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Model of statistical estimation «Program of Productive Inclusion» MIPRO-Ecuador

Modelo de estimación estadística «Programa Inclusión Productiva» MIPRO-Ecuador

Juan C. Escobar Sailema, es profesor e investigador en la Escuela de Formación de Soldados del Ejército (Ecuador). (juan.escobar145@gmail.com) (https://orcid.org/0000-0002-5076-1129).

Abstract

This research demonstrates the incidence of demand estimates on the profitability of the enterprises advised within the «Productive Inclusion» program carried out by the Ministry of Industries and Productivity-Mipro (Ecuador). The academic-practical contribution that derives from the present object of study will be inputs for this Ministry, its corresponding zones, departments and for those who give adequate use of the final product. The objective of this work is to determine the incidence of a statistical estimation model of the demand in the improvement of the profitability of the enterprises, which includes evaluating the estimation model of the used demand to determine the levels of profitability, the variables of incidence, and to identify the components of a statistical estimation model. These objectives were achieved through data collection, numerical measurement, and statistical analysis of the data. The target population is comprised of 702 enterprises, classified into 4 productive sectors: trade in goods, trade in services, manufacturing and agriculture. Establishing a sample of 248 observations with a 95% confidence level and a standard deviation of 0.5, the result obtained is the design of a statistical estimation model of the demand and its applicability, whose accuracy is statistically and financially acceptable, which means the improvement of the profitability of the enterprises assessed and the fulfillment of the institutional objectives.

Resumen

La presente investigación demuestra la incidencia de estimaciones de demanda sobre la rentabilidad de los emprendimientos asesorados dentro del programa de «Inclusión Productiva» que lleva a cabo el Ministerio de Industrias y Productividad-Mipro (Ecuador). El aporte académico-práctico que derive del presente objeto de estudio serán insumos para dicho Ministerio, sus respectivas zonales, direcciones y para quienes den uso adecuado del producto final. El objetivo de este trabajo es determinar la incidencia de un modelo de estimación estadística de la demanda en el mejoramiento de la rentabilidad de los emprendimientos, lo que incluye evaluar el modelo de estimación de la demanda empleado, determinar los niveles de rentabilidad, las variables de incidencia, e identificar los componentes de un modelo de estimación estadística. Dichos objetivos fueron alcanzados mediante la recolección de información, medición numérica y el análisis estadístico de los datos. La población objeto de estudio está comprendida por 702 emprendimientos, clasificados en 4 sectores productivos: comercio de bienes, comercio de servicios, manufactura y agropecuario. Estableciendo una muestra de 248 observaciones con un 95% de nivel de confianza y una desviación estándar 0,5, el resultado obtenido es el diseño de un modelo de estimación estadística de la demanda y la aplicabilidad de este, cuya precisión es totalmente aceptable estadística y financieramente, lo que significa el mejoramiento de la rentabilidad de los emprendimientos asesorados y el cumplimiento de los objetivos institucionales.

Keywords | palabras clave

Statistical, entrepreneurship, analysis, estimation, methods, prospective.
Estadístico, emprendimientos, análisis, estimación, métodos, prospectivos.

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1. Introduction and state-of-the-art

A global, statistical estimation as part of economic science is one of the most important areas in business. These estimates have made it possible to make timely and reliable consumer demand interpretations for the decision-making (Cadena *et al.*, 2017), as well as to have relevant information on product replacement. Alvarado y Pinos (2017), Vergara *et al.*, (2017) and García-Guerrero (2014) mention that the development of the estimates is analyzed with sociodemographic variables that directly affect the demand of a product whether this is a good or service and consequently some economic policy issues that are the cause of changes in the consumer market, axiomatically assuming consumer preferences towards real demand as the main axis for forecasting in companies (Reyes-Sánchez, 2017).

Statistical methods in Latin America are being applied more frequently and discussed on a large scale in different areas such as business, agriculture, manufacturing, productive activities and government; being the fundamental axis in decision-making for business leaders and/or organizations. These are reflected in their economic and financial development and the future impact scenario of their factors. At the same time, the misapplication of estimation methods has been the cause of poor decisions at higher hierarchical levels, poor production planning and low profitability. The most used models have been time series, involving the use of linear regression, simple moving averages, double exponential smoothing, simple exponential smoothing, Naïve Method, ARIMA models (Autoregressive Integrated Moving Average) among others. These models are also used for estimating yield trends of various crop types and even livestock production yields (Delgadillo *et al.*, 2016).

In Ecuador, since 2013 the program called "Productive Inclusion" is carried out by the Ministry of Industries and Productivity (MIPRO), which advises entrepreneurs in the different productive sectors with the elaboration of a business plan and demand projections; this under a financial estimation model as an intrinsic and substantial component, which consists of a five-year predicted financial structure, taking into account indicators such as the rate of production growth, price growth rate, financial discount rate, inflation rate, interest rate, financing term and others considered by the specialist for the analysis and projection. The estimates of nationally advised entrepreneurs keep an error in most cases of more than twenty percent to this day, noting that the model and use of demand estimation tools -forecast- used is at least, very questionable, especially in terms of the current financial performance of the companies implemented, resulting in unfavorable financial performance that leads to low profitability.

