Management Science Letters 16 (2026) 147–156

Contents lists available at GrowingScience

Management Science Letters

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Intertemporal slacks and benchmarking in Angolan universities: A DEA window analysis approach

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C H R O N I C L E

Article history:
Received: January 22, 2025
Received in revised format: July 2, 2025
Accepted: November 30, 2025
Available online:
November 30, 2025

Keywords:
Intertemporal DEA
University benchmarking
Technical efficiency
VRS
SBM
Higher education

A B S T R A C T

This study investigates the dynamics of relative technical efficiency across Angolan universities from 2017 to 2022, aiming to establish operational benchmarks and support strategic decision-making in higher education. Data were collected from eighteen officially recognized public and private institutions using annual statistical reports published by MESCTI. The methodology relies on non-parametric intertemporal models, specifically DEA-VRS and Window DEA, which capture performance variations across consecutive time windows. Results include efficiency scores per institution and time frame, input and output slacks required to achieve technical efficiency, and identification of reference peers for benchmarking purposes. Findings reveal a consistently declining trend in average efficiency over the period, with UCC being the most frequently referenced unit. Critical variables such as enrollment and course offerings underscore the need for diversification and alignment with labor market demands. Estimated slacks offer actionable insights for policy and cost optimization. As a methodological extension, the study proposes investigating the relationship between variable-level inefficiencies (SBM) and global efficiency scores (CRS) to better understand interwindow performance trajectories.

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1. Introduction

Over time, universities have played important roles in the development of human capital, which is necessary to support the activities of companies, which in turn contribute, with their greater or lesser degree of specialization, to the desired technical and technological progress of societies. As a result of their research and development activities, universities constitute true hubs for producing solutions for the day-to-day operations of organizations, whether operating in the public or private sector. When aligned with knowledge and expertise production policies, universities can become an important innovation cluster serving the economic development of nations. From this perspective, the optimization of processes related to efficiency in the combination of resources made available to different higher education institutions (HEIs) has been attracting growing interest from researchers in the field of university management. In a scenario that, on a global scale, has been experiencing accelerated changes, in the social, economic and even geostrategic spheres, which bring about increasingly demanding challenges, solutions to challenges of a multidimensional and intertemporal nature find in universities a privileged space for the search for new ways of responding to these same challenges. In Angola, the first HEIs were established with the emergence of the University Study Centers in 1962, precursors of the University of Luanda in 1958, which later gave rise to the Universidade Agostinho Netoin 1985, which was the only public university until 2009 (Silva & Mendes, 2011). Regarding the evaluation of the performance of HEIs in Angola, its main targets have been the institutional aspect, aiming to assess, mainly: the quality of educational activity, the accreditation and certification of HEIs, as well as harmonization and comparability with international standards. The higher education subsector in Angola is overseen by the Ministry of Higher Education, Science, Technology and Innovation of Angola (MESCTI), which annually produces, in partnership with the National Institute of Statistics of Angola (INE), the main statistics in this area. Given the above, this study aims to analyze the dynamics of relative technical efficiency, present in the internal processes of Angolan universities, for benchmarking purposes in the period between 2017-2022.

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ISSN 2816-8151 (Online) - ISSN 2816-8143 (Print)
© 2026 by the authors; licensee Growing Science, Canada
doi: 10.5267/j.msl.2026.2.001

Within the scope of this study, it was not possible to find statistics related to the evaluation of the technical efficiency of Angolan universities, using the proposed DEA approach. From this perspective, it was possible to observe that, in a poorly structured and irregular manner, the evaluation processes of the first, largest and most important HEI in Angola, Universidade Agostinho Neto, have been solely institutional in nature, in no way linked to the evaluation of its relative technical efficiency, which has not allowed for the obtaining of important insights in the operational and strategic scope, both for managers and regulators.

