = 1 \\ 0 \le x_i \le 1;\ i = 1,2,\dots,n\end{cases}$$

Where
N is the headline number of titles;
x_i is the proportion of capital invested in title i;
r_i is the result on title i;
$r_i = E(R)$is the expected resultat of title i;
σ_{ij} is the covariance of results of title i and j;
$\sigma_{ij=\mathrm{cov}(R_i,R)j=E[(R-(R)(R_i-E(R_j))]_j}$
w is the coefficient of risk aversion characterizing the investor: with $0 < w < 1$ ($w \cong 1$ means a high risk aversion)
The mathematical formulation of portfolio section problem given below is due to Markowitz [18]. It has become the reference formulation because it had generated other

2.2. Multi-objective formulation

The multi-objective paradigm has emerged over the past forty years. It is a realistic model and it allows to cohabit several conflicting objectives (see [5], [15], [19], [20]).
In view of the problem (PS), we see that it is a bi-criteria problem, which can be formulated as follow:

$$(\mathrm{BCPS})\begin{cases}\max\sum_{i=1}^{n} R_i x_i \\ \min\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij}x_i x_j \\ \text{such that} \\ \sum_{i=1}^{n} x_i = 1 \\ 0 < x_i < 1;\ i = 1,\dots,n\end{cases}$$

Therefore, the weight w expresses the importance of criterion risk that corresponds to the aversion coefficient, hence the formulation (PS). Theoretically, it is possible to transpose the Markowitz (P) portfolio optimization model to managing a credit portfolio. The titles in this context are replaced by industrial sectors. Knowing the expected return and the variance for each sector as well as all the covariances between the sectors taken two by two, the model makes it possible to calculate what proportion must be placed in each sector, to minimize the total variance taking into account a level of desired yield. In practice, all kinds of application difficulties mean that, this formal approach is very little used for credit management.
On the other hand, there are two methods of managing the credit portfolio, which are derived from general portfolio theory. The first is based on the fact that, the market portfolio must be an efficient portfolio, and therefore constitutes a benchmark for evaluating the bank's portfolio. According to this approach, the bank begins by establishing how much credit each industrial sector holds overall, that is to say from all the credit providers. Then, it calculates the proportion of this credit in relation to all the credit made in the economy. Then, it calculates the proportion of the credit it makes to this sector, compared to the total of its credit portfolio. Finally, it compares its weighting with that of the market to see that it is under, or overweight compared to the market.
Criticisms of the classic portfolio approach have led to an increasing use of multicriteria decision, support methods in portfolios such as in [16], [21 - 23].
The literature review on portfolio management lists several articles, indicating the interest of the subject since the pioneering work of Markowitz [17]. We found around fifty articles on the subject among which we count [13], [14], [24], [16], [24], [25], [26], [27] and [28]. According to Ekeland [4], the problem of portfolio choice is multicriteria since the investor would try to both maximize the return, and minimize the risk. However, by setting a given level of risk, it comes down to a classic problem where you have to maximize the return for a given risk [13], [21]. The metaheuristics are exploited in [13], [29], [40]. Hence, metaheuristic methods are used for the valuation of the stock portfolio, the genetic algorithm and the simulated annealing. [29] makes Portfolio Optimization Forecasts using Artificial Neural Network and Genetic Algorithm.

In [27], [28], [30], [31] and [32], fuzzy numbers appear for the first time in this area and are very well developed. In [14], [16] and [24], the authors introduce the multicriteria paradigm in modeling. A resolution by Goal Programming is exposed in [33], [34]. In several other articles [16], [35 - 37] various related concerns are mentioned; it is inter alia the diversification of the investments, the expected profitability, the management of the portfolio of the capital markets, or mutual funds and finally [24] manages to observe a better choice of the risks on the operation of financial assistance, to clients in relation to financing offers.

