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Determination through neural networks of the standard performance of management indicators in the construction industry

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Abstract

Business management requires information for decision-making, and, therefore, tools that aid in the analysis of that information, with support systems whose purpose is to help managers to identify trends, signal problems, and make intelligent decisions.

For several decades, different economic models and statistical techniques have been used to analyze past performance or to forecast the future of business management indicators. To analyze results, businesses make comparisons with past periods, with other organizations, or with the mean for the industry to which they pertains but there is still uncertainty as to whether business management results are optimal or not given the lack of comparative analysis by way of target parameters.

The purpose of this study is to determine the standardized performance of management indicators, so as to enable comparative evaluation of business results and guide future performance under certain specific conditions, grounding management decision-making.

Artificial neural networks (ANNs) are used as tools for standardization and comparison of the results.

Keywords: Management indicators, standardization, artificial neural networks, decision-making.

Resumen

La gestión empresarial requiere información para la toma de decisiones y, por tanto, herramientas que ayuden en el análisis de esa información, con sistemas de soporte cuyo propósito es ayudar a los directivos a identificar tendencias, señalar problemas y tomar decisiones inteligentes.

Durante varias décadas, se han utilizado diferentes modelos económicos y técnicas estadísticas para analizar el desempeño pasado o para pronosticar el futuro de los indicadores de gestión empresarial. Para analizar los resultados, las empresas hacen comparaciones con periodos pasados, con otras organizaciones o con la media de la industria a la que pertenecen, pero aún existe incertidumbre sobre si los resultados de la gestión empresarial son óptimos o no dada la falta de análisis comparativo por medio de parámetros objetivo

El propósito de este estudio es determinar el desempeño estandarizado de los indicadores de gestión, a fin de permitir la evaluación comparativa de los resultados del negocio y orientar el desempeño futuro en determinadas condiciones específicas, fundamentando la toma de decisiones de gestión. Las redes neuronales artificiales (ANN) se utilizaron como herramientas para estandarizar y comparar los resultados.

Palabras clave: Indicadores de gestión, estandarización, redes neuronales artificiales, toma de decisiones.

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Introduction

Business administration is a field that has undergone rapid development due to current imperatives in a globalized world driven by the ICT revolution. At the same time, the business world is being swept along by the development of new trends that require great organizational effort, in the form of actions that allow companies to achieve and sustain high levels of efficiency, effectiveness, and competitiveness. To this end, business management requires the integration of all corporate systems, founded on the application of models, techniques, and tools that ensure harmonization and account for the decisions to be made.

Business decisions are affected by the constant mutability to which economic phenomena are subject, which inhibits, in many cases, the consideration of past data when making inferences about the future; thus, preparations for a decision, whether simple or complex, becomes an organizational thought activity in which intuition and logic inevitably combine. The process of obtaining statistically significant results is often subject to underlying problems stemming from the inappropriate use of statistical and econometric techniques, as well as the recurring absence or duplication of data; this can result in econometric models that may be useful from the point of view of the causal relationships that they describe, but which are hampered by poor results in the formal statistical parameters or when they used for long periods for which they were not intended. In this context, there is a need for detailed research and analysis in order to equip companies with tools that facilitate decision-making and enable competitive advantage.

Economic models and mathematical statistics are widely used by business professionals and specialists in the analysis of results with economic--financial indicators, as they provide the tools necessary for correct and comprehensive decision-making in the applicable sphere of action or set of processes.

In recent decades, the following indicator-based tools have proven effective: the balanced scorecard of Kaplan and Norton (1997), understood in its early days as a set of indicators that provide senior managers with a comprehensive overview of the business, and now regarded as a management tool that translates a company's strategy into a coherent set of indicators (Nogueira et al., 2004); so-called business intelligence methods, such as digital dashboards; online analytical processing (OLAP); reporting applications; data mining, a highly advanced form of data analysis supported by statistical methods and neural networks; and fizzy logic methods. All these tools are the product of the evolution and adaptation of traditional approaches through the use of a broad, inter-related and intrinsic information base pertaining to the processes studied, supported by a software system that facilitates handling and processing. However, there is no evidence that these methods, despite facilitating internal and external benchmarking, contain parameters for the consideration of points of comparison and identification of differences between present and desired conditions.

