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Evaluation of the Efficiency of Regional Airports Using Data Envelopment Analysis

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Abstract: Background: Small regional airports provide the necessary assistance to enable mobility in isolated areas where access is critical and costly due to poor road infrastructure and geographic constraints. Colombia's air transportation industry has grown astonishingly quickly and dynamically over the past fifteen years. This period was coincident with the establishment and continued implementation of a public policy intended exclusively for the aviation industry and airports. However, there are currently no methods available to measure the efficiency of airports in Colombia, especially small regional airports. Methods: The research presented in this article aims to evaluate the technical efficiency of small regional airports in Colombia, using data envelopment analysis. This efficiency is achieved by considering the minimum infrastructure required to provide services and the administrative forms or properties that provide appropriate levels of this. Results: The study's input and output data are identified, a non-parametric data envelopment analysis methodology is used, and the findings are assessed. Conclusions: The factors directly identified in the research affect the airport administration and, in the options, are available to help citizens transport optimally.

Keywords: bounded fitted measures; efficiency; data envelopment analysis

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1. Introduction

Small regional airports provide the necessary infrastructure to enable mobility in remote areas where access is critical and costly due to poor transportation connections and diverse geographical constraints. Air service can be challenging to justify from a purely economic standpoint due to low population density [1]. A number of nations have decided on a regional strategy that encourages the population's permanence in outlying areas. Therefore, in order for the air transportation service to continue functioning, it may be necessary to subsidize residents' mobility for supply, education, access to health care, and the promotion of tourism, among others [2]. Consequently, small regional airports in remote areas depend on demand artificially created by governments or civil aviation authorities. In some instances, air transport companies receive subsidies to operate on specific routes as a kind of social support to communities located far from cities [3].

Small aircraft require a minimal level of basic infrastructure, such as a runway that is at least 800 m long, which is required even for airports servicing small communities with limited passenger volume. In order to ensure the economic viability of such infrastructure, various modalities of airport management have been applied, ranging from state administration through concession to privatization [4]. For instance, the government of Norway groups the majority of its airports under the management of a single 100% public company. The remaining 42 airports are subsidized by the four largest airports under this arrangement, and the government additionally subsidizes some required public services [5].

There has been research performed by M.J. Farrel in 1957, Charnes, Cooper, and Rhodes, presented the methodology known as Data Envelopment Analysis (DEA). It is based on the linear programming model to generate a parallel analysis of the units of measurement that handle the same number of inputs to produce an optimal result in the outputs, obtaining as a result the limit of the efficient values and the efficiency levels of the set of production units that are being analyzed [6].

The purpose of this article is to assess the technical efficiency of small regional airports in Colombia, as well as to identify the potential levels of efficiency. This is based on the minimal infrastructure necessary to provide their services and administrative structures or ownership that guarantee reasonable service levels.

The article is distributed as follows: the materials and methods are presented in the next section. Then, the results and discussion are described. Finally, the conclusions and bibliography are presented.

2. Materials and Methods

2.1. Regional Air Transportation Industry

Structural changes in the air transport industry over the last quarter century have led to a growing interest in evaluating airport efficiency. While there is a wide range of studies at major airports, there has been very little research at smaller airports at the local and regional levels [7]. The degrees of efficiency at major and small airports appear to vary significantly. Using the Data Envelopment Analysis (DEA) approach, Ahn and Min [8] compare U.S. hub airports with their counterparts and provide evidence of a greater effort to increase hub airport efficiency levels. Based on research of variable productivity parameters for 76 airports worldwide, Omer [9] concludes that larger airports attain higher levels of efficiency. Major airports are technically more efficient, according to Assaf [10], who uses a stochastic frontier analysis to compare the performance of two groups of UK airports. Yoshida and Fujimoto [11] use DEA and an endogenous weight factor of overall production to study Japanese airports and conclude that regional airports in Japan are relatively less efficient. The relative inefficiency of smaller airports can be explained by the low traffic demand in relation to the minimum infrastructure required to produce traffic movements while meeting all safety standards. As a result, operating expenses are substantially greater than at larger airports where passenger traffic contributes to cover total costs, resulting in lower user costs. Consequently, financial support seems unavoidable in order to sustain services. The form and level of financial support required will depend on a number of factors, including the need for new investments and maintenance of existing infrastructure, as well as geographical location, pricing policies, current regulations, and type of airport management or ownership [11].

