Roads Funding Priority Index for Developing Countries using Multivariate Analysis

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***Abstract*: This article presents a new Road Funding Priority Index (RFPI) that simultaneously considers the technical, economic, social and environmental dimensions in order to assist decision makers in their selective processes of high-priority road construction and preservation projects. The RFPI is a decision support tool that was tested on 50 road projects, including 25 unpaved road construction projects and 25 existing paved road preservation projects. The stages of development of the RFPI are: the establishment of a theoretical framework (1), the selection of the relevant indicators (2), the transformation of indicators (3), the normalization of indicators (4), the correlation and significance test (5), the weighting using the principal component analysis (PCA) (6), the aggregation and calculation of the RFPI (7). Ten (10) high-priority road projects were selected based on their RFPI values. Among these high-priority road projects, 60% are preservation projects and 40% are construction projects, which depicts evidence of the importance of maintaining existing roads, but also of the construction of new ones as long as they have an RFPI close to 100. These conclusions demonstrate that the RFPI is a useful tool for improving, in a rigorous scientific method, the process of prioritizing road infrastructure in developing countries.**

***Keywords:* Composite Indicator, Prioritization, Principal Component Analysis, Road Infrastructure.**

I. INTRODUCTION

Roads are crucial for the socioeconomic development of countries. They contribute to the well-being of local communities and poverty alleviation in sub-Saharan Africa. They connect people to markets, schools, hospitals and community centers. Moreover, in order to achieve the United Nations sustainable development goals of 2030 for which the motto is "Transforming our World", governments and international financial institutions must invest wisely in strategic sectors such as road infrastructure.

New road construction is important because of its economic and socioeconomic impact on local communities. New roads open up isolated areas and facilitate national and international trade. It is noteworthy that the densities both per square kilometer of land area and per capita of most road networks in developing countries are very low in comparison to the average density of other parts of the world. Africa's road network density is 204 km per 1000 km^2 with only a quarter being paved, while the world's average is 944 km per 1000 km^2 with more than half of the roads paved (Ken, 2011). However, it is also important to keep the existing roads in good condition to avoid having to restrict accessibility and mobility throughout the year. Moreover, if preventive maintenance work is not carried out timely, the road's condition deteriorates promptly which can lead to major rehabilitation or reconstruction work which is four times more expensive than maintenance work (Burningham et Stankevich, 2005).

The lack of balance between existing infrastructure deterioration rates and the funds allocated to their maintenance ; the trend that prioritizes new infrastructure constructions ; and the absence of quality maintenance performed timely are the challenges being faced in the road infrastructure sector throughout developing countries (DFID, 2016). Moreover, scarce funding for both construction and more importantly maintenance projects is another major challenge ahead. The main goal of this document is the development of a new road funding priority index (RFPI) to select high-priority projects eligible for road agencies and donor funding. The specificity of this study rests in the fact that the RFPI was developed using multivariate statistical techniques by collecting available and accessible data from a road agency. Inputs for sophisticated analysis such as cost-benefit analysis (CBA) using the road network software, Highway design and Management (HDM-4) are complex, time and money consuming for developing countries to prioritize needs. In addition, CBA is exclusively based on economic criteria. Therefore, the RFPI acts as a springboard for the preliminary selection of high-priority roads projects selection that may subsequently be evaluated structurally and functionally to obtain intensive data for CBA using HDM-4.

This paper is structured as follows: literature review on constructing composite indicators, data sources, study area, materials and methods, results and discussion and, finally, conclusion and recommendations.

II. LITERATURE REVIEW

Decision support tools involve the set of methods, analytical approaches, procedures and evaluating frameworks for road projects or road agency policies (Healy et al., 2007). A variety of tools were developed by researchers to assist decision-makers or road managers in the road infrastructure prioritization process. These tools may be split in two groups: single-criterion tools and multicriteria tools. Composite indicators (CI) are considered multicriteria tools.

The composite indicator (CI) is a tool for measuring a complex phenomenon by simultaneously considering several dimensions. CI is an aggregation through many stages of various indicators or sub-indicators to highlight complex and often imperceptible dimensions such as environmental, economical, social or technological development. However, scientists are not unanimous about the use of CI which, of course, implies both pros and cons (OECD, 2008). The pros argue that CI can synthesize complex problems to support decision-makers by granting them with a big picture that will facilitate interpretation, more than if they were to seek trends on various individual indicators. Pros also advocate the idea that the CI is more responsive to public interest since it may be used to compare projects performance as well as to monitor and evaluate projects over time. Pros also believe that CI can contribute to the reduction in size of a large number of indicators or to the incorporation of information into a limited size of already existing indicators. In contrast, the cons argue that CI can lead to the adoption of misleading and weak policies if they were poorly constructed or misinterpreted. This can also lead decision-makers to make over-simplistic choices. In addition, the opponents of CI application also claim that each stage of CI construction requires many choices and acts of judgment, all subjective and which may lead to erroneous results. For instance, the selection and weighting stages are often influenced by policy goals and different challenges stakeholders face. The requirement of intensive data for the construction of the CI is also an argument used by the cons. Although the arguments of researchers against the use of CI could be justifiable, solutions were developed to fill theses gaps in these indices' stages of construction. Thus, uncertainty and sensitivity analysis should be undertaken to check the robustness of CI (Mainali et Silveira, 2015; OECD, 2008; Saisana et Tarantola, 2002). In addition, a composite subindex can be developed for each dimension to avoid simplistic decision-making. The judgments of opinion involved in each stage of the construction of CI must be transparent and based on soundness statistical principles (Saisana, Saltelli et Tarantola, 2005). The development of sub-indices and clustering analysis will make the topic for a further article.

Many types of composite indices were developed around the world. The Human Development Index (HDI) was introduced in 1999 and is since then used to measure the human development of 177 countries based on three components: life experience, adult literacy rate and gross enrollment rates. These components were also used to create sub-indices such as Gross Domestic Product (GDP), Education Index (EI) and Life Experience Index (LEI). The Environmental Sustainability Index (ESI) was developed in 2000 in order to assess the environmental protection suitability of 146 countries over the next decades. The ESI was based on five main components: environmental systems, reducing stresses, reducing human vulnerability, social and institutional capacity and global stewardship. 21 indicators allow to monitor each country's environmental protection evolution. The Economic Vulnerability Index (EVI) was created in 1992 in order to assess the extent to which a country's economy is exposed to uncontrollable exterior forces. The EVI was used to compare 117 countries by considering trade openness, export concentration, dependence on strategic imports and peripheracity as main components (Bandura, 2008).