For instance, the balanced scorecard aids business management through indicators based on the attainment of strategic targets across four perspectives, but it is not oriented toward the search for parameters, models, or standards of performance--that is, the desired performance of business indicators in relation to these perspectives--as part of the assessment of results.

It is precisely this search for standard indicators of behavior that allows business leaders to evaluate the results of their management and decision-making--and which are the main focus of this article.

Business management indicators and methods for identifying standards

Management indicators have been defined by various authors (Rueda, 2011; Cuervo, 1994) as the relationship between quantitative and qualitative variables that allow oversight of a situation, changes, or trends in the object or phenomenon being analyzed, in terms of the targets and goals set and the expected influences.

The management indicators in a control system link goals and impacts with targets and results; emerge from the definition of variables for each target; express performance and results through qualitative and quantitative variables; enable relevant decisions to be made over time; are proactive in character when planned indicators interact with control indicators at management level; and enable ongoing correction through iterative use, thus assuring continual improvement in process results.

The oversight of business results through management indicators allows for organizational comparability or future evolution with regard to a plan or program, provided that desired performance standards are set for the indicators, and that these serve to guide strategic actions.

As part of business management, strenuous efforts are made to put in set performance standards for operational, economic, and financial indicators so that conclusive results are yielded for oversight purposes. Thus, actions been have taken across various social and economic spheres to standardize and homogenize indicators.

Large corporations from the United States, Europe, and Asia have placed importance on the International Financial Reporting Standards (IFRS), which have evolved by way of numerous revisions and changes since the International Accounting Standards Committee (IASC) was founded in 1973. Today, more than half of the Fortune 500 companies present financial statements based on the IFRS standards.

Beyond the presentation of financial information, there have been various studies on the use of business indicators for decision-making and standardization. Focusing on Venezuela, Martínez (2010) proposed a procedure for standardizing the financial indicators used as criteria for the selection of banks for analysis. The study identified the standard value by way of the arithmetic mean of each indicator. For the Cuban case, Arencibia and Hernández de Alba (2010) established a procedure to determine a system of economic--financial indicators and standards for hotel facilities in Varadero, using weighted averages for the period to determine performance patterns.

Methods for the standardization of indicators have been evolving. Three broad areas can be discerned that in turn contain various methods, which differ mathematically and statistically depending on the approach used. These areas are: time series, econometric methods, and artificial intelligence.

Time series explain a variable in relation to its own past, and are less costly in terms of data collection and estimation. Depending on the chronological performance of the variable, these methods establish the main components of the time series (such as trend, cycle, seasonality, etc.) and then forecast future variable values for a given time frame. Examples of these methods are: exponential smoothing, and autoregressive integrated moving average (ARIMA), among others.

Econometric methods are the most widely used in forecasting econometric variables, such as in establishing causality between variables described through unknown functions--usually known as demand functions. Examples of these methods run from simple regression to the statistically sophisticated time varying parameters (TVP), passing through autoregressive vectors (VAR) and the error correction method (ECM), among others.

Finally, artificial intelligence models are based on techniques stemming from rules systems and logic programming, as well as other heuristics. These techniques have been frequently used in forecasting for numerous reasons; for instance, they do not require prior or additional information on the likes of distribution or probability. These models include fuzzy logic, artificial neural networks (ANNs), and genetic algorithms, among others.

Among them, ANNs present significant advantages for this study, such as the following:

- They have explanatory value, in that the network represents the variables that impact the result.
- They can be used for short-term forecasting, as the time factor is incorporated in such a way as to enable a response that facilitates decision-making and timely correction, where necessary.
- They are useful for simulation, since they allow for the possibility of changing conditions (values of the variables incorporated).
- They can be employed to calculate any function.
- They do not require fulfillment of specific data characteristics, such as prior knowledge of probabilistic distribution, as they use the original data rather than transformations.
- They can tolerate incomplete data series.
- They do not depend, for adjustment, on the specific characteristics of the time series pertaining to the original data (cyclical component, trend, seasonality, etc.), unlike other econometric models.
- They allow selection of the best network, through repeated application of different optimization algorithms during network training.