Airports may receive direct financial assistance from regional or federal governments, or they may receive financial assistance from the revenues of other airports controlled by the same corporation or airport authority [12]. It is relevant to consider if the type and level of subsidies affect efficiency. It is possible to argue that subsidies have a detrimental impact on a company's efficiency, but establishing a causal link is difficult [13]. Additionally, since the terrorist events of 11 September 2001, airport security requirements have been tightened and strengthened, resulting in greater fixed expenses and operations [14].

Due to the limits mentioned above, tiny airports cannot afford to cover operating costs; yet it is equally crucial that subsidies are not misused. Airport management has a major impact on staffing levels, outsourcing, and material purchasing. Better pricing or marketing tactics also have the potential to generate non-aeronautical revenue. According to Liebert and Adler [15] "an efficient airport provides vital catalysts that enable the local and regional economy to develop and enhance the quality of life of the region". Therefore, government agencies, civil aviation authorities, and airport operators should assess the effectiveness of regional airports and determine the root causes of any inefficiencies [16].

A number of obstacles must be overcome for the aviation sector to become competitive and efficient, and all chain participants must work together to overcome them. Colombia has invested in this goal, but it still needs to meet the demands and expectations of a market that calls for more work [17].

The growth of civil aviation in the last decade in Colombia (annual average of 10.4% for passengers) has accelerated the efforts of both the public and private sectors. Today, different actors agree on the urgency of achieving an orderly, safe, and sustainable development [1]. To boost the industry by 2030, Colombian Civil Aeronautics has outlined six lines of action. These guidelines are the basis of the country's new Strategic Aeronautical Plan [18]. This strategy is organized around a number of dimensions, such as enhancing institutional skills, increasing connectivity and competitiveness, and creating infrastructure that is environmentally sustainable.

The International Air Transport Association (IATA) has framed the regional challenge as connecting intermediate locations in addition to big cities. IATA claims that in most situations where there is potential demand, efforts should be made to improve the services [19].

Increasing airport efficiency is one of the sector's top priorities. It is evident that the country's largest terminal areas concentrate a great deal of development in this regard, whereas the smaller ones have yet to optimize their investments and, as a result, improve access to the regions, despite significant work having been performed in articulating concessions so that regional airports do not lag behind [20].

The main regional airports, by traffic and size, are concentrated in the capitals of the Andean zone and the Caribbean coast, however, the airport infrastructure reaches all corners of the national geography, from the coasts to the plains and the high Andean peaks.

The Aerocivil of Colombia reported, in 2018, 26 regional airports, which serve to transport people and cargo from one region to another.

Each of these airports fulfill a social and economic function and becomes essential to the geographical region to which it belongs, being a unifying factor in a large country, with long borders, remote archipelagos, and three mountain ranges.

Taking into account that in Colombia there are 26 regional airports which are part of this study, a classification of variables was made through certain selection criteria by units of measurement of greater interest to the leaders who manage the operation of the airports, which allows for finding results in the most applicable resources in them, finding the most effective productivity in each of them, such as: number of workers, money, capacity of the airport in its structure, capacity of attention in its service. Each of these variables were the result of interviews with logistics experts belonging to the airport operating processes. The variables are related to the management of airport resources. Although other variables can be used for the study, a sample is taken that is considered by the expert staff as the most appropriate for the first evaluation of the operational movement of airports in Colombia.

Regional airports in Colombia were the subject of the study. The results indicate that 26 regional airports were chosen for the study's aims. The chosen data included the length of the runway, the number of workers, the operational costs, the number of passengers, and tons of cargo; the first three variables were inputs and the final two were outputs. The information was gathered for the years 2017, 2018, and 2019, and was taken from the Aerocivil databases (state agency in charge of the control and regulation of civil aviation in Colombia).

2.2. Data Envelopment Analysis

One of the primary techniques used in both the public and private sectors to evaluate the effectiveness or performance of producing units is data envelope analysis (DEA). Inputs and outputs are related using this technique to examine such efficiency. A variety of DEA models that are input–output focused have been created [21].