Although all the composite indicators above-mentioned were criticized by some scientists, they are now used around the world to compare and measure the performance of countries. The most common composite index in the transportation infrastructure sector, is the Road Safety Index (RSI). The RSI was developed to compare road safety in several countries. It is based on traffic risks, personal risk, vehicle safety, road situations, road users behavior, socio-economic background, road safety organization and enforcement indicators (Gitelman, Doveh et Hakkert, 2010). The main construction stages on the CIs are (OECD, 2008) : (1) theoretical framework, (2) data selection, (3) imputation of missing data, (4) multivariate analysis, (5) normalization, (6) weighting and aggregation and (7) uncertainty and sensibility analysis. These stages were adapted for the establishment of the RFPI in this paper, whereby the main focus is on how It was developed using principal component analysis (PCA). The construction of CIs with PCA was more widely explored in other fields than the road infrastructure one. Using PCA, (Ouyang et al., 2006) chose 16 surface water quality indicators to evaluate the most influential indicators of seasonal variations. (Fuquan, Lu et Xiang, 2008) developed road security indicators and with PCA to aggregate factors with major and minor influences as well as road traffic characteristics. (Friesen, Seliske et Papadopoulos, 2016) used PCA to socioeconomic status indices that include communities' economic disparities and distribute better health services. A thorough literature review, showed that only one study was conducted on transportation infrastructure projects prioritizing the use of PCA. (Marcelo et al., 2016) developed two sub-indices using PCA to weight indicators. These two sub-indices, the social and environmental index (SEI) and the financial and economic index (FEI), were used to display projects on cartesian plans and identify high-priority projects, high social and environmental priority projects, high financial and economic priority projects and low-priority projects according to available budget. However, the study does not specify whether the assumptions of PCA have been satisfied or not. In addition, the four dimensions (financial, economic, environmental and social) were not aggregated and the identification of projects levels remained very subjective. All these shortcomings were considered in the RFPI development.

III. DATA SOURCE

The data used for the development of the RFPI was collected from a West African road agency. However, the entire statistical sample was not included in this article for reasons of sample size and data confidentiality required by this road agency.

IV. STUDY AREA

The study area is located in one of the members of the Economic community of West African States (ECOWAS). The ECOWAS is an African organization founded in 1962 whose member countries include Benin, Burkina Faso, Ivory Coast, Guinea-Bissau, Mali, Niger, Senegal and Togo (BOAD, 2015). The map in figure 1 shows West Africa with one of the yellow regions representing the study area.

The road network in ECOWAS countries encompasses 247.311 km of classified roads, much of which are in poor condition (BOAD, 2015). In general, the road network is composed of classified roads and unclassified roads. Classified roads include interstate

national roads (INRs) connecting the county's capital to rural or urban centers in the country itself or in neighboring ones as well as national roads (RNs) connecting the provinces with each other, all of which facilitate commercial exchanges of goods and people transportation. Unclassified roads include municipal roads (MR) and rural tracks (RT) which allow or widen access to basic infrastructure such as schools, hospitals, and markets on top of improving rural communities' socioeconomic activities. Surface pavement types are also used to classify roads. Hence, the road network can be subdivided into paved and unpaved roads. The paved roads are composed of asphalt concrete (AC), single or double surface dressings (SD) and concrete pavement (CP). The unpaved roads include earth roads (ER) and gravel roads (GR).
In this article, sections of gravel roads totalling 729 km in length and 812 km of double surface dressing roads were used for the development of RFPI.

Figure 1: Member countries of ECOWAS

source: BOAD (2005)

V. METHODS

The stages of the construction of the RFPI are (1) the establishing of a theoretical framework, (2) the selection of indicators, (3) transformation of indicators, (4) normalization of indicators, (5) test of correlation and signification, (6) the weighting using PCA and (7) aggregation and calculation of RFPI (figure 2).

5.1 Theoretical framework

An adequate theoretical framework defines the multidimensional phenomenon to be measured and its dimensions, and thus constitutes a benchmark for the selection of indicators and weighting methods (OECD, 2008). This framework connects dimensions, indicators and sub-indicators. The theoretical framework in this article was established by a critical analysis of expert opinions in each of the four (4) dimensions such as road design and management engineers, environmentalists, sociologists and senior academic researchers in the pavement field. With this framework (table 1) established, it is clear that in order to be eligible for funding, road projects must show reliable technical performance, be cost-effective and economically justifiable, on top of producing minimal adverse environmental impacts and high social benefits for local populations.
Two types of indicators were used in this study: quantitative and qualitative indicators. The quantitative indicators include continuous values and qualitative indicators involve discrete values that are used to measure social and environmental aspects hardly quantifiable. Theses aspects were evaluated using the Likert scale in indicators transformation stage. The Likert scale is a typical ordinal scale of 3 to 5 points developed by Rensis Likert in 1932 that analysts use to rate or rank their agreement or disagreement with statements. In general, any quantitative measures can be obtained from these statements (Sullivan et Artino, 2013).