3. Application and analysis

Any bank or credit institution uses credit risk assessment instruments, with regard to its customers. The majority of them, use methods based on statistics such as Discriminant Analysis and Credit Scoring [11], [38]. The rating of the sector of granting, or of the applicant for credits is determined by a financial analyst from the accounting documentation of the company, otherwise the quality and availability of the guarantee for individuals. It is based on a proven and documented methodology, as well as on the knowledge of the applicant, and their environment by the financial analyst. It can be revised at any time, by collecting new information deemed relevant for the analysis of credit risk. Compliant with Basel II banking standards, the rating assesses, over a horizon according to the terms of repayment, or honoring its financial commitments.
The purpose of this assessment is to predict the risk of default corresponding either to a default (judicial declaration of a cessation of payment), or to serious cash flow difficulties. The risk measure is provided by the default rates, actually observed (at one year, two years, three years, etc.), which are associated with each score to have a score.
The score is the result of a statistical study and not of an expert opinion. The explanatory variables, derived from accounting information, are economic and financial ratios statistically selected, because of their ability to differentiate between the applicants who are likely to have difficulties and the others [37 - 39].

3.1. Data structure

The data used in this study are provided in the monthly report of the beta bank for 22 months, that is to say; from March 2021 to December 2022. These data represent the nineteen credit granting sectors listed in the table 1. The costs of the monthly loans granted and the monthly risks known by the bank for the different sectors are taken from the bank's monthly report and are expressed in US dollars.

Table 1: Credit Granting Sector

Code	Sectors
A1	AGRICULTURE, FORESTRY AND FISHING
A2	ARTS AND RECREATION
A3	HEALTH
A4	EDUCATION
A5	MANUFACTURING
A6	WATER SUPPLY; SEWAGE, WASTE MANAGEMENT AND REMEDIATION
A7	CONSTRUCTION
A8	GENERAL COMMERCE
A9	HOSPITALITY
A10	TRANSPORTATION AND STORAGE
A11	INFORMATION AND COMMUNICATION
A12	FINANCE AND INSURANCE
A13	REAL ESTATE CONTRUCTION
A14	POWER AND ENERGY
A15	MINING
A16	OIL & GAS*
A17	GOVERNMENT
A18	PERSONAL AND PROFESSIONAL
A19	OTHER

Consider the limits imposed by the availability of data, five criteria have been retained to illustrate the objective variables that influence the decision to grant loans.
These criteria are:
1) The Cost of Credit to Maximize
2) The risk observed by sector to Minimize
3) The theoretical risk by sector to Minimize
4) The default rate by sector to Minimize
5) Profitability by sector to Maximize

If we can explain our criteria:
The Cost of Credit: the bank must take into account the cost of credits, to make a profit based on the capital allocated to the sector in relation to interest rates and related costs (insurance, VAT, administration fees and others).
The risk observed or proven by sector: is the monthly unpaid amount by sector, (Par 30) and that the bank observes non-recovery in its cash.
The theoretical or expected risk by sector: is the variance calculated in relation to the expected return on the amount of credit granted.
The default rate by sector: the ratio of overdue loans by sector (Par 30) to total exposure by sector (Quality of the portfolio).
Profitability by sector: the sector is profitable compared to the bank in terms of market conditions, either general and sectoral economic conditions or in particular, the level of the interest rate.
NB: We decided to take the two risks, because the theoretical or expected risk is a probability, which we have to face when deciding to grant a loan on the other hand, the observed risk is a reality that the bank lives in relation to its recovery mechanism, put in place because the latter is the primary reason, for bankruptcy of financial institutions.
The table below, represents the average values compared to the criteria for the nineteen sectors. And each number represents a sector compared to table 2 below.

Table 2: Natural Data

Sectors	Critères Risk observed Weight	Risk theoretical	Profitability by sector	Cost of Credit	Default rate
	0,1967	0,1967	0,2214	0,2022	0,1830
A1	0,42363636	0,11680484	0,01276787	2,26863636	0,01655828
A2	0,00762461	0,00689272	0,00036333	0,06455698	0,00029802
A3	0,10363636	0,03628306	0,00373494	0,66363636	0,00405074
A4	0,24272727	0,01882048	0,00322331	0,57272727	0,00948726
A5	0,54590909	0,35409131	0,04062900	7,21909091	0,02133744
A6	0,18001811	0,10018314	0,00855199	1,51954545	0,00703620
A7	2,03181818	0,09970425	0,01990007	3,53590909	0,07941579
A8	6,89772727	1,04707535	0,21746567	38,6400000	0,26960507
A9	0,99045455	0,05010860	0,01252996	2,22636364	0,03871298
A10	0,79818182	0,20163931	0,04734933	8,41318182	0,03119779
A11	0,19136364	0,27923031	0,01532605	2,72318182	0,00747965
A12	0,12818182	0,10058703	0,00677917	1,20454545	0,00501012
A13	0,03045455	0,54893365	0,01443580	2,56500000	0,00119035
A14	0,16772727	0,11451892	0,02231499	3,96500000	0,00655580
A15	0,28409091	0,26656159	0,04307973	7,65454545	0,01110400
A16	0,00000000	0,00000000	0,02429886	4,31750000	0,00000000
A17	0,21095238	0,55874230	0,03716926	6,60435335	0,00824530
A18	4,27068182	2,35383522	0,32633820	57,9848218	0,16692418
A19	8,07937500	2,20914185	0,14374247	25,5406250	0,31579103