The purpose of DEA is to measure a variable, called relative efficiency, of a set of n units of a system (s_j) of generation of homogeneous goods or services, starting with that which provides identical outputs. Its main objective is to generate the highest possible output with the least possible resource used, also called resource optimization. It should be considered that the most effective units of measurement are those that represent a value of 1 [22]. To find the efficiency of a model where multiple inputs and outputs are present, a weighted sum must be performed, this weight is assigned to the relationship between the inputs and the output with a value, respectively, this assignment of weights can also be subjective [23].

There are several methods to assess an airport's effectiveness, including DEA, stochastic frontier analysis (SFA), partial factor productivity (PFP), and total factor productivity (TFP). Techniques such as PFP, TFP, and SFA weigh inputs and outputs, produce an index for the outcome, and determine the relative efficiency of airports. The disadvantage of these methods is that in order to build an airport frontier, they need an airport production function [24]. The specification of a production or cost function, however, is not necessary for DEA to estimate the production frontier. Consequently, the most extensively used method for evaluating airport efficiency is DEA [25].

Measuring efficiency in data envelopment analysis (DEA) requires both the identification of a reference point at the boundary of the production possibility set (PPS) and the use of some measure of distance from that point to another under analysis [26].

The basic DEA technique uses a radially oriented efficiency measure, which identifies a point on the boundary with the same mix of inputs (input orientation) or outputs (output orientation) as the observed unit. The conservation of mixing in movements toward the PPS boundary is the feature that makes the resulting distance measure radially [27]. However, radial efficiency measures do not correspond to the Pareto–Koopmans definition of technical efficiency, where efficiency is achieved when an increase in any output (or a decrease in any input) requires a decrease in at least one other output (or an increase in at least one other input) [28].

Another technique is BAM, which was introduced in the data envelopment analysis (DEA) literature by Cooper et al. [29] for the additive model, with the aim of improving the discriminatory power of the Rank Adjusted Measure (RAM) previously defined by Cooper et al. [7]. It is a DEA model, and as such, it is intended to assess the relative technical efficiency of a set of n units. The BAM model is formally a particular weighted additive model, where the weights are dependent on the data. The weights depend on the unit being scored as well as a set of boundaries related to the set of units being scored, to be more precise. The BAM considers a lower-rank bound for each input and an upper-rank bound for each output, presuming that each unit is identifiable by a vector of m inputs or resources that yields a vector of s outputs or goods [30].

The efficiency of the various DMUs and their development over the three-year period of 2017–2019 are also estimated using DEA methodologies. DEA is a non-parametric approach to linear programming that assesses the relative effectiveness of the decision-making units (DMU) through an analysis of multiple variables defined as inputs or outputs. The DMU was evaluated based on a weighted sum of multiple outputs divided by a weighted sum of multiple inputs, without describing the production function directly. This non-parametric approach solved a DMU mathematical model with weights assigned to each linear aggregation to produce the solution to the model [31].

3. Results and Discussion

A bounded adjusted efficiency measure that is based on the non-oriented model was used in the research. The bounded adjusted measure (BAM) has several advantages over the non-oriented model, including a decrease in the number of units that are mistakenly classified as efficient due to an overestimation bias, the discovery of a shorter path to the Pareto frontier for inefficient units, and an estimate of relative efficiency that lies in the interval (0,1) that is deemed more useful from a managerial perspective [29].

The BAM model defines an ideal point that is most near the efficiency frontier in order to determine a shorter route to the boundary. If a DMU shows good results for a specific variable, then this variable has a greater impact on the efficiency score within the scope of the BAM modeling [32]. This assumption is in line with the basic DEA principle that every DMU should be viewed as positively as possible, given the restriction that no other DMU with the same weights is more efficient than 100%. Moreover, the individual weights in the objective function ensured that all variables are incorporated in the analysis and weighted according to their relative importance for the specific DMU. Figure 1 illustrates the methodological strategy developed for this study.

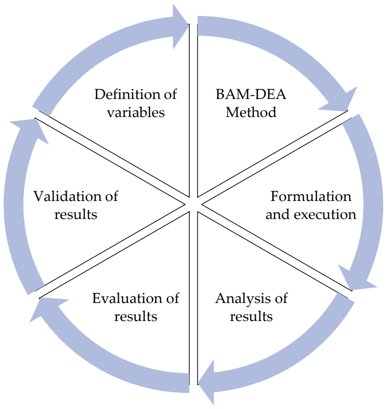

Figure 1. Model methodology to evaluate the efficiency of small regional airports in Colombia using BAM–DEA. Source: Authors' own creation.