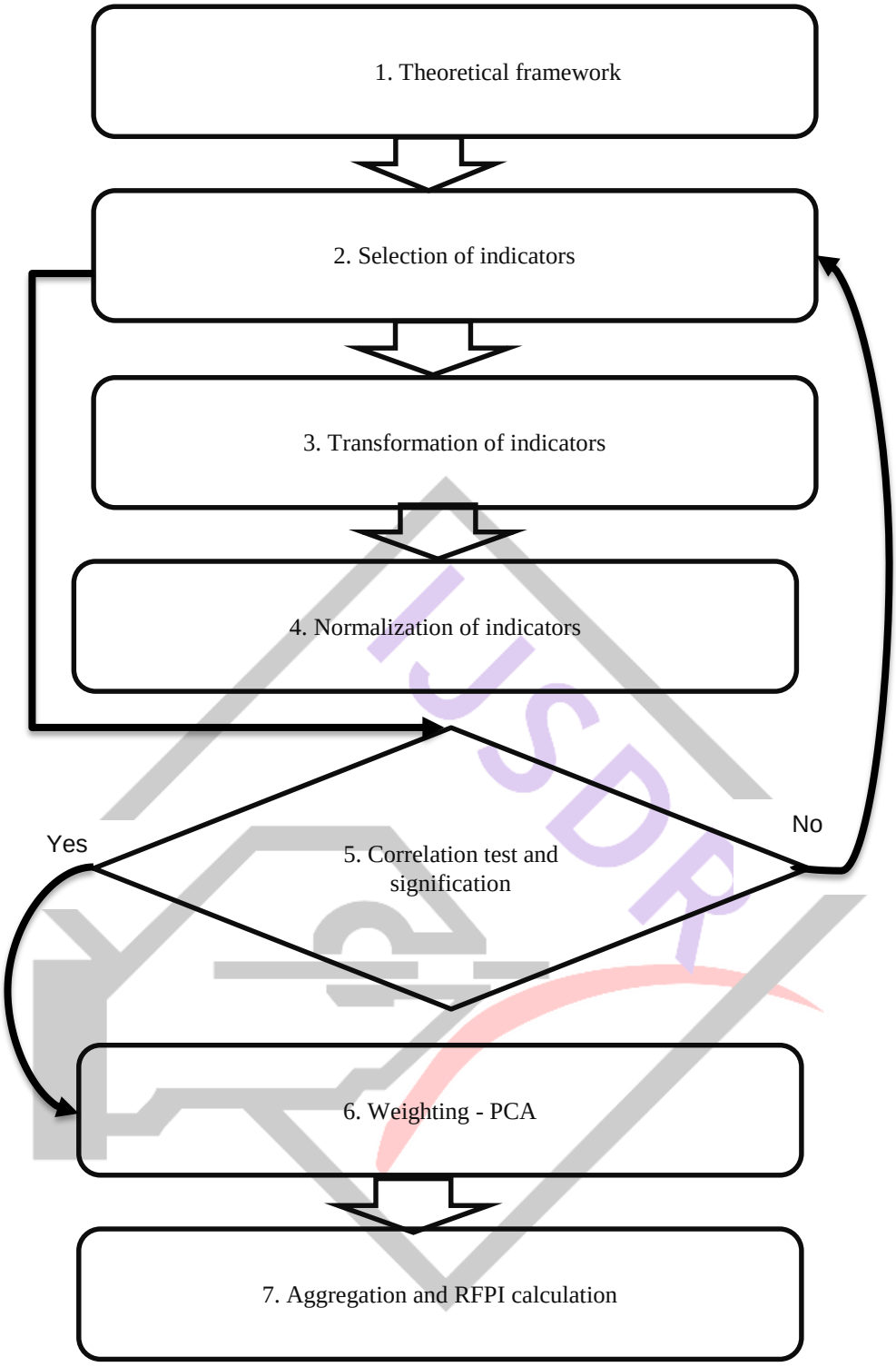


Figure 2: Stages of RFPI construction

5.2 Selection of indicators

The strengths and weaknesses of composite indicators are closely related to the indicator selection criteria. In order to maximize the final overall results' quality, the selection should be based on the relevance, accuracy, availability, accessibility, consistency and interpretability of the indicators (OECD, 2008). For this study, the indicators were selected based on criteria of coherence, interpretability, accuracy, accessibility, assumptions of weighting methods, and sustainable development applicable to road infrastructure in developing countries. Coherence refers to the ability of indicators to be combined in different ways and for different analysis. Interpretability refers to the ability of the analyst to understand, use and analyze the indicators easily. Accuracy reflects the nearness between provided value and true value of indicators. Accessibility reflects the affordability, availability and accessibility of data from road agencies for analysts. The weighting method used in this study is PCA, for which the correlation is a fundamental assumption. The use of PCA to weight the indicators by analysing indicators underlying structure can increase both

the accuracy and the interpretability of final results (OECD, 2008). The selected indicators include social, environmental, economic indicators that are the three (3) pillars of sustainable development (Mainali et Silveira, 2015). In addition, to meet this fundamental assumption, the selected indicators must show signs of a high correlation in between each other. The selected indicators as they appear in table 2 are mainly derived from several extensive literature reviews such as articles on sustainable road prioritization indicators, pavement design handbooks, reports on social and environmental impact assessments from the World Bank or developing countries' road agencies. A total of 15 correlated indicators, including four (4) technical indicators, three (3) economic indicators, four (4) social indicators and four (4) environmental indicators, were selected (see table 2).

The values of all the selected indicators were collected from the road agency of the study area, except for the cases where indicators WLCCT, WLCCTT and RULCC were calculated.

WLCCT consists in vehicles operating costs (VOC) weighted by expected traffic over 20 years at a 4% growth traffic rate. The fuel, lubricant, oil change, spare parts, tire, maintenance, depreciation and crew costs of VOC vary accordingly to geometric characteristics of the road (roughness, altitude, slope, etc.). In this study, WLCCT was estimated using a model of road economic decision (RED-VOC HDM-4) developed by the World Bank (World Bank, 2006).

WLCCTT is produced by weighing the travel time and cost with the expected traffic over 20 years at a 4% growth traffic rate. In addition to the road condition (IRI), the estimation of travel time considers both working and no working time as well as the time needed to transport the goods. In this study, the cost of travel time was estimated using the World Bank's road user costs model (HDM-4 -RUC), considering the IRI value of sections. The inputs of the model originate from the World Bank tools file user costs study in Africa (World Bank, 2006).

RULCC is a major benefit for road projects. These costs, composed of vehicles operating costs, travel time costs and accident costs (not considered in this particular case), were evaluated by comparing the base alternative without project and the alternative with the project. For this study, RULCC was calculated using model HDM-4 – RUC, assuming that with base alternative, the IRI values were those collected from the road agency. As for the alternative with the project, the IRI value is set to 2 m/km, which is due to either road construction or preventive interventions.

Table 1 : Theoretical framework

Road Funding Priority Index (RFPI)				
Dimension	**Impact**	**Indicator**	**Unit**	**Data type**
Technical	Good performance	L	km	Quantitative
		IRI	m/km	
		AADT-LV	veh/h	
		AADT-HV	veh/h	
Economical	Justifiable and cost-effective	WLCVO	$US/km	
		WLCCTT	$US/km	
		RULCC	$US/km	
Social	High benefit	POP	Capita	Quantitative
		BSS	n/a	Qualitative
		M	n/a	
		PU	n/a	
Environmental	Low adverse effects	ESA	n/a	
		PWP	n/a	
		WS	n/a	
		EA	n/a	

Table 2 : Selected indicators

Abbreviation	Description	Reference
L	Length of the road section	(Haas et *al*., 2009); (COST, 2007);(PIARC, 2004); (PIARC, 2012); (Haas, Hudson et Zaniewski, 1994);(Kumar, 2014);
IRI	International Roughness Index	
AADT-LV	Average Annual daily traffic for light vehicle	
AADT-HV	Average Annual daily traffic for heavy vehicle	
WLCVO	Weighted Life Cycle Cost of Vehicle operation	(Amiril et *al*., 2014); (Bhandari, Shahi et Shrestha, 2016); (Mata et *al*., 2013); (Mazziotta et Pareto, 2013); (Shen, Wu et Zhang, 2011); (Wirehn, Danielsson et Neset, 2015); (ADB, 2003);(BAFD, 2015); (FAD, 2001); (Lantran, Baillon et Pagès, 1994); (MCC, 2007); (World Bank, 2017)
WLCCTT	Weighted Life Cycle Cost of Travel Time	
RULCC	Reduction of users life cycle cost	
POP	Population served by the section	
BSS	Basic Social Services	
M	Market	
PU	Processing Unit	
ESA	Ecologically Sensitive Area	
PWP	Place of Water Passage	
WS	Water source	
EA	Erosion Area	

5.3 Transformation of Indicators

The SPSS (Statistical Package of Social Sciences) software was used to perform PCA. Measurements of indicators in primary scales are essential for multivariate statistical analysis using SPSS software. Primary scales encompass nominal, ordinal, interval and proportion scales (Malhotra, 2011). However, the PCA requires that indicators be measured in ordinal or interval scales. Therefore, the BSS, M, PU, ESA, PWP, WS and EA qualitative indicators of the nominal scale were transformed into ordinal scale by using the Likert scale (featured in table 3)

5.4 Normalization of Indicators

All the selected indicators are heterogenous because of the variations in their units and measurement scales. Therefore, it is important to establish an appropriate common comparison structure between them before applying PCA. In this study, the value of the selected indicators were normalized using z-score method, as shown in equation 1.
The z-score normalization method consists in converting all the indicators to the same scales, according to normal distribution with mean 0 and standard deviation 1 (OECD, 2008).

$$Zij = X_{ij} - \mu_j / \sigma j \qquad (1)$$

Where Zij is the normalized value of indicator j for project i, X_{ij} is the initial indicators value j for project i, μ_j is the mean value of indicator j and σj is the standard deviation of indicator j.