Another important aspect of ANNs is that they do not execute instructions but respond in parallel to inputs, making adjustments during the learning stage in which synaptic connections are formed between neurons. These networks are trained to perform certain tasks, unlike conventional systems that are programmed to do so. Moreover, ANNs are tools that can capture and model patterns of behavior; their main advantage is their ability to learn and identify dependences and patterns based on existing information, so that the knowledge acquired can be generalized to unobserved samples. Moreover, this processing results in selection of the best network, which is important because it represents the parameter of comparison for improvement and analysis of the results; thus, it can represent a standard or rule to follow.

Determining and using the standardized performance of management indicators serves to guide the actions and decision-making of managers at different levels and at different times, with planning and oversight driven by the systematic improvement of organizational efficiency and effectiveness.

The use of IT tools to set standards allows companies to gain competitive advantages, perform accurate analysis for decision-making, and use performance to sketch out plans for future actions and strategies.

Procedure for the selection and standardization of indicators

We start off with the conceptualization that management indicators must feed into the management control system through interaction of their three dimensions---strategic, operational, and economic--so that standardization can strengthen levels of efficiency and effectiveness, and decision-making can lead to better results for the company.

We used the expert judgement method, selecting people with an appropriate level of expertise on the topic of study; that is, business management indicators A key input is reliable accounting information.

For the standardization of the indicators, we took the following steps:

1. Identification of the system of business management indicators in the company studied.

We characterized the company studied based on its mission, vision, objectives, and characteristics, as well as the statistical systems, accounting systems, and indicators that it uses. We prepared a list of indicators, including those that the company routinely uses for oversight, as well as others drawn from the practice of other similar organizations, the scientific literature, and the experience of researchers, managers, and officials from the industry.

Based on the literature, we decided on a reasonable number of indicators and ratios that fulfilled the following requirements: first, that they be calculated based on information that is not restricted to financial statements; second, that they be of a number that is suited to the accounting particularities and the prevailing conditions.

2. Expert determination of the system of business management indicators to be employed.

The system of indicators was determined by the group of experts. By experts, we refer to individuals as well as groups of people or organizations capable of offering conclusive assessments of a particular problem, and of making recommendations on a given topic with a maximum degree of competence. This study required the input of specialists with specific competencies in business management themes. Indeed, their correct identification, evaluation, and selection is crucial to the final result.

We submitted the indicators identified in the previous step to the experts for consideration. We selected the indicators by way of Kendall's coefficient of concordance or rank correlation coefficient (W), seeking the experts' validation based on their criteria as well as concordance and coincidence without causation. This method is a measure of the relationship between various ordinations of n objects or individuals. It is useful in studying the reliability of judgements and tests, and in variable grouping.

The selected indicators were shown to the experts, as well as managers of the company. This interaction seeks feedback and security with regard to the path taken.

Finally, we calculated the indicators selected for the areas or processes--operational, economic, and financial--over the chosen period of analysis.

3. Standardization of selected indicator system.

We approached the indicators from each group or system one-by-one in order to establish the standard for each indicator.

For standardization of the system of indicators, we required the aid of an ANN prepared by the Weka software package, to which we applied a group of machine-learning algorithms (Error! Reference source not found.1). Weka requires files with .arff extensions to function, which are prepared taking into account the data from the organization studied.

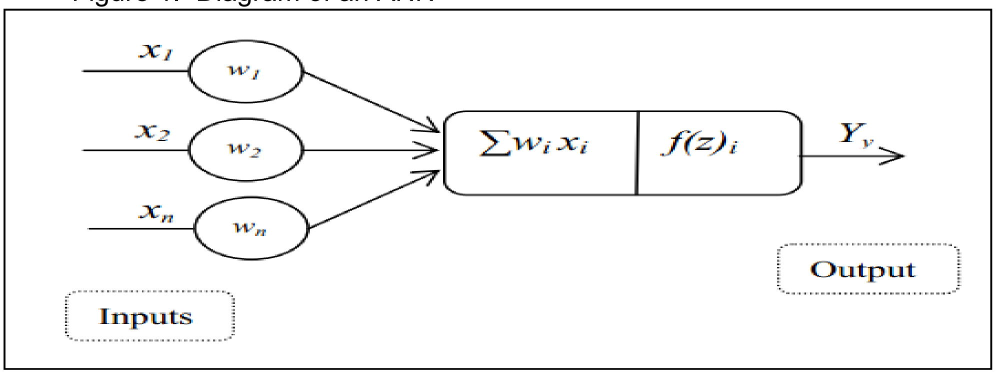
Table 1 Weka algorithms

Algorithms
Ibk
Kstar
CV Parameter
MultiScheme
Regression by Discretization
Conjuntive Rules
Decision Table
Vote

Source: Pérez (2015).