2. Theoretical Approach

2.1 Intertemporal analysis of technical efficiency: A DEA approach

In the literature on corporate performance evaluation, there are two main approaches that support its analysis: parametric and non-parametric. Within the non-parametric approach, the existence of a function production, is not a condition prior to specifying the treatment of the observed data. The analysis, within the scope of Data Envelopment Analysis (DEA), thus finds its object of study in the performance of the different Decision-Making Units (DMUs), which in their resource optimization processes pursue one of two goals: maximizing outputs while maintaining cost levels, or, as in the analysis of this study, minimizing inputs while maintaining the same level of outputs. The initial studies in DEA were authored by Professor William Cooper, whose work summarizes contributions to DEA from an academic perspective of management science and operations research, with recognized contributions to the fields of accounting and economics. Sueyoshi & Goto (2013). Because they do not estimate efficiency scores around a mean, DEA models are sensitive to outliers and computation errors, which can produce biased results (Esmaeeli, Amiri, & Taghizadeh, 2023). However, in their real-world operations, companies use resources composed of multiple inputs and also obtain multiple outputs. This advantage has justified the adoption of DEA in various scenarios where data is captured directly from DMU operating records. Considering the specifications of the adopted model, only the formulation of the DER VRS model will be presented, the justification for which appears in the empirical approach. The DEA Variables Returns to Scales (VRS) model is an extension of the Contants Returns to Scales (CRS) model and differs in the inclusion of scalar u_k, as a way of capturing variations in the production scale of DMUs.

$$\max \theta_k = \sum_{r=1}^{m} u_r y_{rk} - u_k \tag{1}$$

subject to:

$$\sum_{i=1}^{n} v_i x_{ik} = 1 \tag{2}$$

$$\sum_{i=1}^{m} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} - u_k \leq 0 \tag{3}$$

$$u_r, v_i \geq 0 \tag{4}$$

where:

θ_k: Efficiency;
v_i: Input weight i
u_r: Output weight r;
y_{rk}: Quantity of output r consumed by DMU k
x_{ik}: Quantity of input i consumed by DMU k

In addition to the need to capture the effect of variations in the size of DMU operations, whether over a long or relatively long period of time, it is also necessary to capture the dynamic effect of technology and management practices on the efficiency of DMUs. Since DEA is not a form of regression model, but rather an optimization technique based on linear programming and frontier, sample size is not a basic requirement in its approach, and it should be considered a benchmarking tool, focusing on the individual performance of DMUs, and providing a measure of policy changes needed to improve inefficient DMUs. (Cook, Tone, & Zhu, 2014) and (Sengupta, 1995). In this context, in a pioneering study by Bowlin (1987), which aimed to analyze the dynamic behavior present in the performance of US Air Force property maintenance activities, through window analysis, to locate possible inefficiencies, provided important contributions on the DEA window technique in capturing the dynamics present in efficiency scores.

In the DEA literature, there is a consensus that there is no standard methodology for setting analysis windows, however Cooper, Seiford, & Tone (2007), postulate that the number of DMUs must be at least greater than the product resulting from the sum of the total input and the total output, and which has been adopted as a standard for the calibration of DEA windows.

$$n \geq \max. \{[(m)(s)]3(m+s)\} \tag{5}$$

where:
n: number of DMUs;
m: number of inputs;
s: number of outputs.

The study appears as theoretical support for empirical approaches in several studies related to the dynamics of DMU efficiency, as presented in the following mathematical formulations[1]:

$$w = k - p + 1 \tag{6}$$

$$v = n(p-1)(k-1) \tag{7}$$

$$z = (n)(p) \tag{8}$$

$$h = (n)\ (p)\ (w) \tag{9}$$

$$p = \begin{cases} \dfrac{k+1}{2} & \text{when it is even} \\ \dfrac{k+1}{2} \pm \dfrac{1}{2} & \text{when it is odd} \end{cases} \tag{10}$$

where:
w: number of DMUs;
v: variation in the number of DMUs;
z: number of DMUs in each window;
h: number of different DMUs;
p: window width ($p \leq k$),
k = Periods to which the data refer.