Valencia-Cruzaty (2017), Moscoso-Escobar and Botero-Botero (2013) and Toca-Torres (2010), consider entrepreneurship as the most used formula in times of complex economic situation, framing all economic and social sectors for its development. In addition, it is recognized as a catalyst for the economic growth of countries, implemented both by private enterprise internally, as well as in the public sector (government), creating new products, markets, generating employment and well-being for the population.

Therefore, it is necessary to implement new models, methodologies, techniques, tools and estimation tools for the proper development of entrepreneurship in terms of profitability, as well as ensuring adequate investment and financing, while being important to obtain reliable sources of information, thus generating effectiveness in predicting future business events. It is also important to introduce to the analysis success factors that minimize risk in the implementation and operation of the business such as: production based on real demand, estimation indicators and forecasting methods according to the productive sector.

Predicting the future scenario of organizations and all production processes for a better financial performance has historically been a purely technical and complicated task, because optimal prediction is required for a proper management of productive factors that affect planning. In doing so, entrepreneurs have been able to determine the company's ability to acquire and produce the required amount required for supplies and products demanded, and thus predict in advance the budget needed to avoid errors within its using models based on quantitative methods contrasted with causal variables, plus the use of probabilities that complement each other to generate more accurate predictions (Lao-León *et al.*, 2017).

Boada (2017a) presents a study in which it is verified through real data how the Bayesian Dynamic Linear Model of Order 1 can be applied on the residuals - difference between the estimates and the current historical ones - taken randomly from a Model of Multiple Regression, thus obtaining a complement to the statistical estimation model, which generates a factor that favors from waste and adjusts according to the most recent historical data, unifying two trends: Bayesian statistics and the frequent statistics into a single model, concluding that: a) the most accurate valuation or rigorous analysis of causal variables as a statistical modeling procedure ensures the predictive power of multiple regression models, in addition; b) the simulation of future scenarios close to reality will depend on the correct use of the techniques used in the model plus the strategies generated by the predictor and finally; c) it is mentioned that establishing a statistical modeling procedure complemented by quantitative and qualitative techniques serves as a fundamental tool for the creation of an optimal prediction model.

Moreno-Arenas (2016) proposes the design of a statistical estimation model (forecast) from time series methods. This model aims to reduce the demand variability of packaging inputs, concluding that: a) the use of time series methods accurately identifies changes in variable dynamics in terms of obtaining reliable information; b) measuring inventory rotations from projection standardization is the result of time series analysis, which helps to improve the company's storage situation and; c) ERP-enterprise resource planning systems as a source of information improve the type of analysis and reduce data deviation.

Boada (2017b) exposes the design of an automated prediction tool based on different market variables. It is based on a detailed analysis of the causal variables identified, and then it develops a software called "Demand Projection System" to predict sales, analyzing price, product, billing, manufacturing, future planning of strategic sales management, among others; (a) the design and adaptation of correct estimation techniques in order to obtain more effective forecasts; b) considering

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the automated projection system as a statistical tool and not as a competitor of the estimator and; c) also ensuring the valuation, simulation and optimal evaluation of various future scenarios, being the fundamental basis of the long-term plans of the different areas of the company, such as finance and accounting.

Sánchez and Gavira (2016) take into account the hierarchy of the series containing the necessary unobserved components of time series (random variations, cyclicality, trend, and seasonality), this to make a short-term estimate, contributing in this way to the development of the forecast theory of hierarchical series. In addition, the most efficient model for forecasting monetary income for the case study is determined, using as a criterion the mean absolute scaled error (MASE), concluding that for this study: a) the most efficient method of forecasting is ARIMA , without ruling out that several methods (TD-ETS, COMB-ARIMA, TD-ARIMA and MO-ARIMA) can be employed with a better result; b) the application of the method depends on the complexity of the study and the variability of the series; (c) also highlighting the importance of contrast on the evaluation and determination of the most suitable methods with other approaches.

Contreras *et al.* (2016) consider forecasting as a tool that provides a quantitative estimation of probability, also considering the development of future estimates on the storage of perishable products due to the impact of economic and social estimates that they generate with erroneous estimates. Hence, the interest in incorporating time series forecasting techniques with the aim of determining the most reliable method to estimate optimal storage volumes and to be able to predict requirements in the supply chain, concluding that: a) the forecasts developed using the weighted mobile averages technique are the most acceptable in product mobility planning; b) thus ensuring storage availability, extension of expiry and market supply for as long as possible and; c) maintaining a balance between market demand and production.

Espino-Timón (2017) aims to determine the existence of open source tools that meet the requirements for predictive analysis and the operation evaluation of these tools in different areas, the two main tools identified are: R, with the graphical interface R-Studio, and Weka, which allow to detect patterns in the base data to establish more optimal future forecasts. Statistical analysis tools (SPSS, SAP Business Suite or SAS Software Package), used by large corporations, companies, organizations, governments and universities are also mentioned, concluding that: a) R-Studio and Weka has greater power and flexibility in terms of its application, which can be used for a preliminary analysis of the predictive model of demand, emphasizing b) the use thereof for the handling and processing of larger databases for their storage capacity and; c) better management and analysis of R-Studio is mentioned as a complement to a predictive analysis.