3.2. The multi-criteria decision support methods used in this study

For our study, we will use the AHP and TOPSIS methods, and to have the relative weights of each criterion, we needed the support of credit managers.

Given the schedule of Congolese bankers, we decided to formulate a questionnaire on the criteria selected. Each respondent was asked to give a score, on a scale of 0 to 10 in order to calculate the average of the scores assigned to the criteria by the credit, analysts to obtain a matrix of judgments. This matrix of judgments will be the input information for the TOPSIS and AHP methods.

The Joint Analysis gave objectively the weight of each criterion retained by the Orthoplan under SPSS.

Considering the means at our disposal, we conducted our experiment on a sample of 100 respondents at the rate of 5 credit analysts per bank.

Thus, with a quota of 5 respondents per bank, we obtained 100 correctly completed questionnaires. The Joint Analysis by SPSS provided the following results:

Table 3: Criterion Importance Values

Criteria	Importante value
Cost of credit	20,2259632
Risk observed	19,6695716
Risk Théoratical	19,6695716
Defaut Rate	18,2984642
Profitability by Sector	22,1364294

3.2.1. The analytic hierarchy process (AHP) method

The AHP method is a multi-criteria analytical approach to decision support. It is fundamentally based on complex calculations using matrix algebra. The method consists of representing a decision problem by a hierarchical structure reflecting the interactions between the various elements of the problem, then making pairwise comparisons of the elements of the hierarchy, and finally determining the priorities for actions.

It should be noted that to arrive at drawing up the judgment matrices AHP (matrices of comparison by pairs), we will use the following formulas:

$$Imp(a_i, a_k) = \begin{cases} Arr\left(\frac{S(a_i)-S(a_k)}{m} + 1\right) \ if \ S(a_i) > \ S(a_k) \\ \frac{1}{Arr\left(\frac{S(a_k)-S(a_i)}{m}+1\right)} \ Else \end{cases}$$

Where $Arr(x)$ denotes the integer closest to the real x and m the mean deviation.

$$m = \frac{max - min}{n}$$

Where:
max: the highest score
min: the lowest score
n: the number of criteria

The following table gives a matrix of pairwise judgments of the criteria in relation to the above formula using the table of relative weights:

Table 4: Level 0 Judgement Matrix

	Risk Theoretical	Risk Observed	Profitability by Sector	Cost of credit	Default Rate	Geometric Mean	Clean Vector
Risk Theoretical	1,00000	1,00000	0,25000	3,00000	0,50000	0,82187591	0,12670803

Risk Observed	1,00000	1,00000	0,25000	3,00000	0,50000	0,82187591	0,12670803
Profitability by Sector	4,00000	4,00000	1,00000	6,00000	3,00000	3,10369115	0,47849387
Cost of credit	0,33333	0,33333	0,16667	1,00000	0,25000	0,34127875	0,05261470
Default Rate	2,00000	2,00000	0,33333	4,00000	1,00000	1,39765424	0,21547537
Total						6,48637597	1,00000000

Let's analyze the relevance of the judgments matrix

Calculation of the Own Proper Value λ_{max}

λ_{max} is the arithmetic mean of all λ_i : $\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n}\lambda_i$

Calculalion of the Consistency index

The difference, if observed, between λ_{max} et n is an indicator of the inconsistency of human judgments.

$$CI = \frac{\lambda_{max} - n}{n-1}$$

Calculation of the coherence ratio (CR)

The consistency index (CI) must be associated with a value, in a completely randomized (random) matrix.

$$CR = \frac{CI}{RI}$$

The table provided by Saaty only tells us about the values of RI for n≤15. Extrapolating these values allowed us to expand the table to $n = 20$.