The ANN is an element that possesses an internal state (level of activation), which receives signals that allow it to change states. That is, it possesses an activation function that will determine whether or not a neuron changes state, depending on the information received. These networks are collections of interconnected neurons, grouped into layers (x_1, x_2,.., x_i) through their neurons, which are represented in Figure 1 by circles. The inputs are multiplied by the respective weights (w), which in turn express the relative importance of each input in the determination of the output. This information is evaluated by an activation function 〖f(z)〗_i, which will determine the final output y_y. (Lippman 1987).

Figure 1. Diagram of an ANN



Source: Lippman (1987)

In a strictly linear sense, the result y for moment *t* could be presented as follows:

$$y_t = w_1x_1 + w_2x_2 + \cdots + w_nx_n = \sum_{i=1}^{n} w_ix_i$$

The ANN's learning is based on gradual adjustments in w, until location of the precise values that train it for the efficient solution of a problem. Knowledge is represented in the magnitude w between neurons, and the ANN learns by modifying the values of *w*.

The basic learning goal involves reducing the magnitude of the errors (e) between the target and the output, which means that the network is close to the desired output. In terms of a minimization problem, we have:

$$Min_w E$$

Where *w* is the set of network parameters and *E* is an error function that evaluates the difference between network outputs and desired outputs. The function is defined as:

$$E = \frac{1}{N}\sum_{n=1}^{N} e(n)$$

Where *N* is the number of patterns and *e(n)* is the error committed by the network for pattern *n*, given by:

$$e(n) = \frac{1}{2}\sum_{i=1}^{n_c} (s_i(n) - y_i(n))^2$$

Where $\boldsymbol{Y(n)} = (\boldsymbol{y_1(n)}, \dots, \boldsymbol{y_{n_c}(n)})$ and $\boldsymbol{S(n)} = (\boldsymbol{s_1(n)}, \dots, \boldsymbol{s_{n_c}(n)})$ are the vectors of outputs and desired outputs for pattern *n*, respectively.

Normally, the learning stage involves the gradual introduction of all examples following a given pattern, to determine whether a convergence criteria has been achieved. However, it is possible to assume that the learning has ended when *w* remains stable $\boldsymbol{\frac{dw_i}{dt} = 0}$.

The procedure is applied to a database in a given period, from which the indicators that form the base of the learning patterns are extracted. For each training set, we selected input neurons, the number of instances of the indicator to be analyzed (annual performance), and a neuron in the output layer (which is what distinguished the desired state of the business management). Then, we began the learning stage, in which the neural network was adjusted to a mathematical function that seeks to minimize errors through an iterative numerical calculation process. This is one of the advantages of using an ANN, as it guarantees minimal error and includes options to eliminate variables that distort the prediction. After this we performed a test with the data not used for training, which led to the score obtained. We determined the standard based on the set of data not used in the training, in order to use them to compare the results yielded by the software.

For this study, we used SAEIE (software for the analysis of economic indicators based on artificial neural networks) with registration number 0737-03-2017; this software utilizes a process that is transparent for users, who need only select the indicator and the period of analysis in order to set the standard--predictive neural network. The results can be shown through the values as well as graphically, in order to aid understanding.

4. Analysis and communication of results to company managers.

The purpose of this stage was to analyze all available information through a comparative method. Our analysis was based on the following premises:

a. The analysis took into account the entire period defined.

b. We compared the results of the analysis for the period with the results of the standardized indicators obtained using the SAEIE tool.