According to the figure above, each of the components is explained below:

Definition of variables. This refers to the identification of the input and output variables, a fundamental element for identifying the sample size. The variables selected will be the main factors that should directly affect the decisions made. The sample size was also limited to regional airports.

BAM–DEA method. According to the variables identified in the previous point and the purpose of the decision makers, the BAM–DEA model was formulated mathematically and then developed.

Bounded Adjusted Measurement (BAM)—is a specific weighted additive model where the weights depend on the data. The weights depend on the unit being graded, as well as a set of limits associated with the set of units. The limits associated with the BAM variable returns to scale (VRS) model, known as "range limits", are easy to obtain.

The traditional Models aim to determine the efficiency at 100% considering this as the optimum; instead, BAM allows for a suitable range of efficiency to work by efficiency variables or gaps through the supplied data, which allows, in the case of the airports, identification of a greater amount of efficiency in the Measurement Units.

Execution of the model. There are several computer applications to develop the calculations, such as LV-DEA-Solver, Frontier Analyst, DEA Frontier, EMS, etc. In this research, the SEUMOD application (own authorship) was used for the development of the proposed mathematical model.

Analysis of the results. The information on the efficiency of each of the regional airports in Colombia is externalized. During the analysis of the results, attention was paid to the parameters of the model in order to obtain appropriate results that will serve decision makers in the task of optimizing efficiency.

Validation of the results. The information obtained was analyzed and each of the regional airports was projected to reach the optimum efficiency level. A sensitivity analysis of the results was performed using a bootstrap procedure.

The results are obtained to identify the efficiency results of the airports and carry out a projection of them, taking the most efficient as references. This projection is possible through the software used, which allows for the definition of who their peers are and, based on this information, establishes an improvement plan for airports that were not the most efficient. As for the example in R4 airport has an average efficiency of 71.82%; to reach 100%, its references are the R5 airport and the R14 airport. This means that it needs: 58% of the R5 and 6% of the R14.

- NempleadosR4 = 19 workers of R5 $\times$ 0.58 + 27 workers R14 $\times$ 0.06.

- NempleadosR4 = 12.64 = 13 workers for R4 if you want to reach 100% in relation to the 10 workers you have today. The decision is to hire 3 workers.

The classification of variables through certain selection criteria by units of measurement of greater interest, help to identify results regarding the resources of greater applicability in airports that allow for the observation of the most effective productivity, such as: number of workers, money, capacity of the airport in its structure, attention capacity in its service. Each of these variables were the result of interviews with logistics experts belonging to the airport operating processes. The variables are related to the management of airport resources. Although other variables can be used for the study, a sample is taken that is considered by the expert staff as the most appropriate for the first evaluation of the operational movement of airports in Colombia.

4. Validation

The results obtained after applying the methodology are presented below:

Definition of variables. The definition was performed for 26 regional airports in Colombia. Once identified, the inputs and outputs were divided into subgroups of discretionary and non-discretionary variables. Non-discretionary variables are those that are assumed to be outside the control of management or are exogenously constrained [33].

While changes in non-discretionary variables are not available to management, comparative advantage variables are not included in the objective function; these describe the environment in which airports operate. Therefore, the non-discretionary variables are considered when determining the efficient objectives in the same way as the DMU discretionary variables.

In the chosen benchmarks, the efficient and inefficient DMUs employed the same number of inputs to generate at least the same number of outputs. For instance, to ensure realistic comparisons, an airport with a short runway for takeoff and landing can only be compared to another airport with the same technical constraints.

The correlation of the variables was analyzed (Table 1) and it was found that the variables used are slightly correlated, then, the operational costs of discretionary variables, such as input and production of tons of cargo, were defined as discretionary output variables.

Table 1. Correlations among variables. Source: Authors' own creation.