Arias-Vargas (2017) mentions the use of standard deviation for the calculation of a safety inventory, in this case the forecast model is identified as a simple average that has the effect of increasing the investment in safety inventories. To avoid this, it is proposed to use the standard deviation of the forecast errors associated with the forecast model to be applied, concluding that: b) in conjunction with the use of enterprise software (ERP or others) as a complement to the company's inventory assur-

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ance model; c) minimizing the impact of data variability on the security inventory, this to achieve the required service levels with minimal security inventories.

2. Materials and method

According to Herrera *et al.* (2010), descriptive research is applied as the first level for the implementation of this research paper, which served to examine the characteristics under study, define the subject and formulate the hypothesis, in addition to selecting the data collection technique and identify reliable sources of consultation, establishing the causes and effects of the object of study.

According to Romero (2012), correlational research is applied where the degree of relationship of the variables, statistical estimation model (independent variable) and profitability (dependent variable) is established, determining the incidence of the independent variable in solving the problem. Finally, applied research is used, which brings theoretical knowledge to the practical and in turn to the application, in order to improve the demand estimates of the advised entrepreneurs within the program "Productive Inclusion" led by the Ministry of Industries and Productivity (MIPRO) of Ecuador.

3. Population and sample

3.1. *Population*

The population consists of 702 national entrepreneurs composed of 36 variables, knowing exactly the number of elements comprising the population and determining the same of finite character.

3.2. *Sample*

In this investigation, due to the nature of the subject-matter, the type of random probabilistic sampling stratified is applied with proportional fixation, since the idea is to highlight the subgroups of entrepreneurships in the different productive sectors, observing the relationships between them and decreasing their variability, while maintaining proportionality to the size of the population.

Sample size: $n = \frac{\sum_{i=1}^{1} N_i P_i Q_i}{NE + \frac{1}{N}\sum_{i=1}^{1} N_i P_i Q_i}$

Size of each stratum: $n_i = n\left[\frac{N_i}{\sum_{i=1}^{1} N_i}\right] = n\left(\frac{N_i}{N}\right) = n(W_i)$

Estimate value: $E = \frac{d^2}{Z_{1-\alpha/2}{}^2}$

Where:

N=702

Z = 95% confidence level equivalent to 1.96 Z value
E = ?
n = 248
p = 0.5
q = 0.5
d^2= 0.05^2
$Z_{1-\alpha/2}$ 2 = 1.96^2

The sample was calculated with 95% confidence level and a standard deviation 0.5, for a population of 702 entrepreneurs from the “Productive Inclusion” program carried out by the Ministry of Industries and Productivity (see Table 1).

Table 1. Stratified Sampling with Proportional Fixation

Group	Ni	Pi	Qi	Pi*Qi	N*P*Q	Wi	ni
Trade of goods	283	0.5	0.5	0.25	70.75	0.4031339	100
Trade of services	136	0.5	0.5	0.25	34	0.19373219	48
Manufacture	182	0.5	0.5	0.25	45.50	0.25925926	64
Agriculture	101	0.5	0.5	0.25	25.25	0.14387464	36
Total	702				176	1	248

Source: Own elaboration from the data obtained by Setedis-Mipro

According to López (2014), for a sample to be representative, it must contain at least 30% of all cases. In this sense, it is clarified that out of 702 entrepreneurships comprising the population through the application of the statistical stratified sampling method, 248 observations are obtained as a sample calculation, fully representative of the population with more than 30% as established by the above author (*op. cit*), therefore the calculation of the sample for the present study is evidenced.

4. Analysis and results

This study presents information on 702 companies registered in the database [Data_Emprendimientos_Mipro_xlsx] (data purified), cumulative from 2013 to 2017, classified in 4 productive sectors: Trade of Goods, Trade of Services, Manufacturing and Agriculture (see Tables 2 and 3).

Table 2. Distribution by Province [Enterprise]

No.	Provinces	Frequency	%
1	Azuay	18	2.6%
2	Bolívar	31	4.4%
3	Cañar	17	2.4%
4	Carchi	25	3.6%
5	Chimborazo	34	4.8%

No.	Provinces	Frequency	%
6	Cotopaxi	25	3.6%
7	El Oro	36	5.1%
8	Esmeraldas	27	3.8%
9	Galápagos	1	0.1%
10	Guayas	42	6%
11	Imbabura	28	4%
12	Loja	27	3.8%
13	Los Ríos	33	4.7%
14	Manabí	103	14.7%
15	Morona Santiago	13	1.9%
16	Napo	33	4.7%
17	Orellana	21	3%
18	Pastaza	12	1.7%
19	Pichincha	68	9.7%
20	Santa Elena	23	3.3%
21	Santo Domingo	27	3.8%
22	Sucumbíos	19	2.7%
23	Tungurahua	23	3.3%
24	Zamora Chinchipe	16	2.3%
Total		702	100%

Source: Own elaboration from the data obtained at Setedis-Mipro

According to Table 2, the largest number of companies implemented are in the province of Manabí, with 14.7%, corresponding to the implementation of 103 and a negligible value in the Galapagos province with 0.1%. It can also be seen that the provinces with more entrepreneurships are the provinces of Pichincha (capital Quito) and Guayas (capital Guayaqui) with 9.7% and 6%, respectively, being the two provinces with the highest density of population of Ecuador.