5.5 Correlation test and signification

This study seeks to develop RPFI using PCA. However, the application of PCA requires the satisfaction of certain hypotheses. The indicators must be quantitative, highly correlated, linear, normally distributed, and the sample size must be large enough. In this study, Kaiser-Meyer-Olkin adequacy (KMO) index and Barlett's test of sphericity (p-value) were used to confirm the hypotheses of PCA. These hypotheses can only be confirmed if the KMO index is at least 0.5 and the p-value is no more than 5% (Malhotra, 2011). The confirmation of theses hypotheses implies that PCA can be used as a weighting method and that its results are interpretable.
Regarding the size of data, there is no clear consensus. We do know, however, that using a large data size minimizes the probability of errors, maximizes the accuracy of the statistical probability evaluation and increases the generality of results (Osborne et Costello, 2004).

Table 3 : Transformation of indicators

Indicator	Ordinal scale	Priority	Description
BSS	3	High	The number of basic social services close to the section is greater than or equal to 4
	2	Medium	The number of basic social services close to the section is between 2 and 4
	1	Low	The number of basic social services close to the section is less than 2
M	3	High	The number of markets crossed by the section is greater than or equal to 2
	2	Medium	The number of markets crossed by the section is less than 2
	1	Low	The section does not cross any market
PU	3	High	The number of processing units close to the section is greater than or equal to 2
	2	Medium	The number of processing units close to the section is less than 2
	1	Low	No processing units close to the section
ESA	1	High	Greater than or equal to 1 area
	2	Low	0 Area
LPE	1	Very high	Greater than or equal to 3 places
	2	High	Between 2 and 3 places
	3	Medium	1 place
	4	Low	0 place
WS	1	High	Greater than or equal to 3 sources
	2	Medium	Between 2 and 3 sources
	3	Low	1 source
	4	Very low	0 source
EA	1	High	Greater than or equal to 3 areas
	2	Medium	Between 2 and 3 areas
	3	Low	1 area
	4	Very low	0 area

5.6 Weighting using PCA

The PCA was used for indicators weighting mainly because of its abilities to explore the underlying properties of data through the use of rigorous statistical technics and to confirm the multidimensionality of the phenomenon to be measured. In addition, PCA assigns different weights to each indicator that is more recommended and appropriate than to arbitrary weighting each indicator equally (WDGPH, 2013).

5.6.1 A brief description of PCA

The PCA is a technic used for simplifying or reducing a large number of correlated quantitative indicators to a smaller size of uncorrelated indicators called *principal components*, which are linear combinations of the initial indicators. The principal components are partitions of the initial indicators' total variance. The first component, C_1 (equation 2), is the linear combination of the initial indicators with the highest contribution to total variance. The second uncorrelated principal component, C_2 (equation 3), is set so that it counts for the second-highest contribution to total variance, and so on for the other components C_p (equation 4), up to the limit number p (Jambu, 1991; Li et al., 2012; Malhotra, 2011; OECD, 2008; Pituch et Stevens, 2016).

$$C_1 = W_{11}Z_1 + W_{12}Z_2 + \cdots + W_{1p}Z_p \qquad (2)$$

$$C_2 = W_{21}Z_1 + W_{22}Z_2 + \cdots + W_{2p}Z_p \quad (3)$$
$$C_p = W_{n1}Z_1 + W_{n2}Z_2 + \cdots + W_{pp}Z_p \quad (4)$$

Where C_1, C_2 C_p are the principal components retained, p is the number of principal components retained constituting the greater part of initial normalized indicators total variance Z_1, Z_2, Z_p ; n is the number of initial indicators ; and W_{11}, W_{21}, W_{n1} are weighting coefficients or factorial scores. The establishment of a matrix so that ${W_1}^T W_1 = 1$, with $W_1 = W_{11}, W_{12}, \ldots\ldots, W_{1p}$, the variance of C_1 is the higher eigenvalue of sample covariance matrix. Therefore, the highest eigenvalue of eigenvector matrix amounts to the factorial score of C_1 and so on for C_n. SPSS were used to perform the PCA.

5.6.2 Number of principal components to be retained

The Kaiser criterion, the explained variance and the scree plot are commonly used to choose the number of principal components to be retained. For this study, however, only the first two criteria were used. The Kaiser criterion suggests to retain as principal components all the components whose the eigenvalues are greater than or equal to 1 (OECD, 2008). According to the explained variance criterion, the components that contribute for more than 60% to the total variance are considered as principal components (Malhotra, 2011).

5.6.3 Principal components rotation

A rotation of the retained principal components helps interpreting the PCA results. In this study, varimax rotation was performed after the extraction of principal components. Varimax is an orthogonal rotation method which minimizes the number of indicators highly correlated with each of the principal components to simplify the interpretation of the retained principal components (Pituch et Stevens, 2016). The correlation coefficient between principal components and the initial indicators after rotation is named loading.

5.6.4 Selection of explicative indicators

Explicative indicators are initial indicators with higher loading after principal components rotation (Malhotra, 2011). The rules for selecting explicative indicators are based on empirical considerations and can be adjusted accordingly to the analysis's goal. In this study, the loading of indicators equal to or greater than 0.5 after varimax rotation is considered as an explicative indicator.

5.6.5 Determination of indicators weights

The weights give information on each indicator's influence in the composition of RFPI. The weight of each indicator was determined by calculating the product of the explicative indicators' factorial score for each principal component after rotation, as well as its variance (equations 5 and 6).

$$A\,j = W_{jp}N_p \quad (5)$$

$$N_p = V_p / \sum_{n=1}^{p} V_p \; ; \; p < n \;\; et \; \forall \, j \quad (6)$$

Where A_j is the weight of indicator j; n is the number of indicators; p is the number of retained principal components ; j is the number of explicative indicators; W_{jp} is the weight coefficient of explicative indicator j of principal component p; N_p is a proportion of normalized principal components explained variance; and V_p is the proportion of principal components p's explained variance.

5.7 Aggregation and determination of RFPI

5.7.1 Aggregation and total scores of projects

Through aggregation, we combine indicators and their weights using linear or geometric methods in order to determine the total score of each project. In this study, linear aggregation was chosen because it was assumed that the total scores of projects are proportional to the weight of indicators and that the indicators can compensate for each other. Equation 7 was used to determine the total score of each project.

$$IC_i = \sum_{j=1}^{n} A_j Z_{ij} \quad (7)$$

Where IC_i is the total score of projects i, A_j is the weight of indicator j and Z_{ij} is the normalized value of indicator j for project i.

5.7.2 Determination of RFPI

The RFPI was established by standardizing the total score from 0 to 100. The equation 8 was used in the RFPI establishment process.

$$IPFR_i = (IC_i - IC_{imin} / IC_{imax} - IC_{imin}) \, x100 \quad (8)$$

Where $IPFR_i$ is the road funding priority index of project i ; IC_i is the total score of projects i; IC_{imin} is the minimum total score of projects i; and IC_{imax} is the maximum total score of projects i.