	Runway Length	Number of Employees	Operation Cost	Passengers	Cargo Ton
Runway Length	1	0.67	0.78	0.54	0.62
Number of employees	0.67	1	0.56	0.47	0.52
Operation Cost	0.78	0.56	1	0.58	0.68
Passengers	0.54	0.47	0.58	1	0.88
Cargo ton	0.62	0.52	0.68	0.88	1

BAM–DEA method. The BAM model with scaled variables implemented with discretionary and non-discretionary variables is formulated in Equation (1).

$$Max\ \theta(\lambda, S) = 1 - \frac{1}{m+s}\left(\sum_{i=1}^{m} \frac{S_{io}^{-}}{L_{io}^{-}} + \sum_{r=1}^{S} \frac{S_{ro}^{+}}{U_{ro}^{+}}\right) \tag{1}$$

Subjected to:

$$\sum_{j=1}^{n} x_{ij}\lambda_j + S_{io}^{-} = x_{io} \qquad \forall\, i = 1, \ldots, m \tag{2}$$

$$\sum_{j=1}^{n} x_{kj}^{ND}\lambda_j \leq x_{k0}^{ND} \qquad \forall\, k = 1, \ldots, l \tag{3}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - S_{ro}^{+} = y_{ro} \qquad \forall\, r = 1, \ldots, s \tag{4}$$

$$\sum_{j=1}^{n} y_{pj}^{ND}\lambda_j \geq y_{po}^{ND} \qquad \forall\, p = 1, \ldots, q \tag{5}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{6}$$

$$\begin{array}{ll} \lambda_j \geq 0 & \forall j = 1, \ldots, n \\ S_{io}^{-} \geq 0 & \forall i = 1, \ldots, m \\ S_{ro}^{+} \geq 0 & \forall r = 1, \ldots, s \end{array}$$

where subscript o is the DMUo index of the unit under research; n is the number of DMUs to evaluate; m is the number of discretionary inputs; l is the number of non-discretionary inputs; s is the number of discretionary outputs; q is the number of non-discretionary outputs. i is input, r is output, and j is the DMU to evaluate. *Sio* and *Sro* are input and output variables that lead to identification of the sources and level of inefficiency in the corresponding discretionary DMUo inputs and outputs. The bounds of the model are defined by:

$$\begin{array}{l} L_i^{-} = \max(x_{ij}) - \min(x_{ij})\ \{x_{ij} : j = 1, \ldots, n\},\ i = 1, \ldots, m \\ U_r^{+} = \max(y_{rj}) - \min(y_{rj})\ \{y_{rj} : j = 1, \ldots, n\},\ r = 1, \ldots, s \end{array}$$

where L_i is the lower bound and U_r is the upper bound. A DMU was considered relatively efficient if and only if there is no output deficit or resource loss in the optimal solution.

Formulation and execution of the model. It should be noted that, in the first stage of calculation, and assuming variable returns to scale, the set of efficient units was determined for the years 2018, 2019, and 2020. Only five of the 26 DMUs analyzed appear to be efficient under BAM in the three years analyzed, DMU R3, R5, R14, R23, and R26 (Table 2). R22 was efficient in 2020 and 2019 but lost its efficiency level in 2018.

Analysis of the results. The study found that R3, R5, R14, R23, and R26 were the most effective regional airports. The majority of these are found in the region of Urabá (Colombia), which is highly intriguing because this region is crucial to the nation due to its production of bananas and other exportable goods (See Figure 2).