Table 3. Number of enterprises by Proportional Afixation

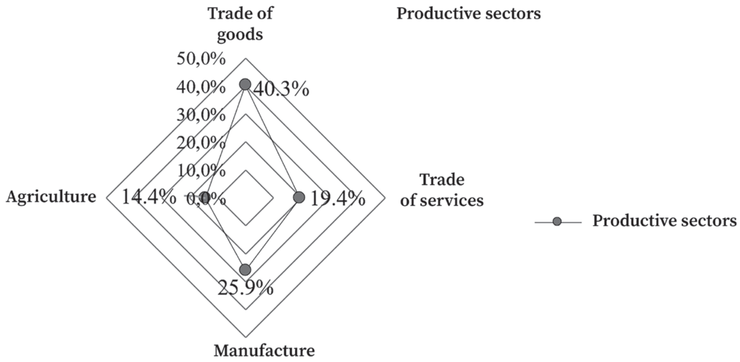
No.	Productive areas	Frequency	%
1	Trade of goods	100	40%
2	Trade of services	48	19%
3	Manufacture	64	26%
4	Agriculture	36	14%
	Total	248	100%

Source: Own elaboration from the data obtained at Setedis-Mipro

Figure 1 shows a percentage of 40.3% of entrepreneurs advised in the goods trade sector, followed by the manufacturing sector with 25.9%, representing more than 50% of the variable in question, while the manufacture sector accounts for

19.4%, and the agricultural sector covers 14.4% at the national level. This shows that entrepreneurs mostly choose businesses with a commercial nature.

Figure 1. Percentage of entrepreneurships per Province



Source: Own elaboration from the data obtained at Setedis-Mipro

Then the analysis on the variables is carried out; error levels of the forecast and profitability of the entrepreneurships (% of utility or profit margin and % error as incident variable).

Table 4. General Error Matrix on Real Value

Factor	Productive areas					
e_t	C.B	C.S	M	A	$\Sigma\, e_t(+)\,(-)$	%
$e_t\,(+)$	74	40	47	30	191	77%
$e_t\,(-)$	26	8	17	6	57	23%
TOTAL	100	48	64	36	248	100%

Source: Own elaboration from the data obtained at Setedis-Mipro

- C.B: Trade of goods
- C.S: Trade of services
- M: Manufacture
- A: Agriculture

As observed in Table 4, the percentage of underestimators relative to the real value is 77%, noting that the projections made in the advised entrepreneurs were lower than the current value, while the percentage of overestimations is 23%, i.e., there were entrepreneurships that exceeded the real value achieved.

Table 5. General matrix of the percentage of statistical error on estimates

Factor	Productive areas					
e_t	C.B	C.S	M	A	Σe_t <;> 10%	%
$e_t < 10\%$	5	2	3	2	12	5%

Factor	Productive areas				
$e_t > 10\%$	95	46	61	34	236	95%
TOTAL	100	48	64	36	248	100%

Source: Error type table by production sectors

- C.B: Trade of goods
- C.S: Trade of services
- M: Manufacture
- A: Agriculture

According to Table 5, 95% of entrepreneurships on 248 observations exceed 10% of the margin of error in their predictions. Only 5% of forecasts are within the statistically acceptable margin of error. According to Lamas (2016), the statistical error for any estimation study is between 0-10% of the maximum margin of error, this depending on the appropriate confidence level; however, it will be up to the researcher to define the margin of error admitted, taking into account the type of estimate and the factors affecting them.

3.1. *Analysis of the forecast error by productive sectors*

The analysis of $\boldsymbol{e\%} = \left(\frac{y_t - \hat{y}_t}{y_t}\right) * \mathbf{100}$ (Hanke, 2015).

Where:
e_t : forecast error
Y_t : real value
$\hat{Y}_t$: forecast value

Table 6. Analysis Descriptive Error (%) Goods Trade Sector

Statistics	Values
N.-Valids	100
Lost	0
Mean	61.72
Standard error	2.831
Mean	68
Moda	97
Standard deviation	28.312
Variance	801.577
Asymmetry	-.552
Standard asymmetry error	.241
Kurtosis	-.885
Standard Kurtosis error	.478
Range	94
Minimum	3

Statistics	Values
Maximum	97
Percentiles .25	37.25
.50	68.00
.75	84.75

Source: Own elaboration from the data obtained at Setedis-Mipro

According to the descriptive statistics presented in Table 6, the average error over 100 observations is 61.72%, with a standard deviation of 28.312%. In addition, it can be seen that half of the entrepreneurships had an error rate in their forecasts of less than 68%, while 97% was the most common error rate on a 1-100 percent scale, the difference between the minimum and maximum error forecast rate was 94%, and 50 percent of the entrepreneurships had an error in their forecasts between 37.25% and 88.75%. The distribution is asymmetrical negative, i.e., the largest amount of data is grouped to the right and has kurtosis, which means that there is very little grouping of data in the central region, being able to identify that the data has great variability or dispersion relative to its mean.