Table 5: Random Indices Corresponding to the Orders of the Matrix

n	1	2	3	4	5	…….	13	14	15	16	17	18	19	20
RI	0.00	0.00	0.58	0.90	1.12	……..	1.56	1.57	1.59	1.62	1.66	1.71	1.77	1.84

Saaty suggests that if CR> 0.1 the set of judgments may be inconsistent enough to be reliable.

In order not to repeat the same calculations on the 19x19 matrices of judgments in relation to the different criteria, we will summarize in this table below, on the different analyzes of relevance for the matrices of judgments.

Table 6: Analysis of the Relevance of Level 1 Matrices

	Risk Theoretical	Risk Observed	Profitability by Sector	Cost of credit	Default Rate
λ_{max}	19,4358335	20,04086894	19,928284	19,927274	20,0855103
CI	0,02421297	0,057826052	0,05151522	0,0515122	0,06030613
RI	1,77	1,77	1,77	1,77	1,77
CR	0,01367964	0,03267009	0,02910464	0,02910294	0,03407126

With regard to this table above, we note that CR <0.1 for each of the criteria and we can conclude with certainty that the judgments expressed on these criteria is reliable and not random.

Table 7: Global Matrix and AHP Scores

	Risk Theoretical	Risk Observed	Profitability by Sector	Cost of credit	Default Rate	
Sectors	Weights (Proper Vector of Level 0)					AHP Score
	0,12670803	0,12670803	0,47849387	0,0526147	0,21547537	
A1	0,04752531	0,06160384	0,0140758	0,0140758	0,04740247	0,03151738
A2	0,08436779	0,09981620	0,01006963	0,01006963	0,08414971	0,04681785
A3	0,07562156	0,09770866	0,01010898	0,01010898	0,07822854	0,04418762
A4	0,06336296	0,09770866	0,01010898	0,01010898	0,06302879	0,03935919
A5	0,04418121	0,02826637	0,03154093	0,03154093	0,04406701	0,03542671
A6	0,07489937	0,06464754	0,01187566	0,01187566	0,07470577	0,04008623
A7	0,01468124	0,06464754	0,01710314	0,01710314	0,01458173	0,02227722
A8	0,00341507	0,00855028	0,20657560	0,20657560	0,00342063	0,11196724
A9	0,02843491	0,08733055	0,01407580	0,01407580	0,02836140	0,02825537
A10	0,03331279	0,04630999	0,03583338	0,03583338	0,03322668	0,03627979
A11	0,07069139	0,03671708	0,01500641	0,01500641	0,07050866	0,03677243
A12	0,07562156	0,06464754	0,01187566	0,01187566	0,07542608	0,04033295
A13	0,08134540	0,01836871	0,01459878	0,01459878	0,08113513	0,03787074
A14	0,07489937	0,06233161	0,01887386	0,01887386	0,07470577	0,04350959
A15	0,06287594	0,03671708	0,03222126	0,03222126	0,06271341	0,04324542
A16	0,08750248	0,10077863	0,02030244	0,02030244	0,08727629	0,05344542
A17	0,06815894	0,01791990	0,02839475	0,02839475	0,06798276	0,04063619
A18	0,00656820	0,00276431	0,37817943	0,37817943	0,00655122	0,20344847
A19	0,00253450	0,00316548	0,11917951	0,11917951	0,00252795	0,06456420

Referring to the table above, we have the weighting of each sector in relation to the AHP method and we will compare the score of the AHP method in relation to the ranking of the bank.

Table 8: AHP – Bank Beta Sector Ranking Comparison

Sector	AHP Score	AHP Rangement	Beta bank storage	Raw Data	Percentage
A1	0,03151738	17	13	2,268636364	0,01276787
A2	0,04681785	5	19	0,06455698	0,00036333
A3	0,04418762	6	17	0,663636364	0,00373494
A4	0,03935919	12	18	0,572727273	0,00322331
A5	0,03542671	16	6	7,219090909	0,040629