2.2 Empirical evaluation of educational institutions: aspects and scope

Efficiency can be understood as the capacity demonstrated by a given company to avoid wasting resources in the process of obtaining a given result (Barbosa & Fuchigami, 2018). With regard to universities, sometimes the business aspect is not directly linked to their corporate purpose. Therefore, depending on their ownership, they can be public or private, both subject to principles based on production theory, related to cost efficiency. Thus, proper functioning of HEIs, depends on competent management, capable of enhancing their efficiency (Silva E. A., 2020). The vast majority of research on university evaluation has focused on their departmental or institutional performance, and the work of Tomkins and Green can be highlighted. (1988), at an international level and Mendes' publications (2014), Silva (2016) within the Angolan context. However, these record shave been reversed, since the results of a study that reviewed publications indexed by the Web of Science database from 1978 to 2010 show that, overall, about two-thirds of DEA articles incorporate empirical data, while the remaining third is purely methodological (Liu, Lu, Lu, & Lin, 2013). When the focus is on their operational performance, it is found that public universities are mostly at the center of the analysis. (Halkos, Tzeremes, & Kourtzidis, 2012), (Aziz, Janor, & Mahadi, 2013), (Nazarko & Šaparauskas, 2014) and (Visbal-Cadavid, Martínez-Gómez, & Guijarro, 2017), can be pointed out as references. Another dimension targeted in the evaluation of universities, particularly public ones, has been their financial performance, particularly state-owned ones, given that these are publicly funded and, therefore, belong to all citizens. Since the allocation of financial resources presupposes a corresponding return on investment, which finds its source upstream and its corresponding application downstream, the activity of universities is, from this perspective, eminently economic, subject to the rules of the education market in which they operate, with their main product (knowledge) being one of the main drivers of economic prosperity Gryshchenko, et al. (2021), Alanazi & Benlaria (2023) can be pointed out as studies that cover this methodological line. In its extended Pareto-Koopmans version, total efficiency would be that which a given company would achieve if and only if none of its inputs or outputs could be improved without the inputs and outputs of other companies being affected in the opposite direction, so that, for the whole of social sciences, the effective level of efficiency will hardly be known unless empirical information is available Cooper, Seiford and Zhu (2011).

[1] The application of the proposed mathematical formulations appears in the following topic. See table 6.

The early days of DEA studies were dominated by analysis of the education sector, partly as a reflection of early research by Charnes, Cooper and Rhodes (1981) which applied the methodology to evaluate the efficiency of monitoring large-scale teaching programs in public education, with the recent trend in efficiency studies in the education category clearly focusing on the higher education sector (Liu, Lu, Lu, & Lin, 2013).

In this line of thought, this study benefits from the theoretical and empirical assumptions of the DEA model and the application of the window analysis technique, already presented in point 2.1, which serve to provide a quantified view of the efficiency of Angolan universities, based on the observation and systematization of the data analyzed in the reference period.

3. Empirical Approach

To conduct the empirical part of the study, the sample data were collected from the statistical yearbooks of higher education in Angola, published by MESCTI, for the time period (2017 to 2021-2022). Since 2020, academic terms in Angola have assumed a biennial format. Thus, table 1 presents the 18 universities with published and available data for the period analyzed. Since there were no values excessively positioned at the extremes in the sample, in order to preserve the sample size, in the few cases where missing data were recorded, these were filled in using the averages found from the observed data for the variables in question. Thus, the condition of maintaining all DMUs with more than 95% of available data in the sample was met. Thus, table 1 presents the different universities analyzed, using information contained in Carvalho (2012), with regard to the validation of the dates of its foundations.

Table 1
Universities analyzed

Acronym	Designation	Ownership	Central	Established
UAN	Universidade Agostinho Neto	Public	Luanda	1962
UCAN	Catholic University of Angola	Private	Luanda	1992
UNIPIAGET	Universidade Jean Piaget de Angola	Private	Luanda	2001
ULA	Universidade Lusiadas Angola	Private	Luanda	2002
UNIA	Universidade Independente de Angola	Private	Luanda	2005
UGS	Universidade Gregório Semedo	Private	Luanda	2007
ONE	Universidade Methodista de Angola	Private	Luanda	2007
WORTH	Universidade Oscar Ribas	Private	Luanda	2007
UPRA	Universidade Privada de Angola	Private	Luanda	2007
UTANGA	Universidade Técnica de Angola	Private	Luanda	2007
UNIBELAS	Universidade de Belas	Private	Luanda	2007
UJES	Universidade José Eduardo dos Santos	Public	Huambo	2009
UKB	Universidade Katyavala Bwila	Public	Benguela	2009
UNIKIVI	Universidade Kimpa Vita	Public	Uige	2009
ULAN	Universidade Lueji A'Nkonde	Public	Dundo	2009
UMN	Universidade Mandume ya Ndemofayo	Public	Lubango	2009
UON	Universidade Onze de Novembro	Public	Cabinda	2009
UCC	Universidade Cuito Cuanavale	Public	Menongue	2014