Table 7. Descriptive Error Analysis (%) Trade of Service

Statistics	Values
N.-Valids	48
Lost	0
Mean	64.13
Standard error	3.293
Mean	72.50
Moda	79.00
Standard deviation	22.813
Variance	520.452
Asymmetry	-1.004
Standard asymmetry error	.343
Kurtosis	.704
Standard Kurtosis error	.674
Range	96
Minimum	0.3
Maximum	96
Percentiles .25	48.50
.50	72.50
.75	79.00

Source: Own elaboration from the data obtained at Setedis-Mipro

As can be seen in Table 7, the average error over 48 observations is 64.13 percent, with a standard deviation of 22.813%. In addition, it can be seen that half of entrepreneurships had an error rate in their forecasts of less than 72.50%. 79 was the most common error rate on a 1-100 percent scale; while the difference between the minimum and maximum error rate of the forecast was 96 percent, and 50% of the entrepreneurships had an error in their forecasts between 48.50% and 79%. The distribution is asymmetrical negative, i.e., the largest amount of data is grouped to the right and has kurtosis, therefore there is more data in the central region, identifying that the data are approximately 64.13% of forecast error.

Table 8. Descriptive Error Analysis (%) Agricultural Sector

Statistics	Values
N.-Valids	36
Lost	0
Mean	57.94
Standard error	4.482
Mean	69
Moda	83
Standard deviation	26.891
Variance	723.140
Asymmetry	-.512
Standard asymmetry error	.393
Kurtosis	-1.134
Standard Kurtosis error	.768
Range	87
Minimum	5
Maximum	92
Percentiles .25	36
.50	69
.75	81

Source: Own elaboration from the data obtained at Setedis-Mipro

According to the descriptive analysis data in Table 8, the average error over 36 observations is 57.94% with a standard deviation of 26.89. In addition, it can be seen that half of the entrepreneurships had an error rate in their forecasts of less than 69%. 83 was the most common error rate on a 1-100 percent scale, the difference between the minimum and maximum forecast error percentage was 87 percent, and 50% of the entrepreneurships had an error in their forecasts between 36% and 81%. The distribution is asymmetrical negative, i.e., the largest amount of data is grouped to the right and has kurtosis, therefore it can be shown that there is very little data around 57.94% of forecast error.

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Table 9. Analysis Descriptive Error (%) Manufacturing Sector

Statistics	Values
N.-Valids	64
Lost	0
Mean	71.19
Standard error	3.320
Mean	78.00
Moda	97
Standard deviation	26.556
Variance	705.234
Asymmetry	-.903
Standard asymmetry error	.299
Kurtosis	-.099
Standard Kurtosis error	.590
Range	94
Minimum	4
Maximum	98
Percentiles .25	51.50
.50	78
.75	97

Source: Own elaboration from the data obtained at Setedis-Mipro

According to the sections in Table 9, the average error over 64 observations is 71.19%, with a standard deviation of 26.55%. In addition, it can be seen that half of the entrepreneurships had an error rate in their forecasts of less than 78%. 97 was the most common error rate on a scale of 1-100 percent. The difference between the minimum and maximum error rate of the forecast was 94%, and 50% of the entrepreneurships had an error in their forecasts between 51.50% and 97%. The distribution is asymmetrical negative, i.e., the largest amount of data is grouped to the right and has kurtosis, consequently there is very little grouping of data or a lot of variability around the mean 71.19%.

3.2. Strata profitability analysis

For the profitability analysis, the % U or profit margin is taken into account as a composite variable $\% \mathbf{U} = \frac{\mathbf{UN}}{\mathbf{VT}}$ which is processed and represented in the following analysis. According to Daza-Izquierdo (2016), profitability is a condition or ability of organizations to generate or earn income from an investment, i.e., it is the culmination of a result of any economic activity, considering that profitability is the interpretation of profits and surplus in percentage or absolute terms according to certain indicators. In this case, the profitability condition is established based on percentage profit or profit margin.

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Table 10. Numerical and Percentage Representation of Utility

Factor	Productive areas					
Utility	C.B	C.S	M	A	Σ Utility	%
U (-)	22	8	23	14	67	27%
U (+)	78	40	41	22	181	73%
Total	100	48	64	36	248	100%

Source: Own elaboration from the data obtained at Setedis-Mipro

UN = net utility
VT = Total sales
Unidades = Percentual

As evidenced in Table 10, 73% of advised entrepreneurships make a profit, while 27% generate loss. In addition, it is clear that the sectors where the most entrepreneurships are concentrated are Trade of Goods and Manufacturing.

According to López (2016), the different ways of "making a company" make profit margins have a great diversity and disparity between business units and even between productive sectors. The author (*op. cit*.) mentions that an acceptable or good profit margin is the one that exceeds 20%, indicating that commonly industries with competitive companies obtain small profit margins, so to be profitable they generate large volumes of sales. In contrast, small innovative businesses generally obtain higher profit margins, this because sales volumes increase by the small number of competitors. Increased profit margins are also considered for the application of economies of scale.