A6	0,04008623	11	15	1,519545455	0,00855199
A7	0,02227722	19	10	3,53590909	0,01990007
A8	0,11196724	2	2	38,64	0,21746567
A9	0,02825537	18	14	2,226363636	0,01252996
A10	0,03627979	15	4	8,413181818	0,04734933
A11	0,03677243	14	11	2,723181818	0,01532605
A12	0,04033295	10	16	1,204545455	0,00677917
A13	0,03787074	13	12	2,565	0,0144358
A14	0,04350959	7	9	3,965	0,02231499
A15	0,04324542	8	5	7,654545455	0,04307973
A16	0,05344542	4	8	4,3175	0,02429886
A17	0,04063619	9	7	6,604353349	0,03716926
A18	0,20344847	1	1	57,98482181	0,3263382
A19	0,0645642	3	3	25,540625	0,14374247
Total	1			177,6832208	1

We note that according to a certain hierarchy or priority, Sectors A8, A18 and A19 are the same according to AHP as the Bank but the other sectors do not have the same priority vis-à-vis the bank as of AHP but we will we support a study to verify if this difference is random or well founded.

Table 9: Comparison of the AHP Portfolio to That of the Beta Bank

Statistics	Value
Student Test	1,00000000
Correlation Coefficient	0,94188442

Board 9 informs us that there is no significant difference between the portfolio provided by AHP and that applied by the bank under study. There is even a very high correlation (94.19%) between the two portfolios.

3.2.2. The TOPSIS method (technique for order by similarity to ideal solution)

The TOPSIS method aims to choose a solution that comes closest to the ideal solution (best on all criteria) and departs as much as possible from the worst solution (which degrades all criteria). Its principle consists in determining for each alternative a coefficient between 0 and 1 on the basis of the Euclidean distances between alternative on the one hand and the ideal favorable and unfavorable solutions.
By applying the TOPSIS algorithm, we have the score in the table below:

Table 10: TOPSIS – Bank Beta Sector Ranking Comparison

Sector	TOPSIS Score	TOPSIS Rangement	Beta bank storage	Raw Data	Percentage
A1	0,04375702	15	13	2,26863636	0,0127678
A2	0,04398253	10	19	0,06455698	0,0003633
A3	0,04393682	12	17	0,66363636	0,0037349
A4	0,04361487	16	18	0,57272727	0,0032233
A5	0,04692672	7	6	7,21909091	0,040629
A6	0,04396079	11	15	1,51954545	0,0085519
A7	0,04060374	19	10	3,53590909	0,0199000
A8	0,09673115	2	2	38,64	0,2174656
A9	0,04259461	18	14	2,22636364	0,0125299
A10	0,04847255	5	4	8,41318182	0,0473493
A11	0,04391064	13	11	2,72318182	0,0153260
A12	0,04388948	14	16	1,20454545	0,0067791
A13	0,04298708	17	12	2,565	0,0144358
A14	0,04579332	9	9	3,965	0,0223149
A15	0,04855077	4	5	7,65454545	0,0430797
A16	0,0470979	6	8	4,3175	0,0242988
A17	0,04619492	8	7	6,60435335	0,0371692
A18	0,12424943	1	1	57,9848218	0,3263382
A19	0,06274565	3	3	25,540625	0,1437424
Total	1				1

We note that according to a certain hierarchy or priority, TOPSIS and the bank under study agree on the rankings of the sectors A8, A14, A18 and A19, but the other sectors do not have the same priority vis-à-vis the bank. Let us rely on a statistical analysis to verify whether this difference is random or well founded.

Table 11: Comparison of the TOPSIS Portfolio to That of the Beta Bank

Statistics	Value
Student Test	1,00000000
Corrélation Coefficient	0,983032963

Table 11 informs us that there is no significant difference between the portfolio provided by TOPSIS and that applied by the bank under study. There is even a very high correlation (98.30%) between the two portfolios.

4. Conclusion and perspectives

Outlook The best known scientific approach in the field of portfolio management, was proposed by Markowitz in 1952. It consists in determining the set of "efficient" portfolios based on two parameters, namely the expected return and the expected variance of yields. A decision rule is then used to choose, from this set, the portfolio that maximizes the expected utility of the investor. Although attractive, this model, commonly known as the "medium-variance model", faces, in practice, several obstacles which severely reduce its scope for investors and managers. Our study was part of a series of discussions with credit managers, in order to retain a certain number of determining criteria in the granting of a credit and, a questionnaire was given to them to evaluate these by giving them marks, in order to highlight the weight of each criterion. Saaty's consistency index allowed us to agree that, our managers' judgments were sound and reliable. The study, based on data available on the Congolese banking sector, succeeded in establishing a benchmark of the ideal distribution of a bank's loan portfolio, by sector in order to improve the latter's profitability while reducing risks default. This benchmark established on exclusively quantitative bases is based on the results of two distinct Multicriteria Decision Support methods: AHP and TOPSIS. It can help banks assess the quality of their credit portfolio (or at least its distribution by sector) compared to the latter, which is derived from aggregates for the entire banking sector. It would benefit from being usefully combined with a more qualitative analysis, which escapes the spectrum of this study, taking into account the quality and availability of the guarantee, trackrecord, etc. Student's test as the correlation coefficient have shown that, the results of our different methods are in perfect correlation with the data of our bank, and the difference of the ranks of the sectors between our methods on the data of the bank is random, it is that is, not significant.