The analysis of the statistical data, as well as the analysis and interpretation of the financial statements, as one of the final expressions of the information system, enables efficient measurement of the results for business management and for each subsystem, in correspondence with the particularities that define the production processes or services. However, it must be recalled that the indicators do not constitute an end in themselves; rather, the results are the product of various factors generated as part of the processes, and as such their proper interpretation is vital for decision-making that allows for problem solving. Therefore, the preparations for a decision, whether simple or complex, becomes an organizational thought activity in which intuition and logic are inevitably combined. Having access to accurate information at a time when decisions are made is crucial for companies to gain competitive advantage since they can achieve superior performance levels by comparing results with the standards.

Once information is communicated to a company's managers, executives, and owners, a strategy can be sketched out in accordance with the interpretation of the information obtained.

It is worth noting that the procedure for determining the standard behavior of management indicators is based on the characteristics, databases, and processes selected, constituting an internal motivation for the organization’s systematic improvement.

Results and discussion

The use of scientifically validated protocols is common in disciplines such as epidemiology (see, for example, (Bartholomew et al., 2016; Hockenhull et al., 2012)), which employ them for the development of effective behavioral-change and risk-prevention interventions. Describing the stages of a process and assessing its effectiveness contributes to improving and replicating it in the future. However, there are few examples of protocols developed for social marketing or for improving the quality of life of individuals at risk of exclusion (R. G. Rivera, Castro Sanchez, et al., 2019).

Our study focuses on a company engaged in road construction and maintenance.

1. Identification of the system of business management indicators.

We prepared the initial list of indicators on the basis of the universe of classic textbook indicators, the current provisions for this type of company, and exchanges with specialists from several of the company’s management areas; then we reviewed the existing documentary material and information base, taking into account the results of the company's operational, economic, and accounting/financial processes. In total, we presented the following to the experts for their consideration: 18 operational indicators, 18 economic indicators, and 16 financial indicators.

2. Expert determination of the system of business management indicators to be employed.

First, we undertook our search for experts, taking into account years of experience in topics related to economics, finances, and operations (such as technical issues, human resources, logistics, and commerce) as well as knowledge of the fundamental activities and processes of the company studied. This resulted in the identification of 11 possible experts. The selection was carried out in accordance with the competence coefficient (K), calculated as the mean of the sum of the argumentation (Ka) and knowledge (Kc) coefficients. The process yielded a □ Crombach’s value of 0.93, proving that the measurement instrument is excellent. The results of each of the possible experts are presented in Table 3.

Table 3. Calculation of competence coefficients of the possible experts

Possible Experts	Ka	Kc	K	Experts
E1	0.87	0.9	0.885	Sí
E2	0.87	0.8	0.835	Sí
E3	0.86	0.8	0.83	Sí
E4	0.74	0.6	0.67	No
E5	0.88	0.8	0.84	Sí
E6	0.96	0.8	0.88	Sí
E7	0.86	0.8	0.83	Sí
E8	0.68	0.6	0.64	No
E9	0.65	0.5	0.575	No
E10	0.84	0.8	0.82	Sí
E11	0.81	0.7	0.755	No

Source: compiled by author

As experts, we qualified the seven individuals whose competence coefficient proved high (K ≥ 0.8). We presented the experts were presented with a survey containing 52 indicators from which to choose (18 operational indicators, 18 economic, and 16 financial), asking each of them individually to assign an order of importance to the indicators within each group, to the extent that they considered them to reflect or to enable measurement of business efficiency.

This is Kendall's concordance method, whose coefficient (W) establishes the concordance between the criteria and the priority of importance of the indicators, according to the experts, consecutively and in descending order, from 1 (most important) upward (least important). Using the number of importance (Ai) that the experts attributed to each indicator, we calculated:

- Σ Ai for each indicator, where i: number of experts (7)
- $\boldsymbol{T} = \frac{\sum_{j=1}^{m}\sum_{i=1}^{n} A_{i,j}}{m}$, where j represents the indicators; m = 18 for the operational and economic indicators, and 16 for the financial indicators.
- The indicators whose Σ Ai is below the T value are the most important, while those that are above are the least important.
- Finally, we calculated W, the concordance criteria that must be in the interval 0.5 ≤ W < 1 to express that the concordance has no causation; that is, there is a community of preference among the experts given their knowledge and good judgement.
- Having obtained these results, we proceeded to the selection of indicators that, by order of priority, should receive the most attention. The decision criteria is the mean (T) value. And the decision rule is: if Σ Ai < T, the indicator i is selected.