Table 11. Measure of the Current Profitability Index Model

Productive areas	Profit < 20%	Profit > 20%	Profit (-) loss	Total
C.B	21	57	22	100
C.S	4	36	8	48
M.	19	22	23	64
A.	4	18	14	36
Total Numerical	48	133	67	248
Total Percentual	19%	54%	27%	100%

Source: Own elaboration from the data obtained at Setedis-Mipro

As evidenced in Table 11, 54% of advised entrepreneurships make a profit greater than 20% considered acceptable, while 27% generate loss, and 19% generate a profit of less than 20%, considered to be insignificant.

3.2. Evaluation of the current model vs. the proposed model

According to Render *et al.*, (2015), in order to evaluate an estimate model used, the following elements are considered that are contrasted with those of the current model.

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Table 12. Weighting Elements of the Estimation Model «Holmes Method»

Com	C1	C2	C3	C4	C5	C6	Total	Order	Proportion
C1	-	1	1	1	1	1	5	1	33.33%
C2	0	-	0.50	0.75	0.75	0.75	2.75	2	18.33%
C3	0	0.50	-	0.50	0.50	0.50	2	3	13.33%
C4	0	0.25	0.50	-	0.75	0.50	2	3	13.33%
C5	0	0.25	0.50	0.25	-	0.75	1.75	4	11.67%
C6	0	0.25	0.50	0.50	0.25	-	1.50	2	10%

Source: Own elaboration from the data obtained at Setedis-Mipro

1: Very important
0.75: Significantly important
0.50: Important
0.25: Significantly less important
0: Unimportant

C1: Obtaining input data
C2: Development of a solution
C3: Solution test
C4: Result Analysis
C5: Sensitivity Analysis

Table 13. Current Model Assessment

No.	Components	Description	Orden	Valoración
1	Getting Input Data	Statistical procedures	1	-
2	Solution Development	Model Manipulation	2	18%
3	Solution Test	Statistical tests	3	-
4	Result Analysis	Determination of solution implications	3	13%
5	Sensitivity Analysis	Sensitivity Tests	4	12%
6	Implementation of the result	Sensitivity Solution	2	10%
		Total	-	53%

Source: Own elaboration from the data obtained at Setedis-Mipro

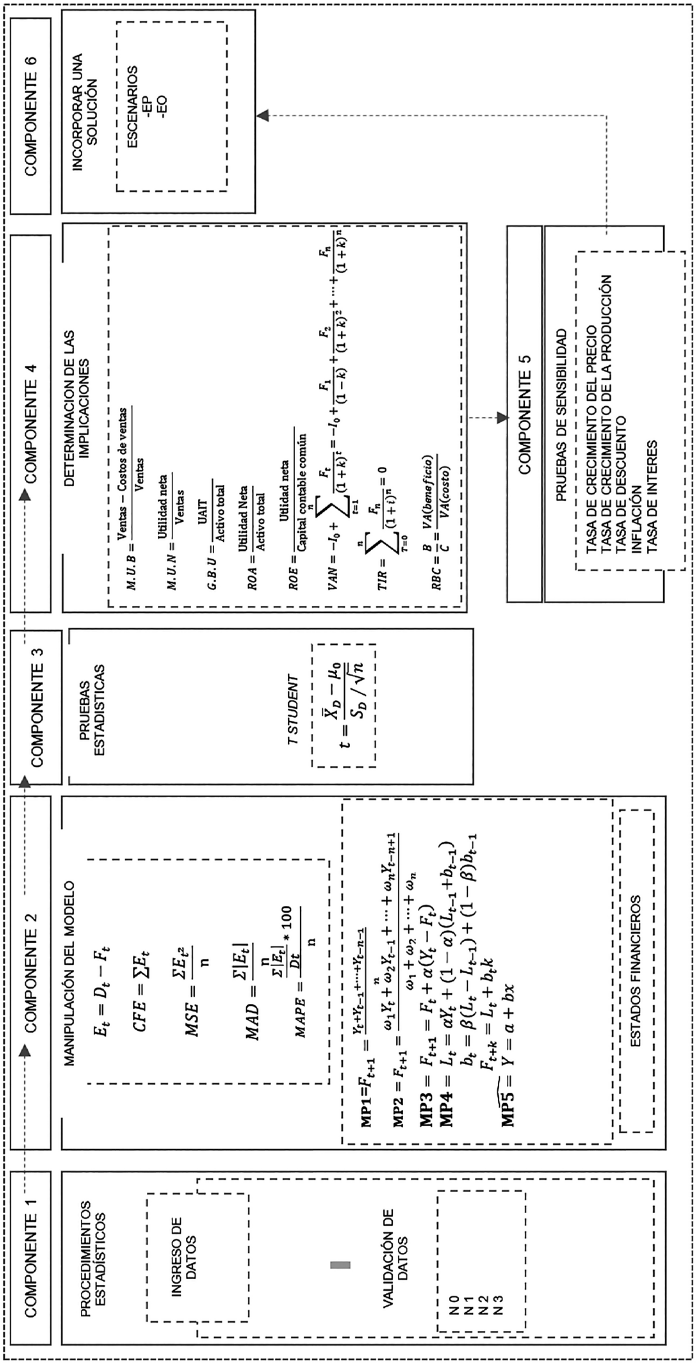
As noted in Table 13, the effectiveness of the current model is 53%, considering for component C1 a probability of 0.5 failure and 0.5 success in the procedure. This by assuming that there are problems of manipulation and incorrect data entry, however, for MEED-JCES-2018, a procedure is established for irrigation management that mitigates this type of problems.