References

[1] MacLean L.C. and Ziemba W.T.: Handbook of the Fundamentals of Financial Decision Making, World Scientific, May 10, 2013. https://doi.org/10.1142/8557.

[2] Nakhla M., La pratique de le recherche opérationnelle en gestion, Presses des Mines – Transvalor, 24/11/2022.

[3] Ashford R.W., Berry R.H., Dyson R.G., Operational Research and Financial Management, European Journal of Operational Research (1988), 36, p. 143-152. https://doi.org/10.1016/0377-2217(88)90419-5.

[4] Ekeland I.,"Finance: un nouveau domaine des mathématiques appliquées",Revue Française de Gestion (1993), p. 44-48.

[5] Roy B., "Des critéres multiples en recherche opérationnelle: Pourquoi?", Operational Research Õ87, Rand, G.K. (Ed.), Elsevier Science Publishers, North Holland, 1988, p. 829-842.

[6] Gouiaa R. and Ouedraogo M.: L'impact de la gestion du risque de crédit sur la performance des banques commerciales canadiennes, Revue Organisations & territoires, Volume 31, Number 1, 2022,p 69-91. https://doi.org/10.1522/revueot.v31n1.1449.

[7] Monnier P., Le Petit Banque « L'Essentiel en Bref », Dunod, 22/02/2023.

[8] Azzouz E., La gestion du risque crédit par la méthode scoring: Cas de la Banque Populaire de Rabat-Kenitra. REMAREM, 2009, pp.291.

[9] Zopounidis C., La gestion du capital risque, Paris, Economica, 1990.

[10] Zopounidis C., Evaluation du risque de défaillance de l'entreprise: Méthodes et cas d'application, Paris, Economica, 1995.

[11] Jacquillat B. et Solnik B., Marchés financiers : gestion de portefeuille et des risques, Paris, Bordas-Dunod, 1990.

[12] Badaj F., L'aide multicritère à la décision et la structure financière des PME. International Journal of Accounting, Finance, Auditing, Management and Economics. Volume 2, Issue 5 (September, 2021), ISSN: 2658-8455.

[13] Kapiamba Nt, Ulungu E.L. and Mubenga K.: Simulated Annealing vs Genetic Algorithm to Portfolio Selection. International Journal of Scientific and Innovative Mathematical Research. Vol 3, Issue 5, May 2015, PP 18-30.

[14] Mark T. Leung and al. : Using investment portfolio return to combine forescasts : A multiobjective approach. European Journal of Operational Research 134,84-102, 2001. https://doi.org/10.1016/S0377-2217(00)00241-1.

[15] Roy B. et Bouyssou D., Aide multicritère à la décision : méthodes et cas , Paris, Economica,1993.

[16] Hurson C. and Zopounidis C. : Gestion de portefeuille et Analyse multicritère. Edition *Economica* 1997.

[17] Markowitz H. :Portfolio selection. Journal of Finance 7:77-91, 1952. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x.

[18] Markowitz H.M.: Portfolio Selection, efficient diversification of investment. New Haven and London, Yale University press, second printing, 1970.

[19] Kapiamba NT, Mubenga K, Ulungu E.L : Revue des principales méthodes de résolution du problème d'affectation en présence de critères multiples. Annales de la Faculté des Sciences (UNIKIN). Vol 1, (2016) 97-104.

[20] Meyer, P., Contributions au processus d'Aide Multicritère à la Décision : Méthodes, Outils et Applications, Habilitation à Diriger des Recherches en Informatique, Université Paris Dauphine, 2013.