The order of priority of the indicators selected is determined according to the value of Δ:

$$\Delta = \Sigma \text{ Ai } - \boldsymbol{T}$$

Greatest priority is given to the indicator that presents the highest Δ value. The indicators with negative Δ values are not selected, as they do not fulfill the condition:

$$\Sigma \text{ Ai} < \text{T}$$

The selection process for the operational indicators is shown in Table 4.

Table 4. Application of Kendall's concordance method for the selection of operational indicators.

No	Indicators	E1	E2	E3	E4	E5	E6	E7	∑Ai	Δ	Δ²	T
I	Energy intensity	2	3	5	5	4	4	4	27	-40	1,600	
2	Quality index	I	6	4	3	2	2	2	20	-47	2,209	
3	Asphalt consumption/m²	4	13	2	9	7	10	5	50	-17	289	
4	Asphalt consumption/ hundreds of thousands of liters CML (maintenance)	11	10	13	12	5	13	12	76	9	81	
5	Aggregates consumption/m²	3	I	7	4	I	5	7	28	-39	1,521	
6	Aggregates consumption /CML (maintenance)	6	11	14	13	14	12	14	84	17	289	
7	Diesel consumption /100 m² mechanized cutting	8	2	3	7	9	8	9	46	-21	441	
8	Gasoline consumptio /100 m² mechanize cutting	12	12	16	14	13	14	13	94	27	729	67
9	Average workers/km of roadway	7	4	I	2	8	I	3	26	-41	1,681	
10	Staff	18	17	17	18	17	18	17	122	55	3,025	
11	Turnover	13	14	15	10	16	16	10	94	27	729	
12	Transportation	9	15	8	11	10	9	11	73	6	36	
13	Pay scale	17	16	18	15	18	17	18	119	52	2,704	
14	Sales rhythm	14	5	12	16	11	7	6	71	4	16	
15	Customer renewal	16	18	9	17	12	15	16	103	36	1,296	
16	Dependence on suppliers (procurements)	5	7	6	6	15	6	8	53	-14	196	
17	Diversification (procurements)	15	8	11	8	6	11	15	74	7	49	
18	Road construction and maintenance cycle[1]	10	9	10	I	3	3	I	37	-30	900	
		171	171	171	171	171	171	171	1,197		17791	

Test statistics

N	7
Kendall's W[a]	.749
Chi-square	89.155
df	17
Asymptotic significance	.000

Source: Compiled by authors based on SPSS output

The indicators selected in the study are presented in Table 5.

[1] Time invested in construction and maintenance/Total time invested in products marketed

Table 5. Operational indicators selected by the experts

	Operational Indicators	Δ	Order of priority
I	Quality index (QI)	-47	1st
2	Average workers/km of roadway	-41	2nd
3	Energy intensity (EI)	-40	3rd
4	Aggregates consumption/m²	-39	4th
5	Road construction and maintenance cycle	-30	5th
6	Diesel consumption /100 m2 mechanized cutting	-21	6th
7	Aggregates consumption/m²	-17	7th
8	Dependence on suppliers (procurements)	-14	8th

Source: compiled by author

We followed the same steps for the economic and financial indicators; of these, Table 6 presents those chosen by the experts, in order of importance. The W values for the economic and financial indicators (0.751 and 0.711, respectively) show that, as with the operational indicators, the concordance is without causality; that is, there is a community of preference among the experts, given their knowledge and good judgement.

Table 6 Economic and financial indicators selected

Order of priority	Economic indicators selected	Δ	Financial indicators selected	Δ
I	Total income	-52	Immediate liquidity or acid-test ratio	-38
2	Sales return	-51	Economic return	-37
3	Net Sales	-49	Solvency	-29
4	Total costs and expenses	-32	Available liquidity	-27
5	Total cost/Total income	- 21	Inventory turnover	-22
6	Salary expenses/Total income	-17	Accounts receivable cycle	-17
7	Material expenses/Total income	-11	General liquidity	-13
8	Labor productivity	-5	Working capital	-12
9	Mean salary/Labor productivity correlation	-2	Financial return	-2
10	Income for the period	-1	Indebtedness	-1

Source: compiled by author

The experts ultimately selected a total of 28 indicators, of which eight corresponded to the operational area, ten to the economic area, and ten to the financial area. The experts placed the greatest importance on the indicators that they considered to be exhibitors of efficiency, having selected those that demonstrate efficiency in the use of production resources (raw materials and supplies) in the technological process. This was also true of their selected group of economic indicators, which expressed efficiency in the use of resources (means, objects, and labor), as well as the financial indicators (fundamentally pertaining to profitability and liquidity).