3.3. Methodology of the proposed operating model "MEED-JCES-2018"

According to Render *et al.*, (2015, pp. 31-34) models "must be fully functional, easy to solve and understand, realistic and modifiable, as well as feasible in obtaining requirement of input data". The authors further emphasize that the development of the model must be thorough in order for it to be solved and more similar to the reality of prediction.

The proposed model is hereinafter referred to as 'MEED-JCES-2018'. This model will cover the approaches and inputs of different authors, and will be more strongly evidenced by quantitative methods of forecasting, specifically those of time series. In addition, financial and statistical parameters are presented that will allow accurate measurement of the forecasts and the level of profitability (see Figure 2).

Figure 2. Design of the model proposed MEED-JCES-2018



Source: Own elaboration

1. Input-data: for the data entry the proposed methodology is established according to validation levels, after such validation the data enters the «MEED-JCES-2018».
2. Model manipulation: the data is processed, the error that best fits that series is established, and the method that has the least error present is applied (for the identification of the least error the MAPE is taken into consideration by the ease of interpretation).
3. Statistical test: statistical data provided by the 'MEED-JCES-2018' on the application of the different forecasting methods is obtained to be compared with the data produced by IBM SPSS or Minitab software (in this case the use of other type of software proposed by the analyst is taken into consideration). The purpose of this comparison is to identify how effective the model is.
4. Determination of implications: an analysis of the profitability indicators is carried out and it is determined how profitable the business is based on the data obtained.
5. Sensitivity test: The sensitivity test includes manipulation of price growth rates, production, inflation, discount rate.
6. Provide the solution: in the incorporation of the solution it is recommended to establish at least 2 scenarios (pessimistic - optimistic), based on the sensitivity of the variables.

Finally, it is suggested for the statistical prediction phase to contrast the results with the SPSS, R-Studio, Minitab, and Stat-Graphics.

3.5. Contrast of the current model vs the proposed model

The following, as an interpretation of the final results, is the analysis on the contrast of the elements before and after the application of the "MEED-JCES-2018".

Table 14. Contrast of Model Application % U

Statistics	Before the implementation of the MEED	After the implementation of the MEED
N.-Valids	248	248
Lost	0	0
Media	32.1008	46.8226
Average	28.8000	44.0000
Moda	64.00	74.00
Standard deviation	21.31471	19.26968
Variance	454.317	371.321
Asymmetry	.501	.878
Standard asymmetry error	.155	.155
Kurtosis	-.499	.608
Standard kurtosis error	.308	.308
Range	97.00	97.00

Statistics	Before the implementation of the MEED	After the implementation of the MEED
Minimum	.00	20.00
Maximum	97.00	117.00
Percentiles .25	16.0000	31.0000
.75	48.9500	59.0000

Source: Own elaboration from the data obtained at Setedis-Mipro

3.6. Verification of the hypothesis

Step 1.-Hypohesis scenario

Ho: The variable and $e_t\%$ (relative error) does not significantly affect the profitability (% U of or profit margin) of the companies ($\tilde{x}_1 = \tilde{x}_2$)

H1: La variable $e_t\%$ (error relativo) sí incide significativamente en la rentabilidad (% U o margen de utilidad) de los emprendimientos ($\tilde{x}_1 \neq \tilde{x}_2$)

Step 2.-Levels of significance

Confidence level: 95%, α = 100% - 95% = 5% = 0.05.
Error type 1. - Chance of rejection of Ho when true.
Error type 2. - Probability of accepting Ho when false

Step 3.-Test Statement

If p < = 0.05 Ho is rejected
If p> = 0.05 Ho is accepted

Step 4.-Decision Rule

If p < = 0.05 is rejected Ho and H1 is accepted.

The ritual of statistical significance is carried out for the selection of the hypothesis test. The Kolmogorov-Smirnov test is applied for a sample on the variable difference (error of the forecast before- after the application of the MEED) and on the variable difference (% U current model - % U proposed model), in order to check if the variables study are distributed or belong to a normal distribution

Table 15. Kolmogorov-Smirnov test for a sample

Factors	Descriptive	Difference $e_t\%$	Difference %U
N		248	248
Normal parameters[a,b]	Media	37.8560	-14.7218
	Desv.	21.62097	3.52447
Maximum difference	Absolute	.202	.219

Factors	Descriptive	Difference e_t%	Difference %U
Extremes	Positive	.153	.219
	Negative	-.202	.206
Test statistic		.202	.219
Asynical sig. (bilateral)		.000[c]	.000[c]

Source: Own elaboration from the data obtained at Setedis-Mipro

Ho: Hypothesis of homogeneity
H1: of differences

Table 15 shows a p-value of 0.00 < 0.05, which allows to reject the Ho and accept the H1, and confirms that there is no homogeneity, i.e., the data distribution of the variables under study is not equal in its structure or in its form – does not belong to a normal distribution, thus the Wilcoxon range test will be applied.