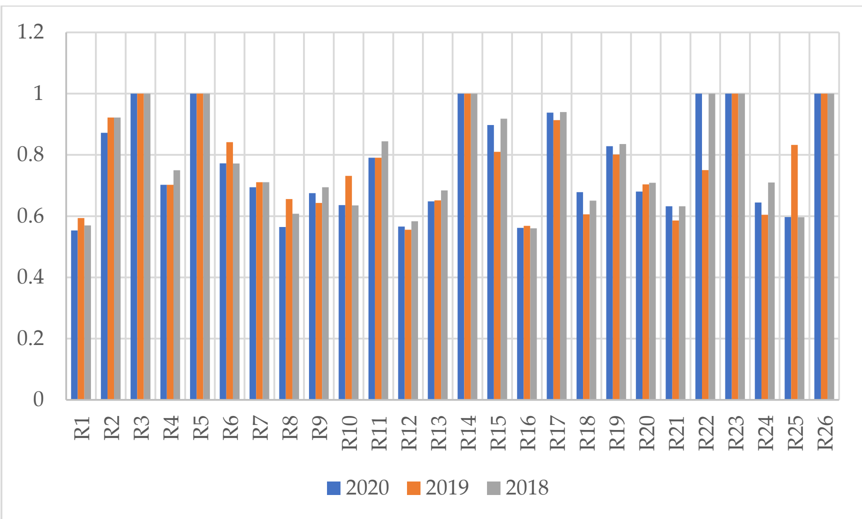

Figure 2. Regional airport efficiency. Source: Authors' own creation.

Table 2. Efficiency indices based on the BAM model for small regional airports in Colombia (2018, 2019, and 2020). Source: Authors' own creation.

Small Regional Airport	2020	2019	2018	Scale Effects
R1	0.5531	0.5938	0.5698	Decreasing
R2	0.8720	0.9218	0.9218	Decreasing
R3	1.0000	1.0000	1.0000	Constant
R4	0.7023	0.7023	0.7500	Decreasing
R5	1.0000	1.0000	1.0000	Constant
R6	0.7725	0.8417	0.7718	Increasing
R7	0.6943	0.7108	0.7108	Decreasing
R8	0.5645	0.6557	0.6077	Decreasing
R9	0.6748	0.6432	0.6945	Increasing
R10	0.6362	0.7317	0.6352	Decreasing
R11	0.7906	0.7906	0.8444	Increasing
R12	0.5661	0.5555	0.5835	Decreasing
R13	0.6480	0.6515	0.6841	Decreasing
R14	1.0000	1.0000	1.0000	Constant
R15	0.8974	0.8102	0.9184	Increasing
R16	0.5618	0.5685	0.5602	Decreasing
R17	0.9381	0.9135	0.9400	Increasing
R18	0.6781	0.6058	0.6508	Increasing
R19	0.8283	0.8009	0.8356	Decreasing
R20	0.6802	0.7038	0.7088	Decreasing
R21	0.6324	0.5859	0.6322	Increasing
R22	1.0000	0.7501	1.0000	Increasing
R23	1.0000	1.0000	1.0000	Constant
R24	0.6444	0.6047	0.7096	Increasing
R25	0.5969	0.8327	0.5966	Decreasing
R26	1.0000	1.0000	1.0000	Constant

In Table 2, a general technical efficiency is observed, that is, the technical and scale effects are included: which indicate the increases in production that are the result of the increase of all the factors of production in the same percentage. These can be:

- Constant: The percentage increase in Output is equal to the percentage increase in productive resources (Inputs).
- Increasing: The percentage increase of the Output is greater than the percentage increase of the Inputs.
- Decreasing: The percentage increase of the Output is less than the percentage increase of the Inputs.

Evaluation of the results. The most significant variables of the study were runway length and number of employees. It was possible to identify the region of Antioquia where most of these small airports are located, as well as to identify the year in which efficiency is reduced in a small proportion, due to the application of incorrect public policies for air transportation in Colombia.

Validation of results. A thorough analysis of the information gathered led to the creation of each airport's optimal degree of efficiency. After formalizing the data projection, it became clear that work needed to be undertaken, notably on the runway length variable, which, in certain circumstances, should be increased or decreased, to obtain the best degree of efficiency for small regional airports. It was also evident that the number of employees played a very important role in raising the level of efficiency of small regional airports in Colombia.

5. Conclusions

The variables analyzed were runway length, number of employees, operating cost, as well as passengers and ton of cargo. These variables were slightly correlated.

Based on the literature, we assume that a BAM model with variable returns to scale is best suited to measure airport efficiency [34]. Calculations using variable returns to scale are important for economies, as small regional airports are likely to experience increasing returns to scale. Additionally, they guarantee the efficiency score's invariance, allowing variables to include zero or negative values in the analysis, which is required because some airports have no goods movement [35]. Variable returns at the BAM scale are incorporated in the restrictive convexity in the model.

Given that Colombia tends to increase the number of passengers and goods transported by air because of the challenges for land transportation due to bad roads and the geography of the country's mountain range, it is suggested that future studies increase the number of variables considered in order to complete this study.

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