VI. RESULTS AND DISCUSSION

6.1 Correlation of indicators

The KMO index and Bartlett's test of sphericity are common criteria used to check the degree of correlation and the multicollinearity of indicators. As featured in table 4 , the KMO index is 0.637, which is greater than 0.5 (Malhotra, 2011). The null hypothesis is rejected since the Bartlett's sphericity test gives a chi-square of 464.946 with 6 degrees of freedom significant at 5% (p-value less than 5%). We can therefore agree that PCA is appropriate for this study. Some analysts recommend the application of PCA only in cases where the KMO is at least 0.6 (Antony et Rao, 2007). This hypothesis is satisfied with KMO index equal to 0.637. In addition to the correlation and multicollinearity, all the indicators of this study were normalized to satisfy the quantitative data requirement of PCA. The sample of this study was composed of 50 road projects and 15 indicators, all of which the ratios between the number of road projects and the number of indicators were greater than 3:1, as suggested by (OECD, 2008). Hence, the size requirement is satisfied as well. We may conclude that all the hypotheses of PCA are satisfied and the results, interpretable.

Tableau 4 : KMO index and Bartlett's sphericity test

KMO Measure of sampling adequacy		**0,637**
Bartlett's test of sphericity	Chi-square	464.976
	Degree of freedom	105
	Significance	0.000

6.2 Number of retained principal components

The interpretation of the PCA results begins by selecting the number of principal components to be retained. Given that there are as many components as indicators, some criteria were applied to extract the number of principal components relevant to the study. The table 5 shows the results of components extraction with varimax rotation method to facilitate the interpretation. The first five (5) components stand for the principal components accordingly to the Kaiser criterion, who requires that their eigenvalues be greater than 1. The contribution to the total variance of principal components 1, 2, 3, 4 and 5 is respectively 21.75%, 17%, 12.79%, 11.65% and 10.45 %. Thus, the first five (5) components contribute to 73.64% of the total variance, which is greater than 60% of total variance according to explained variance criterion (Malhotra, 2011). Hence, this criterion confirms that the first five (5) components can be considered as principal ones. It is very rare that the number of retained principal components equals the number of dimensions specified in the theoretical framework: the number of principal components to be retained is solely based on statistical technic while the number of dimensions depends on multidisciplinary experts and decision-makers' considerations. However, based on the highest loading values (table 6) of each the principal components, 1 and 4 can be described as technical, 2 as environmental and 3 and 5 as social. In addition, finding various principal components gives clear indication on the multidimensionality of measured phenomenon. Therefore, the use of a single principal component for weighting of indicators is not recommended.

6.3 Explicative indicators and weighting coefficients

The explicative indicators are initial indicators that the loading is greater than 0.5. As a reminder, loadings are correlation coefficients between the initial indicators and each principal component, and their values navigate between 1 and -1. The loading matrix, as featured in table 6, shows the explicative indicators (italic, bold and underlined value) whose loadings are greater than 0.5 in absolute value. Some researchers recommend the consideration of the initial indicators as explicative indicators with a loading greater than or equal to 0.8 (Doukas et al., 2012; Keeley et McDonald, 2015; Ouyang et al., 2006; Shrestha et Kazama, 2007). However, according to (Freudenberg, 2003; Jambu, 1991) the literature, the criterion of the loading at least equal to 0.5 is mostly recommended. We should mention that when applying varimax rotation, each explicative indicator exclusively belongs to one principal component; this implies that a principal component may have several explicative indicators, but the five components can never have the same explicative indicators simultaneously. On the other hand, the interpretation and determination of weighing coefficient become a complex task. Thus, as presented in table 6, the explicative indicators of the first component 1 are AADT-LV, WLCVO and WS; the explicative indicators of the first component 2 are IRI, RULCC, BSS, ESA and PEP; the explicative indicators of the first component 3 are M and PU; the explicative indicators of the first component 4 are AADT-HV and WLCCTT; and the explicative indicators of the first component 5 are L and POP.

After identifying the explicative indicators of table 6, the weighting coefficient indicators (italic, bold and underlined value) are identified in a matrix of components coefficients as featured in table 7.

6.4 Weights of indicators

The weights represent the relative importance of each indicator. The indicator with higher weight influences the RFPI in a greater way. The contributions to total variance of the five (5) principal components are presented in table 8. As depicted in table 9, these variances are normalized by using equation 6. Thus, the weight presented in table 10 is determined by using equation 5. Researchers as (Antony et Rao, 2007; Krishnan, 2010) have already used a similar procedure in determining the weights of indicators. They concluded that this method was relevant and appropriate for assessing the importance of indicators.

Table 5 : Extraction of principal components

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	**Cumulative %**
1	4.290	28.599	28.599	4.290	28.599	28.599	3.263	21.750	**21.750**
2	2.452	16.347	44.946	2.452	16.347	44.946	2.550	16.999	**38.750**
3	1.863	12.421	57.367	1.863	12.421	57.367	1.918	12.789	**51.538**
4	1.409	9.396	66.762	1.409	9.396	66.762	1.748	11.650	**63.188**
5	1.031	6.873	73.635	1.031	6.873	73.635	1.567	10.447	**73.635**

Table 5: Loading's matrix: rotation varimax

Indicator	**Components**				
	1	2	3	4	5
L	-0.226	-0.229	-0.060	0.262	***0.754***
IRI	-0.308	***0.627***	0.168	-0.502	0.074
AADT-LV	***0.905***	-0.094	0.208	0.240	0.026
AADT-HV	0.319	-0.163	-0.058	***0.873***	-0.009
WLCVO	***0.875***	0.035	0.269	0.332	0.041
WLCCTT	0.495	0.129	0.425	***0.595***	0.287
RULCC	0.256	***0.641***	0.515	-0.029	0.200
POP	0.205	0.133	0.030	-0.148	***0.842***
BSS	0.244	***-0.647***	0.292	0.012	0.057
M	-0.075	-0.178	***0.842***	-0.091	0.133
PU	0.192	-0.122	***0.634***	0.081	-0.225
ESA	-0.047	***0.733***	-0.032	-0.071	0.008
PEP	-0.452	***0.531***	-0.263	0.304	-0.284
WS	***-0.844***	0.021	0.158	-0.086	0.051
EA	0.239	***0.581***	-0.176	-0.045	-0.060

Table 6: Components weighting coefficient matrix

Indicator	Component				
	1	2	3	4	5
L	-0.175	-0.068	-0.061	0.220	***0.507***
IRI	-0.032	***0.215***	0.125	-0.228	0.050
AADT-LV	0.297	-0.009	-0.007	-0.048	-0.029
AADT-HV	-0.078	0.013	-0.027	***0.554***	-0.020
WLCVO	***0.250***	0.054	0.043	0.045	-0.025
WLCCTT	-0.014	0.122	0.195	***0.358***	0.129
RULCC	0.032	***0.276***	0.266	0.006	0.079
POP	0.102	0.045	-0.103	-0.161	***0.553***
BSS	0.054	***-0.255***	0.113	-0.094	0.001
M	-0.146	-0.056	***0.493***	-0.008	0.009
PU	-0.033	-0.024	***0.374***	0.048	-0.217
ESA	0.003	***0.293***	0.004	0.025	0.013
PEP	-0.225	***0.237***	-0.021	0.380	-0.153
WS	-0.370	0,005	0.218	0.166	0.041
EA	0.145	***0.228***	-0.124	-0.053	-0.025

Table 7 : Explained variance of principal components

Principal components					
1	**2**	**3**	**4**	**5**	**% of total variance**
21.75	17.00	12.79	11.65	10.45	73.64