[21] Hurson Ch., Zopounidis C., "On the Use of Multicriteria Decision Aid Methods to Portfolio Selection", The Journal of Euro-Asian Management (1995), vol. 1, no.2, 69-94.

[22] Snopek L. and Lhabitant F.S. : Guide complet de construction et de gestion de portefeuille, Maxima - 27 Septembre 2018.

[23] Siles M.V. : Guide de base planification de crédit et gestion de portefeuille (Analyse du risque de crédit). Broché - 3 Novembre 2017.

[24] Rakotoarivelo J.B.: Analyse comparative de méthodes multicritère d'aide à la décision pour le secteur financier, Rapport de recherche IRIT n° IRIT/RR-2015-07-FR ; 22 Mai 2015. UNIVERSITE PAUL SABATIER DE TOULOUSE

[25] Aftalion F., Poncet P. and Portait R.: La théorie moderne du portefeuille. Collection Que sais-je? Presse Universitaire de France (PUF), Décembre 1998.

[26] Despotis D.K, Yannacopoulos D. et Zapounidis C., « A review of the UTA multicriteria method and some improvement », foundations of computing and Decision Sciences (Vol. 15, n°2, 1990), p.33-76.

[27] Wang, Y.M, Elhag, T.M.S. : Fuzzy TOPSIS Method Based on Alpha Level Sets with an Application to Bridge Risk Assessment. Expert Systems with Applications, 31, 309 – 319 (2006). https://doi.org/10.1016/j.eswa.2005.09.040.

[28] Olcer, A.I, Odabasi, A.Y. : A New Fuzzy Multiple Attributive Group Decision Making Methodology and its Application to Population/Maneuvering System Selection Problem. European Journal of Operational Research, 166, 93 – 114 (2005). https://doi.org/10.1016/j.ejor.2004.02.010.

[29] Solin M.M., Alamsyah A., RikuMahu B. and Saputra M.A.A., Forcasting Portfolio Optimization using Artificial Neural Network and Genetic Algorithm, The 7th International Conference on Information and Communication Technology, ICoICT 2019 https://doi.org/10.1109/ICoICT.2019.8835344.

[30] Nadia E.M. & Ousman A. : Fuzzy TOPSIS Method in the Selection of Investment Boards by Incorporating Operational Risks ; Proceedings of the World Congress on Engineering 2011 Vol I WCE 2011, July 6 - 8, 2011, London, U.K.

[31] Parra A., Terol A.,A.T and Rodriguez Uria M.V: A fuzzy goal programming approach to portfolio selection. European Journal of Operational Reseach 133, 287-297, 2001. https://doi.org/10.1016/S0377-2217(00)00298-8.

[32] Buckley, J.J. : Fuzzy Hierarchical Analysis. Fuzzy Sets and Systems, 17 233 – 247 (1985) https://doi.org/10.1016/0165-0114(85)90090-9.

[33] Sang M.L. and Delton L.C. : Goal programming for portfolio selection. The Journal of Portfolio Management, 22-26, 1980. https://doi.org/10.3905/jpm.1980.408744.

[34] Sang M.L. and Lerro A.J. : Optimisation of the Portfolio selection for mutual funds. The Journal of Finance, Vol 28, 1087-1101, Décembre 1973. https://doi.org/10.1111/j.1540-6261.1973.tb01443.x.

[35] Norbert Fogarasi, Janos Levendovszky: Sparse, mean reverting portfolio selection using simulated annealing. Algorithmic Finance, 2013, vol. 2, issue 3-4, pages 197-211 https://doi.org/10.3233/AF-13026.

[36] Sang M.L. and Delton L.C. : Goal programming for portfolio selection. The Journal of Portfolio Management, 22-26, 1980. https://doi.org/10.3905/jpm.1980.408744.

[37] Teghem J. Pirlot M. : Résolution de problèmes de Recherche Opérationnelle par les métaheuristiques. Lavoisier, 2003.

[38] Baesens: "Developping intelligent systems for credit scoring using machine learning techniquess " Ph.D, Lueven, 2003 f Bardos: "analyse discriminante ", Dunod, 2001.

[39] http://www.defaultrisk.com/ f basel Committee publications:
[40] Khaloozadeh H and Ghoreishi S., Optimal Portfolio Allocation based on two Novel Risk Measures and Genetic Algorithme, International Journal of Business and Development Studies, Vol 10, pp 95-113, 2018.