In the reviewed literature on the nonparametric evaluation of HEIs Mojahedian, et al. (2020) and Egorov & Serebrennikov (2023), it is common to use variables such as personnel costs as input, the number of students completing courses, and the training offering as output variables. In this study, variables of this nature were also adopted, whose characterization appears in table 2.

Table 2
Characterization of variables

Variable	Measurement
Teachers {I}	Group formed by professors of different categories, who ensure the normal teaching-educational process, in the different universities in the sample.
Administrative staff {I}	Support team for activities that enable universities to fulfill their primary function, related to the research and teaching process. Their scope of work at universities ranges from asset and service management to personnel management.
Enrolled Students {I}	Indicator provided by the number of students who, for the first time or in subsequent years, are eligible to attend a given academic year.
Graduates {O}	Provided by the number of students who successfully complete the undergraduate course program in each academic year prior to the reference year.
Courses {O}	Value provided by the set of training offers, made available by each university, considering the undergraduate courses, made available for the completion of admission exams in each year and at each university.

Given the heterogeneous nature of the DMUs analyzed, in terms of their age, ownership, funding sources, and the various regulatory frameworks to which they are generally subject, the model adopted in this study assumes variable returns to scale, aiming to more accurately capture the operating conditions of the universities analyzed. table 3 presents the different characteristics attributed to the model used.

Table 3
Model specification

Parameters	Description
Model	Radial DEA
Guidance	Input
Type of efficiency	Pure technique
Border shape	Piecewise linear
Estimation	Linear programming
Hypotheses	Variable returns to scale
Homogeneity of DMUs	Only Angolan universities in operation and authorized by MESCTI
Number of inputs	3
Number of outputs	2
Number of DMUs	18

The description of the variables and descriptive measures used in the discussion of the results and conclusions namely, the mean, standard deviation, and outliers are presented in Table 4. Their adoption as measures for characterizing the sample data is based on the low variance presented by the data, resulting from the low prevalence of outliers, as mentioned when characterizing the sample. Since DEA is a nonparametric technique, the data are obtained directly from the context under study, in this case, Angolan universities. Normalizing the variable values is not essential, since the analysis and interpretation of the results are not performed around a regression line.

Table 4
Descriptive statistics

Variables	Minino	Maximum	Average	Standard deviation
Teachers	32	1000	264	206
Administrative staff	8	923	232	191
Enrolled students	615	24145	6338	4593
Graduates	59	3022	640	419
Courses	2	53	16	9

Table 5 presents the results of the correlation tests performed. Having initially considered the volume of training offered, based on the courses with enrolled students, these output indicators were found to be positively correlated. Thus, to avoid redundancies that would introduce bias in the efficiency scores, overvaluing the DMUs under analysis, the number of enrolled students in each academic year was used as a proxy for training offered. From an initial sample size of 90 observations, a Pearson correlation matrix was obtained, assuming a significance level of 1%. The results show that all variables present a positive and significant correlation at the specified significance level.

Table 5
Correlation matrix

Variables	Teachers	Administrative staff	Enrolled students	Graduates	Courses
Teachers	1	,0864**	0.751**	0.492**	0.850**
Administrative staff	0.864**	1	0.653**	0.394**	0.771**
Enrolled students	0.751**	0.653**	1	0.503**	0.791**
Graduates	0.492**	0.394**	0.503**	1	0.524**
Courses	0.850**	0.771**	0.791**	0.524**	1

** Correlation is significant at the 0.01 level (2 tails).

4. Results and discussion

To understand the dynamics of efficiency scores over the reference period and fulfill the study's objective, based on the theoretical assumptions presented in the DEA window literature review, table 6 presents the different possibilities for configuring the window to be adopted. Given that the stability of the number of different DMUs follows a geometric progression, the criterion for adopting the width of the analysis window was the number of different DMUs each width provides. Therefore, a three-year window width was adopted, ensuring greater discretion in the scores obtained.

