CIÊNCIAS SOCIALMENTE APLICÁVEIS:

INTEGRANDO SABERES E ABRINDO CAMINHOS

JORGE JOSÉ MARTINS RODRIGUES
MARIA AMÉLIA MARQUES
(Organizadores)

VOL V

EDITORA ARTEMIS
2022

CIÊNCIAS SOCIALMENTE APLICÁVEIS:

INTEGRANDO SABERES E ABRINDO CAMINHOS

JORGE JOSÉ MARTINS RODRIGUES
MARIA AMÉLIA MARQUES
(Organizadores)

VOL V

EDITORA ARTEMIS
2022

Editora Chefe	Profª Drª Antonella Carvalho de Oliveira
Editora Executiva	M.ª Viviane Carvalho Mocellin
Direção de Arte	M.ª Bruna Bejarano
Diagramação	Elisangela Abreu
Organizadoras	Prof. Dr. Jorge José Martins Rodrigues Prof.ª Dr.ª Maria Amélia Marques
Imagem da Capa	cienpies
Bibliotecária	Janaina Ramos – CRB-8/9166

EDITORA ARTEMIS
2022

Editora Artemis
Curitiba-PR Brasil
www.editoraartemis.com.br
e-mail:publicar@editoraartemis.com.br

Editora Artemis
Curitiba-PR Brasil
www.editoraartemis.com.br
e-mail:publicar@editoraartemis.com.br

Dados Internacionais de Catalogação na Publicação (CIP)

C569 Ciências socialmente aplicáveis: integrando saberes e abrindo caminhos V / Organizadores Jorge José Martins Rodrigues, Maria Amélia Marques. – Curitiba-PR: Artemis, 2022.

Formato: PDF
Requisitos de sistema: Adobe Acrobat Reader
Modo de acesso: World Wide Web
Inclui bibliografia
ISBN 978-65-87396-63-7
DOI 10.37572/EdArt_250822637

1. Ciências sociais. 2. Pesquisa. I. Rodrigues, Jorge José Martins (Organizador). II. Marques, Maria Amélia (Organizadora). III. Título.

CDD 301

Elaborado por Bibliotecária Janaina Ramos – CRB-8/9166

Editora Artemis
Curitiba-PR Brasil
www.editoraartemis.com.br
e-mail:publicar@editoraartemis.com.br

APRESENTAÇÃO

O livro que ora se encontra nas vossas mãos, no seu quinto volume, é por tradição um livro de temática interdisciplinar e transdisciplinar no campo das ciências sociais aplicadas. É interdisciplinar porque cruza várias disciplinas do saber, ficando a sua transdisciplinaridade a dever-se aos múltiplos campos do conhecimento abrangidos por estes dezassete trabalhos, qual mosaico árabe.

A metodologia seguida na organização do volume privilegiou os conteúdos dos artigos, procurando-se seguir uma lógica em que cada artigo possa contribuir para uma melhor compreensão do artigo seguinte, originando conhecimento. Este método originou quatro eixos de investigação, a saber: Informação: a energia que move os sistemas, Investigar ou a liberdade de desestabilizar o *status quo*, Investigar no feminino, Informação: um instrumento transversal.

O eixo 1 – Informação: a energia que move os sistemas, enquanto conhecimento é a energia que move os sistemas, está presente nos primeiros sete artigos. O eixo 2 – Investigar ou a liberdade de desestabilizar o *status quo*, glosa a liberdade intelectual para gerar conhecimento, sendo fulcral em qualquer sociedade, é o assunto ocupado pelos quatro artigos seguintes. O eixo 3 – Investigar no feminino, realça o equilíbrio entre corpo e mente, a híper sexualidade da mulher negra e a caracterização socioeconómica de uma cooperativa de mulheres, é ocupado pelos três artigos seguintes. O eixo 4 - Informação: um instrumento transversal, foca-se na evidência empírica de os dados, devidamente trabalhados, geram informações valiosas, seja para a otimização da informação em *call centers*, da segurança rodoviária ou do enquadramento legal da atividade de acompanhamento arqueológico.