Next, we determined the selected indicators for a given period. In this case we utilized the period 2013–2107, with the operational indicators presented in Table 7.

Table 7 Company's operational indicators over the period 2013–2017

Operational Indicators	2013	2014	2015	2016	2017
Quality index (QI)	6.2	6.3	6.5	5.4	4.8
Average workers/km of roadway	0.94	0.93	0.93	0.92	0.91
Energy intensity (EI)	0.0067	0.0066	0.00661	0.0065	0.00662
Aggregates consumption m^3/m^2 construction	0.032	0.04	0.045	0.031	0.036
Road construction and maintenance cycle, average days	255	278	256	238	259
Diesel consumption /100 m^2 mechanized cutting	0.045	0.048	0.0451	0.051	0.046
Asphalt consumption, ltr/m^2 (potholes)	2.1	2	2.2	1.9	2
Dependence on suppliers (supplier procurements/total procurements)	0.32	0.4	0.48	0.52	0.55

Source: Organization's database

3. Standardization of selected indicator system.

We executed the procedure using information from the operational, economic, and financial indicators for the period 2013--2017; and for the group of tests, the real data for 2018.

The functioning is argued when input neurons, the number of instances of the indicator to be analyzed (annual performance), and a neuron in the output layer (which is what distinguished the state of the business management) are selected for each training set. Then, we began the learning stage, in which the neural network is adjusted to a mathematical function that seeks to minimize errors through an iterative numerical calculation process. This is one of the advantages of using an ANN, as it guarantees the performance of the indicators with minimal error and includes options to eliminate variables that distort the prediction, allowing the standard performance of the indicators to be determined. We obtained the standard based on the set of data that were not used in the training, in order to use these data to compare the results yielded by the software; then, we conducted a test with road maintenance and construction data that were not used for training (for 2018), which gave rise to the score obtained.

The results for the three groups of indicators, obtained using the SAEIE tool are shown in Table 8. It should be noted that the larger the set of historic data inputted into the tool, the greater the precision of the standard performance that will be established. This is primarily because of the type of learning employed by SAEIE, supervised learning, which is based on learning through trial and error from the set of data inputted.

Table 8 Results of standard indicators (SAEIE) and comparison with 2018

Operational Indicators	**Real 2018**	**Standard**
Quality index (QI)	5.8	4.6
Average workers/km of roadway	0.92	0.91
Energy intensity (EI)	0.0063	0.0066
Aggregates consumption m^3/m^3	0.03	0.038
Road construction and maintenance cycle, average days	242	252
Diesel consumption on mechanized cutting	0.04	0.048
Asphalt consumption	2	2.1
Dependence on suppliers	0.49	0.6
Economic Indicators (UM – monetary units)	**Real 2018**	**Standard**
Total income (thousands of monetary units - UM)	15,100.2	14,925.2
Sales return	0.51	0.7
Net sales (thousands of UM)	15,120.6	14,482.1
Total costs and expenses (thousands of UM)	7,115.9	7,062.5
Total cost/Total income	0.4856	0.4908
Salary expenses/Total income	0.275	0.2808
Material expenses/Total income	0.232	0.2
Labor productivity (UM/worker)	1,985.71	2003.6
Mean salary/Productivity correlation	0.252	0.242
Working capital (thousands of UM)	7,435.30	7,496.3
Financial Indicators	**Real 2018**	**Standard**
Immediate liquidity or acid-test ratio	6.69	6.98
Economic return	1.042	1.12
Solvency	7.49	5.72
Available liquidity	5.45	6.05
Inventory turnover (times)	37.04	58.14
Accounts receivable cycle (days)	26.4	32
General liquidity	7.23	7.28
Working capital (thousands of UM)	5,512.4	5,067.3
Financial return	1.012	2.07
Indebtedness	0.1338	0.2054

Source: Compiled by authors based on application of the SAEIE tool and the company information base.