Table 6
Criteria for defining the DEA window

Variables	Formulas	p = 2 years	p = 3 years	p = 4 years
Number of windows	w = k - p +1	5 – 2 + 1 = 4	5 – 3 + 1 = 3	5 – 4 + 1 = 2
Number of DMUs in each window	(n) (p)	18 (2) = 36	18 (3) = 54	18 (4) = 72
Number of different DMUs	(n) (p) (w)	(18)(2)(4) = 144	(18)(3)(3) = 162	(18)(4)(2) = 144
Variation in the number of DMUs	n (p - 1) (k - 1)	(18)(1)(4) = 72	(18)(2)(4) = 144	(18)(3)(4) = 216

Table 9 summarizes the average efficiency scores obtained for each DMU in each year analyzed. The Efficiency Measurement System was used to obtain these scores. (Dortmund Patente Nº 1.3, 2000), in a second phase, SPSS 26.0 was used (2019) for descriptive analysis of data and correlation between variables, and finally Microsoft Excel was used (2019), for

the cross-referencing and calculation of the final results, for the cross-referencing and calculation of the final results. The results show that only the UCC was efficient, despite there being DMUs whose standard deviation in relation to their average score is minimal.

Table 7
Summary of results by year (%)

Ranking	DMUs	2017	2018	2019	2020-2021	2021-2022	Average	Standard deviation
1st	UCC	100	100	99	100	100	100	0
2nd	UAN	100	100	88	100	94	96	5
3rd	UPRA	83	82	78	97	100	88	10
3rd	UNIA	49	100	100	93	100	88	22
4th	UNIBELAS	100	100	91	87	55	87	19
5th	UTANGA	76	96	100	84	67	85	14
5th	UGS	64	100	80	100	81	85	15
7th	ULAN	100	100	56	56	74	77	22
8th	ONE	53	58	55	100	100	73	25
9th	UMN	100	59	63	55	61	68	18
10th	ULA	65	63	68	73	68	67	4
11th	UJES	100	65	60	53	46	65	21
12th	WORTH	68	61	61	60	66	63	4
13th	UKB	100	48	60	49	51	62	22
14th	UCAN	50	63	49	47	73	56	11
14th	UON	32	100	44	50	56	56	26
15th	UNIPIAJET	56	43	47	51	76	55	13
16th	UNIKIVI	54	56	46	42	69	53	10
#	Average	75	77	69	72	74	#	#
#	Standard deviation	23	22	20	22	18	#	#

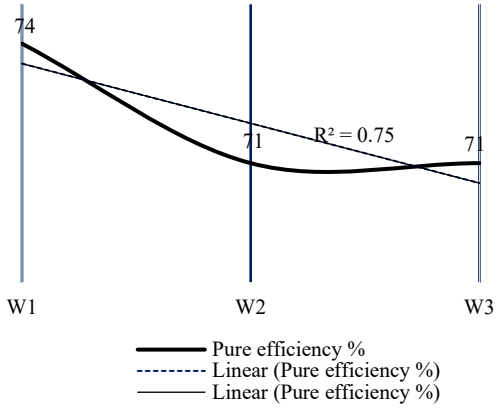

Fig. 1. Dynamics in inter-window efficiency

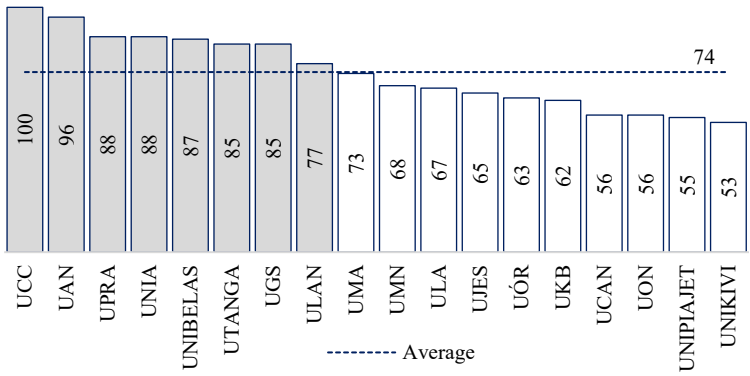

Fig. 2. Efficiency compared to average (%)