Table 8 : Normalized explained principal components

Normalized principal components					
1	**2**	**3**	**4**	**5**	**% of total variance**
0.30	0.23	0.17	0.16	0.14	1.00

Table 9 : Weights of indicators

Indicator	Weights
L	0.072
IRI	0.050
AADT-LV	0.088
AADT-HV	0.088
WLCVO	0.074
WLCCTT	0.057
RULCC	0.064
POP	0.078
BSS	-0.059
M	0.086
PU	0.065
ESA	0.068
PEP	0.055
WS	-0.109
EA	0.053

6.5 Total scores of projects

The scores of projects, which is to say the linear combination of indicators weights and normalized indicator values, were determined by using equation 7. The total scores of the projects are proportional to the weight of the indicators. Consequently, the high and positive weights of indicators provide the higher total scores of projects. In contrast with the negative weights of indicators, the projects' total scores will be lower. As shown in table 10, the weights of traffic indicators (AADT-LV and AADT-HV), the weight of the population indicator (POP), the weight of the vehicle operating costs (CPCVEV) and the weight of the length indicator (L) are higher (> 0.07). They will therefore positively influence the total scores of projects. The weights of the IRI, WLCCTT, RULCC, PU, ESA, PEP and EA indicators are medium and positive (between 0.05 and 0.07), so they will have an average positive influence on the total scores. Since the weights of BSS and WS are negative, they will significantly reduce the total scores of projects. In other studies, indicators with very low weights are excluded from the evaluation of total scores of projects (Farhan et al., 2017). In this particular study, the difference between the weights isn't considerably high, thereby the weights of all the indicators were used in determining the projects' total scores.

6.6 RFPI and road projects ranking

The RFPI of each project is simply a standardization of its total score, generated by using equation 8. As shown in table 11, the projects are clustered by levels of priority. The figures 3, 4 and 5 list the road projects ranked by priority levels. In them, the letter A stands for construction projects and the letter P represents the preservation projects. Thus, the very high to medium priority projects are featured in figure 4, low-priority projects in figure 5 and very low priority projects in figure 6. It is important to mention that the RFPI doesn't favor a specific type of project (construction or preservation), but rather projects with a high sum of performances in all four dimensions (technical, economic, social and environmental). As shown in figure 4, the preservation project P1 (RFPI = 100) is the highest priority project, followed by the construction project A10 (RFPI = 82.24 %) and the preservation project P2 (RFPI = 75.73 %).

Table 10 : Road projects priority levels

Priority level	Range of RFPI
Very high	85-100
High	60-84
Medium	40-59
Low	15-39
Very low	5-14