As can be seen, the standards obtained in comparison with the real data are rather accurate; the SAEIE was developed specifically for the road construction and maintenance company, so its knowledge bases respond to this specific type of organization, and so its results largely approximate reality.

Analysis and discussion of results.

In the analysis, we compared data from the period (2013–2018) with the standard obtained in each of the indicators--and specifically show the process for the operational indicators.

Quality index: We use this indicator is to measure customer satisfaction as part of quality control; the higher this indicator is, the greater the customer satisfaction. This indicator signaled a favorable situation for the period analyzed, exceeding the value of 4--that stipulated as favorable--for each of the years. For each year, the results were superior to the standard performance.

Average workers/km of roadway: This indicator indicates that approximately one worker is used in maintenance activities per kilometer of road; attaining the standard performance will lead to improved productivity. This indicator demonstrated a stable trend over the period.

Energy intensity: This indicator shows efficiency in the use of fuel, as well as consumption per production unit. In this indicator, the values should become progressively lower. For the period analyzed, the trend was stable. A figure of 0.0063 was attained for 2018, which denotes greater efficiency than the standard performance.

Aggregates consumption (m^3/m^2 of construction) exhibited a standard performance of 0.038 m^3, above that of 2014 and 2015; however, in 2018 it achieved 0.030 m^3/m2 of construction, representing a saving in relation to the standard performance.

The road construction and maintenance cycle shows the time, on average, required for execution of a road construction or maintenance project;[2] it depends on various factors such as types of land, magnitude of the project, and the number of vehicles expected to use the road. The standard is an average of 252 days to execute a project; the lowest value is that for 2016 and the highest, for 2014. In 2018 the value attained was value below the standard through improvements in the use of working time.

Diesel consumption (ltr/100 m^2): This indicator measures the number of liters of diesel used for every 100 square meters in the mechanized cutting: the lower the indicator, the better. Over the period, it can be seen that the differences versus the standard performance were insignificant; for instance, 0.040 in 2018 compared with the standard of 0.048.

Asphalt consumption (ltr/m^2): This indicator expresses the number of liters of asphalt consumed for every square meter of road construction and maintenance; this indicator is carefully observed given the importance of saving materials. Over the period analyzed, the real values did not exceed the forecast, with the exception of 2015, when more was spent.

Dependence on suppliers: This indicator shows the relationship between procurements from exclusive suppliers out of total procurements; it is very sensitive, because the concentration of material and equipment procured from exclusive suppliers has an impact on the quality of the project. In 2013, procurement from exclusive suppliers accounted for just 32% of the total; in 2018, this form of procurement amounted to 49% of all purchases, while the highest was 2017 (55%). All these figures are below the standard.

[2] The projects executed over the period are similar

It is important to stress that the operational indicators selected by the experts demonstrate efficiency in the use of production resources--that is, of human resources, raw materials, and supplies--in the performance of the technological process.

With regard to the performance of the indicators by years and the standard performance, we found that in 2013, 2014, and 2016, four of the eight operational indicators presented unfavorable results in relation to the standard. The worst results were those obtained for 2015, with five negative indicators, while 2018 was the year for which the most favorable indicators were achieved, in relation to their respective standards.

Conclusions

Evaluating business management results by way of the standardized performance of management indicators presents the following advantages:

• Because standard performance is determined by the characteristics and conditions of the indicators, they are suitable for orienting actions.

• Feedback promotes the systematization of updates to the system of indicators, and signify a form of comparison in itself.

• Many novel methods, techniques, tools, and forms of computerization--particularly in artificial neural networks--present advantages over traditional methods when it comes to determining standard performance.

The limitations of this study include the need for knowledge and experience on the part of the experts to select the processes that require attention, for an information base, and for experienced staff to record, select, and interpret the information. Moreover, the software requires the greatest possible amount of information for the application of neuron learning, such that the standardized performance of the management indicators achieves the desired effectiveness and efficiency for the ongoing improvement of business processes and management.

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