As can be seen from Fig. 1, the results obtained for the level of adjustment between the efficiency averages is 75%, reducing the existence of a strong and positive relationship between the variables demonstrated. This means that the proportion of variation in the average efficiency scores, inter-window[2], which is explained by the variables included in the model, is statistically significant. Over the analyzed period, the trend in efficiency scores recorded between analysis windows was downward, as shown in Fig. 1. It can be observed that only in the first window did the performance of DMUs exactly match the average scores, considering the performance of each DMU in each of the years, as shown in Fig. 2. Of the 18 DMUs in the sample, only UCC had an efficiency record, with more than half performing below the average. The analyzed period (2017-2022) encompasses the pre- and post-COVID-19 era, which significantly affected academic activities worldwide, with universities being no exception. Such constraint may somehow explain the better performance in the first window (2017-2018-2019: season before COVID19), the beginning of the slowdown in efficiency levels, with records of increase from the second window onwards, precisely starting in the year of the first records of COVID19. From a perspective where the goal is to minimize inputs, table 8 presents the average inefficiency values for each variable and the distance these values are from the optimum, that is, the slack that must be filled to become efficient. The downward trend in inter-window efficiency scores, as shown in Fig. 1, makes it plausible to infer that the trend in inefficiency dynamics over the analyzed period was, conversely, upward. Thus, a visual inspection of the results in table 8 reveals that, within the slack existing for each variable analyzed, the largest sources of inefficiency result from optimization in operational processes. For the cumulative analysis windows, these were: the main outcome to be achieved by a school (number of graduates), number of teachers, and number of administrative staff, respectively.

[2]In this study, the term interwindow serves to characterize fluctuations in both efficiency or inefficiency scores, as well as in the resulting slack.

Table 8
Inter-window inefficiencies

Windows	Teachers		Employees administrative		Students enrolled		Graduates		Courses		Average		Standard deviation	
	Score (%)	Slack	Score (%)	Slack	Score (%)	Slack	Score (%)	Slack	Score (%)	Slack	Score (%)	Slack	Score (%)	Slack
1	27	39	33	34	66	7	11	214	71	0	42	59	26	88
2	20	24	56	23	77	25	29	0	54	0	47	14	23	13
3	24	16	60	17	83	18	22	0	91	24	56	15	32	9
Average	24	26	50	25	75	17	21	71	72	8	48	29	26	25
Standard deviation	4	12	15	9	9	9	9	124	19	14	11	33	6	50

In order to provide a more precise view of the dynamics in the operational processes of the universities analyzed, figure 3 was created based on Table 8, showing the evolution of the inefficiency of each of the variables used in the analysis, as shown in Table 8. Given the distinct pattern in the trajectory of the inefficiency curve for the number of graduates, particular attention will be given to this variable. Thus, it can be observed that the variable with the largest gaps was the number of graduate students in the period 2017-2019, that is, in the first window. However, despite this record, in the same period the percentage of inefficiency for the same variable was not significant, remaining in line with the lower records for the remaining variables in all windows. This indicates the existence of vast room for improvement in internal processes related to the teaching-educational process, which was verified in subsequent years, as indicated by the trajectory in the last two windows. Furthermore, the maintenance of minimum average inefficiency levels combined with the sharp decrease in gap records in the following two windows may be explained by the increasing emergence of new universities, primarily in the private sector, during the period studied. With a pattern that presents congruent trajectories in its inefficiency/slack relationships, the variables related to the cost of administrative staff, number of enrolled students and training offerings, indicates alignment between operational performance and strategic goals. Finally, demonstrating greater stability, the number of faculty members was the variable with a consistent trajectory, indicating a lower exposure to operational risks in the sector, on the part of the universities that are part of the study sample, originating from this component of the inputs. The results in Table 9 quantify the portion of pure technical efficiency that each reference DMU explains in the efficiency level achieved by another. While not always 100%, these values represent the largest portion that a given reference DMU explains in another, considering all resources optimized by the DMUs that form the efficient frontier. The magnitude, or explained portion, thus reflects the best practices of some in relation to others. It is noteworthy that in all three windows analyzed, there is a record of a public university, while in the last window, the most referenced university is also public.