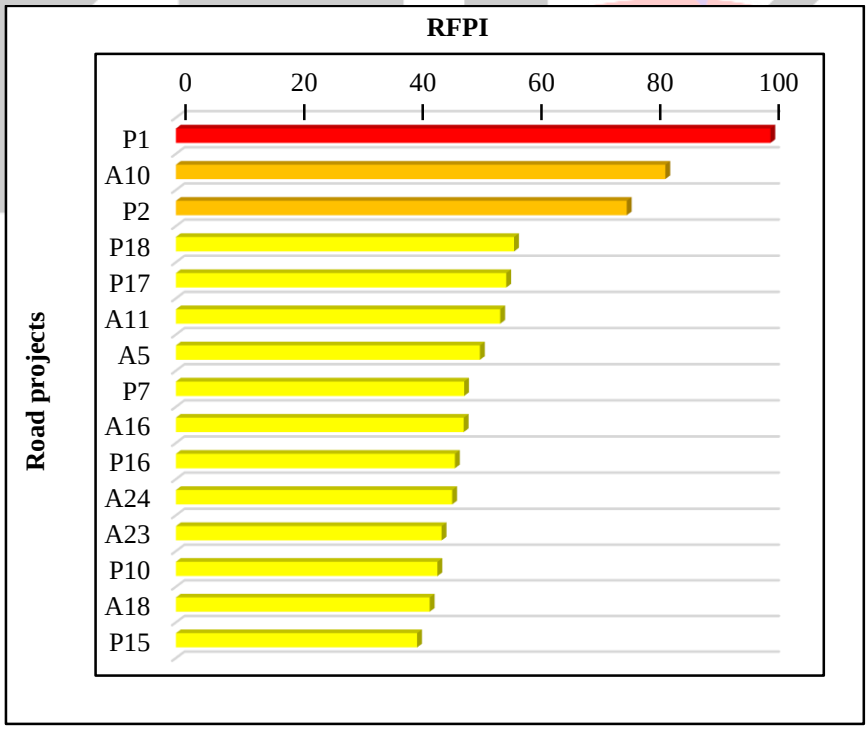


Figure 2 : RFPI of projects : very high to medium

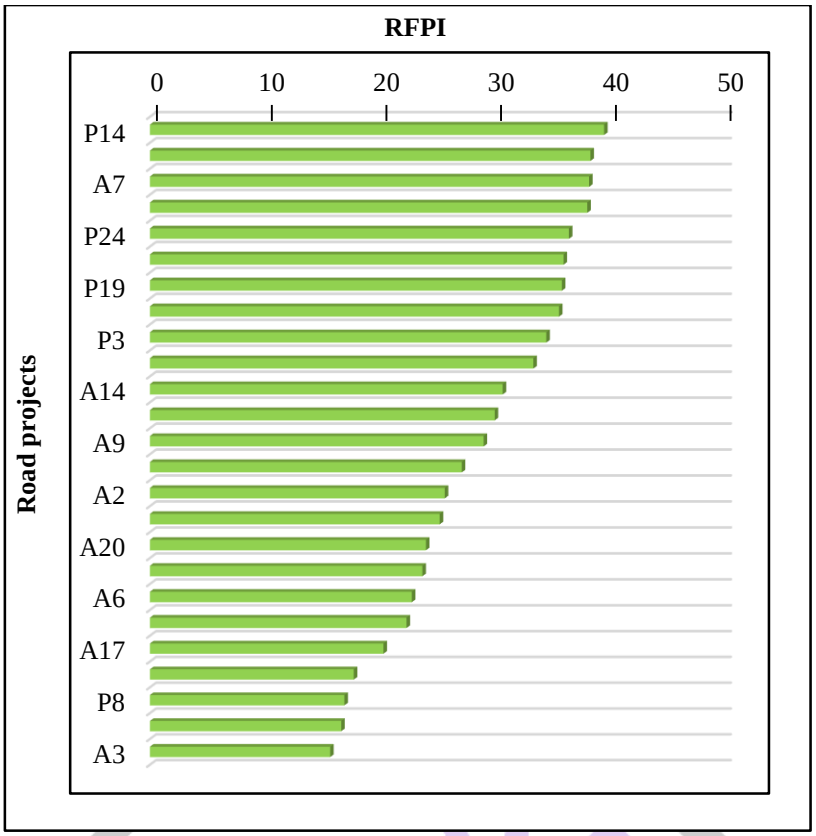


Figure 3: RFPI of projects: low

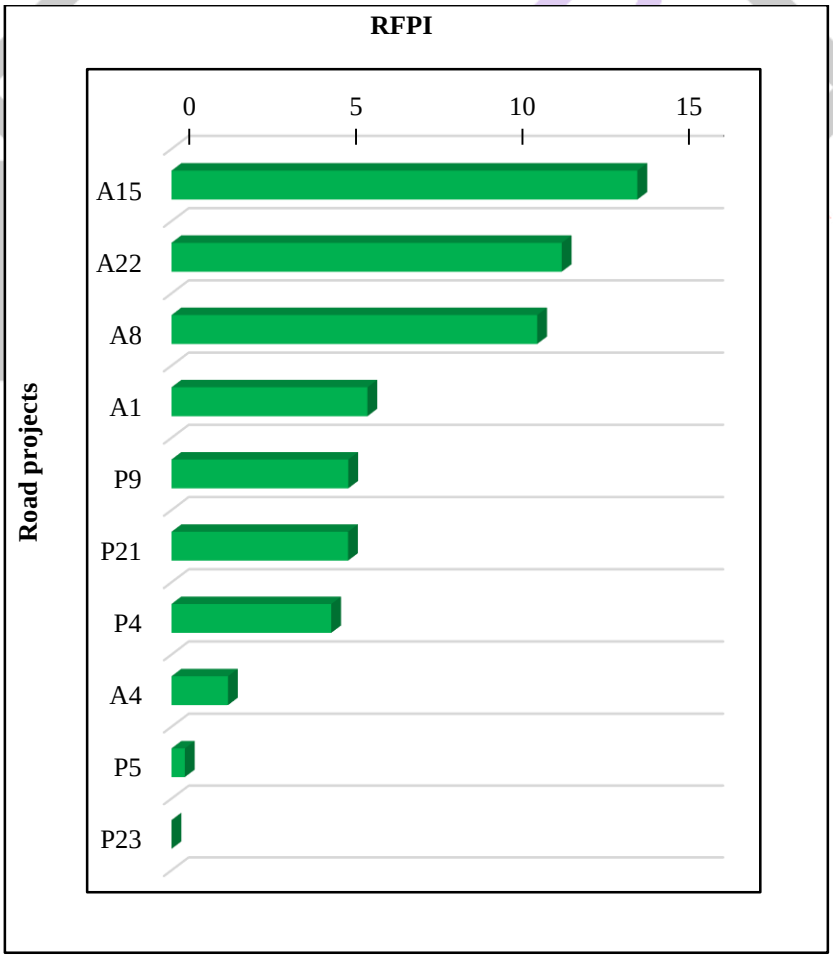
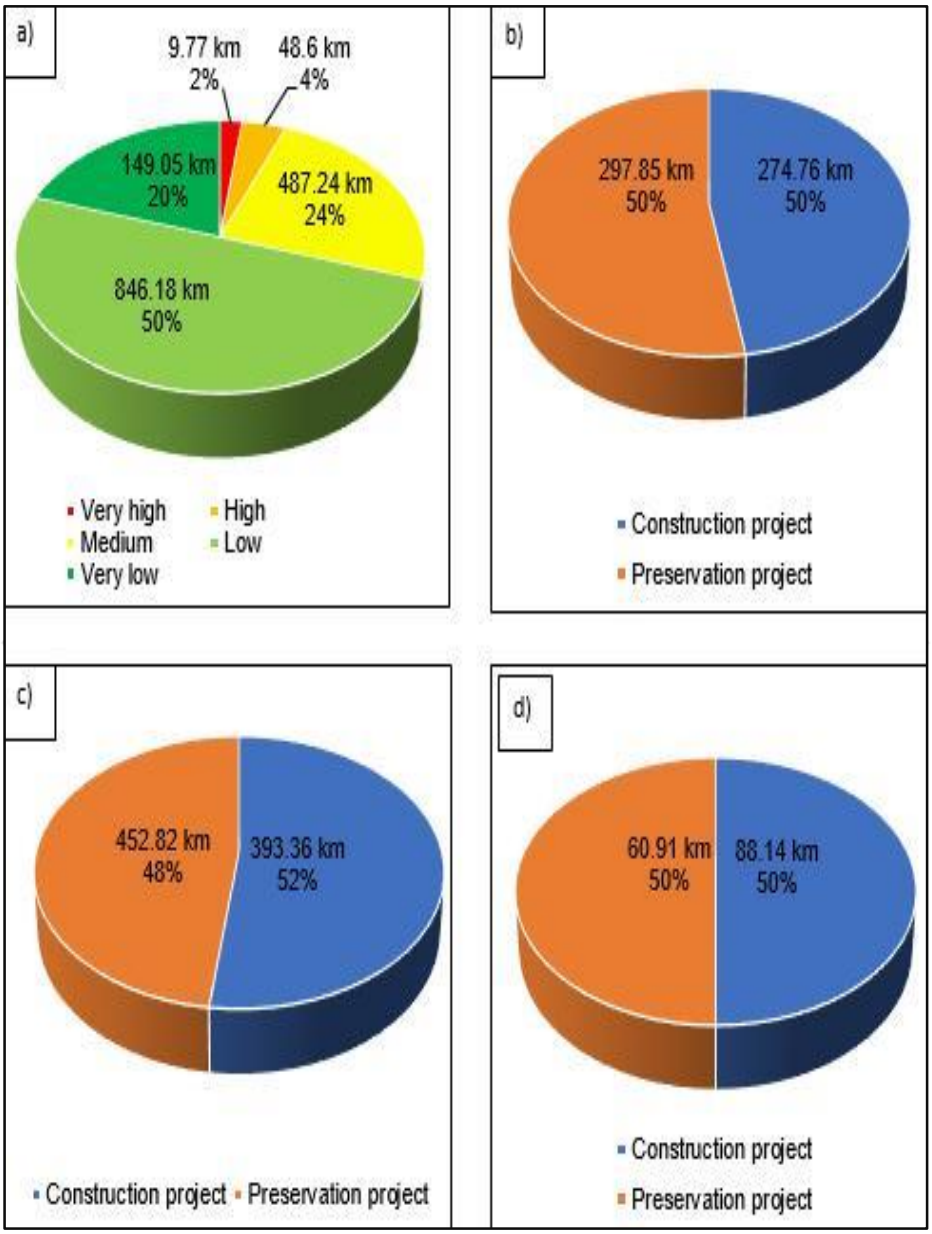


Figure 4 : RFPI of projects: very low

The figure 6 shows the partitions of projects by priority levels and by types of projects (construction and preservation). As shown in figure 6's chart a), by considering partitions and lengths of road projects, the very high priority projects cover 2% and 9.77 km (P1) ; the high-priority projects, 4% and 48.6 km (A10 and P2) ; the medium priority projects, 24% and 487.84 km (P18, P17, A11, A5, P7, A16, P16, A24, A23, A18 and P15) ; the low-priority projects, 50% and 846 km (P14, A13, A7, P20, P24, P22, P1, P6, P3, A25, A14, A12, A9, P25, A2, P13, A20, A19, A6, P12, A17, P11, P8 and A21) ; and the very low priority projects, 20% and 149 km (A15, A22,A8, A1, P9, P21, P4, A4,P5 and P23). The very high to medium priority construction and preservation projects cover partitions of 50% and 50%, with respective lengths of 274.76 km and 297.85 km (chart b of figure 6). Low priority projects account for 52% of construction projects and 48% of preservation projects with respectively 393.36 km and 452.82 km (chart c of figure 6). As for the very low priority projects, 50% are construction projects and the other 50%, preservation projects (chart d of figure 6)



a) Partition by priority level
b) Partition of very high to medium priority projects
c) Partition of low-priority projects
d) Partition of very low priority projects