Below, in Table 16, the hypothesis subject to verification is presented with the Wilcoxon range test for reacted samples. This was used to compare two (medium) range measurements to determine that the difference is not because of random.

Table 16. Wilcoxon Rank Test

Descriptive	Difference	N	Average range	Sum of Ranges
% Proposed Model Error- % Current Model Error	Negative Ranges Positive Ranges Even Total	237[a] 11b 0c 248	128.39 40.64	30429.00 447.00
% Utility of the Proposed Model- % Utility of The Current Model	Negative Ranges Positive Ranges Even Total	0a 248b 0c 248	0.00 124.50	00.00 30876.00

Source: Own elaboration from the data obtained at Setedis-Mipro

Table 17. Test Statistics

Description	Z	Sig. Asymptotic (bilateral)
% Error with applicability of MEED % Error before the applicability of MEED	-13.377[b]	.000
% Utility of the proposed model- % Utility of the current model	’13.795[b]	.000

Source: Own elaboration from the data obtained at Setedis-Mipro

Step 5.-Decision-making

As can be seen in Table 17, the following is 0.00 < 0.05, which shows the existence of differences between the two assessments on the same group of entrepreneurships, the Z value is higher than the confidence level at 95%=1.96, i.e., the calculated Z-value of -13,377 b and 13,795 b gets in the rejection zone to two distribution queues, so it can be corroborated that there is a significant change in the % of forecast error and the profit percentage after the application of the MEED, therefore, Ho is rejected and H1 is accepted.

4. Discussion and conclusions

The results obtained in the forecasts with the proposed model provide more and more accurate predictions. These come from a disaggregated model based on measures on the medium-ECM quadratic error and medium-PEAM absolute error, depending largely on the balance between the degree of uncertainty and heterogeneity of the data (López *et al.*, 2017).

According to Render *et al.* (2015, pp.31-34) "models must be fully functional, easy to solve and understand, realistic and modifiable, as well as feasible in obtaining input data requirements". The authors (*op. cit.*) emphasize that the development of the model must be thorough in order for it to be solved and be similar to the reality of prediction. After examining the works and publications of several authors, the statistical estimation model of demand called "MEED-JCES-2018" was developed, which establishes primary factors for optimal prediction and a structure for practical management, starting with an information system that analyzes the trend of the series to forecast, the automatic application of time series methods such as: The simple moving average method, weighted moving average, exponential smoothing, double exponential smoothing and linear regression, which together with financial and control statistical indicators help to improve estimates for detecting the presence of mistakes and take corrective action and make better decisions.

The proposal of a model for the calculation of estimates contributes to companies in reducing oversupply, minimizing the costs of materials, production and finished products. The application of a model involves the evaluation and comparison of different quantitative methods, with the aim of obtaining greater precision in terms of its estimation, being Winter Method the most used method (Garduño-García, 2011).

The investigated models clearly explain their structure. In the particular case the model called SysPPAc consists of: an information system, trend analysis, statistical estimation methods, method selection indicators and information generation; this model is clearly functional as it migrates and classifies historical data, applies mathematical estimation models based on time series, average-mobile and smoothing-exponential, selects a number of previous periods, the adjustment factor for the valuation of any pattern and/or trend of the series to be estimated, validates the model, generates critical information reliably and automatically (Montañez-Muñoz, 2010).

Taking into account the trend component, the errors of the estimates and historical autocorrelation, it is advisable to work on a fully and reduced differentiated series in its variance through the application of the natural logarithm - delayed series in a period-, this is reflected in most forecasts studies and estimate models (Peña Figueroa & Paredes Mora, 2016).

The use of statistical and probability tools is established for the analysis of the behavior of the , , the range, the 90 percentile and the 10 percentile - both define the probability of occurrence of 80%-; based on this analysis and the use of forecast methods time series are created and performance parameters are set, the method that best models the behavior of the series is defined through error analysis. Finally, it is evident that the predicted values differ insignificantly from the real ones, i.e., there is a good approximation for predicting future values, concluding that the careful analysis of statisticians contributes greatly to the definition or selection of the most suitable model and consequently the most optimal approach to a real value (Silva-Romero, 2013).

It is recommended to update the model with the inclusion of new methods, techniques and statistical tools for sampling, processing, analysis and data collection, as well as for the contrast of hypotheses. In the same way, it is recommended to use control and monitoring techniques, the inclusion of statistical and financial indicators that guarantee the quality of the information generated by the model. In addition, it is suggested to maintain a good quality database that serves for further analysis, understood by good data quality: its availability, usability, reliability, relevance and quality in its presentation. In addition, to carry out a periodic evaluation of the "MEED-JCES-2018" in order to improve it through the insertion of new tools or computer applications (statistical software) for the prediction process, these improvements should be based logically, technically and scientifically.

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