Table 9
Inter-window benchmarks
(%)

DMUs	Window 1		Window 2		Window 3	
	Reference	Magnitude	Reference	Magnitude	Reference	Magnitude
UAN	UAN	100	UAN	100	UAN	100
UCC	UCC	100	UCC	100	UCC	100
UJES	UJES	100	ULAN	75	UNIA	79
UKB	UKB	100	UCC	67	UCC	100
UNIKIVI	UAN	93	UTANGA	72	UTANGA	72
ULAN	ULAN	100	ULAN	100	UTANGA	72
UMN	UMN	100	ULAN	88	UNIA	87
UON	UAN	94	UON1	100	UCC	64
UCAN	UCAN	80	UCC	73	UCC	74
UNIBELAS	UNIBELAS	100	UNIBELAS	100	UNIBELAS	100
UGS	UGS	100	UGS	100	UGS1	100
UNIA	UNIA	100	UNIA	100	UNIA	100
UNIPIAGET	UTANGA	54	UNIBELAS	50	UTANGA	69
ULA	UCC	54	UGS	40	UCC	61
ONE	UNIA	68	ONE	100	ONE	100
WORTH	UCC	56	UGS	43	UCC	51
UPRA	UNIBELAS	71	UNIBELAS	75	UPRA	100
UTANGA	UTANGA	100	UTANGA	100	UTANGA	100
Most referenced	UAN and UCC	#	**UCC**, ULAN and UNIBELAS	#	**UCC**	#