Figure 5 : Partitions of road projects

It should be noted that the RFPI is a decision-making support tool and its purpose is not to decide on behalf of decision-makers. However, developing countries road agencies and donors financing the majority of road projects in theses countries can screen or select preliminary high-priority road projects eligible for their funding according to their policies and goals based on reliable mathematical tool RFPI. These high-priority selected projects eligible for funding will be further investigated to get intensive input for technical-economic analysis with HDM-4. The selection of high-priority road projects, based on RFPI, significantly reduces the time-consuming and huge expenditure required to conduct a detailed evaluation of the entire roads network. The results of this approach move away from the more traditional one, which was to prioritize the funding of construction projects without any reliable evidence, often for the underlying political prestige, and neglecting road preservation projects or considering them as last resort. As shown in figure 7, the first ten (10) projects were assumed to be high-priority road projects. They totalized a length of 322.63 km, including six (6) preservation projects with a length of 240.73 km and four (4) construction projects with a length of 81.9 km. Assuming that it would cost 288,102 USD/ km to upgrade a gravel road to a double surface dressing and the unit cost of road preservation is 5,580 USD/km, the budget of these high-priority road projects reaches approximately 24,938,824.2 USD, with a budget share of 23,595,553.8 USD for construction projects and 1,343,273.43 USD for preventive work. This unit costs estimates was fetched in the World Bank's Africa Road Project Cost Database (World Bank, 2008).

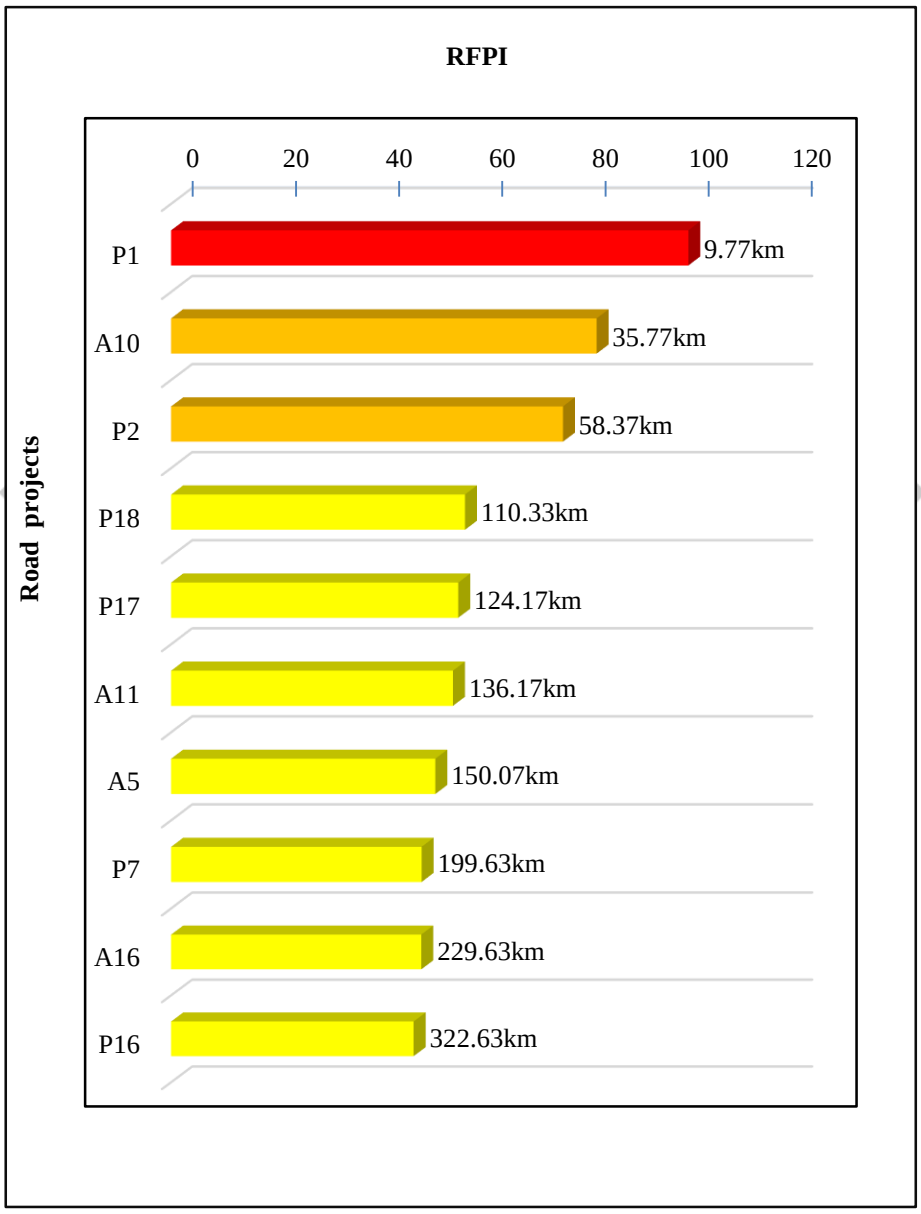


Figure 6 : High-priority projects

VII. CONCLUSION AND RECOMMENDATIONS

When considering the technical, economic, social and environmental aspects, the assessment of road projects becomes a multidimensional phenomenon. The RFPI developed in this article is based on the composite index-construction stages which uses PCA for weighting indicators. The RFPI is a decision-making support tool and its main purpose is to help select high-priority road construction and preservation projects for West Africa Road agencies. Although the PCA may be used to choose the right weights of indicators or to develop the RFPI, the analysts must pay attention to its fundamental assumptions. The KMO adequacy index and Bartlett's sphericity test justify the applicability of the PCA and the interpretation of its results. The latter show evidence of the measured phenomenon's multidimensionality : five (5) principal components were retained accounting of 75.635% of total variance. The RFPIs allowed a selection of the top ten (10) highest priory road projects, with priority levels ranging from very high to medium. The results also indicate that as much as we must preserve roads, we also need to build new ones, given the fact that they are justified by high RFPIs. Preservation project P1, being the highest priority project with RFPI reaching 100, shows the relevance of preserving existing roads. This is, precisely, one of the most chronic problems of a majority of West Africa Road agencies. Moreover, if donors and road agencies face scarce budgets, which is still a reality in many cases, it is recommended that they select high-priority sections or road projects based on RFPI developed in this article, using available and accessible data from road agencies, rather than proceeding with further intensive investigation to obtain more detailed projects data in order to conduct traditional cost-benefit analysis. Because this study does not take into consideration sensitivity and uncertainty analysis, it is essential to do so when determining the RFPI variation range for each project. However, if the various stakeholders reach a consensus of selection, normalization and weighting methods, the developed tool will end up robust. Implementing the RFPI will be more profitable if road agencies or the West Africa government replace the actual cycle of building-neglecting-rebuilding by a more innovative vision which promotes building-maintenance and rehabilitating-maintaining. Perhaps in addition to decision support tools, the Problem-Driven-Iterative-Approach (PDIA) should be explored with the aim to strengthen the management capacities of road agencies in developing countries.

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