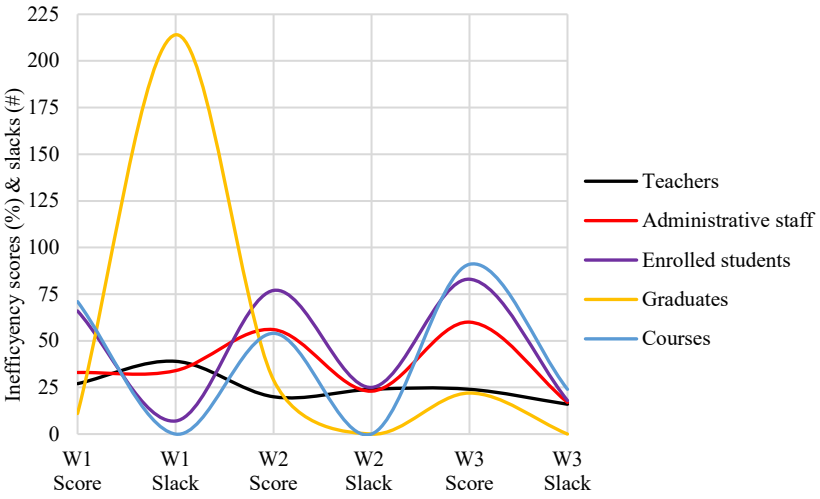

Fig. 3. Dynamics in inter-window inefficiency

5. Conclusions, Policy Implications, and Future Directions

From the perspective of dynamic analysis of the efficiency of Angolan universities, in the period between 2017-2022, both the results and their corresponding critical analysis allowed us to conclude that public universities are the most suitable for the purpose of replicating the best management practices, with UCC being the most referenced. The analysis of the variations that occurred in the variables in each window allowed us to conclude that the efficiency trajectories for the set of universities analyzed presented a consistently decreasing trend throughout the period studied, as evidenced by the value obtained for the association coefficient. Based on the evolution, albeit moderate, of inefficiency levels, the following critical success variables were identified, which should receive particular attention and correction: the number of enrolled students, the number of courses offered, suggesting the diversification of training offerings, the restructuring of courses, and other measures that make courses more attractive and aligned with the job market. From the window indices, namely the average efficiency and inefficiency scores and corresponding slack, it was possible to capture the dynamic effect present in the operational performance of the universities studied, which was decreasing in terms of efficiency and, as expected, increasing in terms of inefficiency. A combined analysis of the results showed that when compared with the average efficiency for all universities in the period between 2017-2022, only three of the public universities are above the line of this indicator. Therefore, this evidence reinforces the usefulness of the timeless analysis of technical efficiency, based on the use of moving averages, a principle presents in the DEA window approach, as a way of capturing the intertemporal effect on the evaluation of efficiency. Within the scope of the implication of policies aimed at improving the performance of the universities analyzed, the results suggest the improvement of their operational optimization capacity, through the adoption of the best practices of their peer's par excellence, thus ensuring greater efficiency resulting from the practice of benchmarking carried out. The estimated slack for each variable analyzed constitutes important management information that universities can use as a policy reference at an operational level, as a way to improve their efficiency with a view to reducing costs.

As a proposed continuation of this study, the possibility of deepening the understanding of the factors is raised, based on the proportional relationship between the evolution trends in overall inter-window efficiency levels and the inefficiencies of the variables when analyzed individually, also inter-window. As a proposed methodological approach, the alternative of relating the slack caused by inefficiency (SBM) to the total efficiency scores (CRS) via a quotient is left, which was not analyzed in this study. In a complementary manner Measures such as the Luenberger index may also be used, which may enable a better understanding of the intertemporal dynamics of operational slack, originating from the effects of university management.

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Appendix

Table A1
Overview of results (%)

DMUs	2017	2018	2019	2020-2021	2021-2022	Average	Standard Deviation
	100	100	100			100	0
UCC		100	98	100		99	1
			98	100	100	99	1
Average	100	100	99	100	100	100	1

	100	100	95			98	3
UAN		100	84	100		95	9
			84	100	94	93	8
Average	100	100	88	100	94	96	5
	83	80	68			77	8
UPRA		84	72	93		83	11
			93	100	100	98	4
Average	83	82	78	97	100	88	10
	49	100	100			83	29
UNIA		100	100	92		97	5
			100	93	100	98	4
Average	49	100	100	93	100	88	22
	100	100	84			95	21
UNIBELAS		100	89	79		89	21
			100	95	55	83	21
Average	100	100	91	87	55	87	21
	76	100	100			92	14
UTANGA		91	100	83		91	9
			100	85	67	84	17
Average	76	96	10	84	67	85	14
	64	100	82			82	18
UGS		100	79	100		93	12
			78	100	81	86	12
Average	64	100	80	100	81	85	15
	100	100	59			86	24
ULAN		100	55	54		70	26
			55	57	74	62	10
Average	100	100	56	56	74	77	22
	53	58	55			55	3
ONE		58	55	100		71	25
			56	100	100	85	25
Average	53	58	55	100	100	73	24
	100	49	52			67	29
UMN		69	67	48		61	12
			70	62	61	64	5
Average	100	59	6	55	61	68	18
	65	65	66			65	1
ULA		61	68	70		66	5
			70	75	68	71	4
Average	65	63	68	73	68	67	4
	100	79	84			88	11
UJES		51	47	51		50	2
			48	55	46	50	5
Average	100	65	60	53	46	65	21
	68	63	60			73	4
WORTH		59	58	56		73	2
			64	64	66	74	1
Average	68	61	61	60	66	75	4
	100	51	65			72	25
UKB		45	56	47		49	6
			59	51	51	54	5
Average	100	48	60	49	51	62	22
	50	60	46			52	7
UCAN		65	45	47		52	11
			57	46	73	59	14
Average	50	63	49	47	73	56	11
	32	100	42			58	37
UON		100	44	48		64	31
			47	52	56	52	5
Average	32	100	44	50	56	56	26
	56	45	42			48	7
UNIPIAGET		40	47	50		46	5
			53	52	76	60	14
Average	56	43	47	51	76	55	13
	54	56	48			53	4
UNIKIVI		56	44	42		47	8
			47	42	69	53	14
Average	54	56	46	42	69	53	10
Overall average	76	80	75	75	78	#	#
Standard deviation	22	20	18	21	17	#	#

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