Com a disponibilização deste quinto livro esperamos gerar inquietude intelectual e curiosidade científica no leitor, incrementando a satisfação de novas necessidades e descobertas, motor de toda a inovação.

Jorge Rodrigues, ISCAL/IPL, Portugal
Maria Amélia Marques, ESCE/IPS, Portugal

SUMÁRIO

INFORMAÇÃO: A ENERGIA QUE MOVE OS SISTEMAS

CAPÍTULO 1 ..... **1**

COMPARACIÓN DEL VALOR DE PERTINENCIA DE LAS NORMAS CONTABLES EN ESTADOS UNIDOS VERSUS LAS NORMAS INTERNACIONALES DE INFORMACIÓN FINANCIERA: EL CASO DE LAS AMERICAN DEPOSITARY RECEIPTS

Aida R. Lozada Rivera

https://doi.org/10.37572/EdArt_2508226371

CAPÍTULO 2 ..... **19**

FERRAMENTA DE APOIO AOS COMANDANTES DAS OPERAÇÕES DE SOCORRO EM INTERVENÇÕES ESTRUTURAIS DAS EQUIPAS DE BOMBEIROS

Pedro Miguel Sousa Barahona
Ana Filomena de Figueiredo Dias
Carla Maria Lopes da Silva Afonso dos Santos

https://doi.org/10.37572/EdArt_2508226372

CAPÍTULO 3 ..... **35**

PERSPETIVA SOBRE O USO DA BIBLIOTECA DIGITAL B-ON PELOS DOCENTES DO ENSINO SUPERIOR – O CASO DO INSTITUTO POLITÉCNICO DE CASTELO BRANCO

Maria Eduarda Pereira Rodrigues
Antonio Pulgarín Guerrero
Margarita Pérez Pulido

https://doi.org/10.37572/EdArt_2508226373

CAPÍTULO 4 ..... **48**

REDE ACADÉMICA WEIWER® E COREOGRAFIAS DIDATICAS: QUE RELAÇÃO?

Teresa Margarida Loureiro Cardoso
Luciano Gamez
Maria Filomena Pestana Martins Silva Coelho

https://doi.org/10.37572/EdArt_2508226374

CAPÍTULO 5 ..... **61**

CONTRIBUIÇÃO DA RETÓRICA PARA A REDAÇÃO DE TRABALHOS ACADÊMICOS DE ALTO IMPACTO: ANÁLISE DO ARTIGO “AS CAPACIDADES DE ORGANIZAÇÕES VOLTADAS AO MERCADO”

Rodrigo Guimarães Motta

Neusa Maria Bastos Fernandes dos Santos
Maria Cristina Sanches Amorim
https://doi.org/10.37572/EdArt_2508226375

CAPÍTULO 6 81

ÉTICA PROFESIONAL EN LA FORMACIÓN DEL CONTADOR PÚBLICO

Teresita de Jesús Sabido-Domínguez
Valentín Alonso-Novelo
Gustavo Alberto Barredo-Baqueiro
https://doi.org/10.37572/EdArt_2508226376

CAPÍTULO 7 92

INNOVACIÓN UNIVERSITARIA, UN ANÁLISIS TEÓRICO INTEGRAL DESDE SUS FUNCIONES MISIONALES

Jennifer Lafont Mendoza
Amelia Espitia Arrieta
Dairo Pérez Sotelo
https://doi.org/10.37572/EdArt_2508226377

INVESTIGAR OU A LIBERDADE DE DESESTABILIZAR O *STATUS QUO*

CAPÍTULO 8 110

A FRAGILIDADE DA LIBERDADE DE IMPRENSA EM MOÇAMBIQUE, HOJE: UMA REFERÊNCIA AO *ETHOS* DO PRESIDENTE FILIPE NYUSI NO DISCURSO DO DIA DO JORNALISTA MOÇAMBICANO E AS MARCAS DO AUTORITARISMO

Dayse Alfaia
https://doi.org/10.37572/EdArt_2508226378

CAPÍTULO 9 125

REFLEXIONES SOBRE LA TRANSFORMACION EN LAS PyMES Y LA GENERACION MILENIO EN TIEMPOS DE PANDEMIA

Jorge Ramón Salazar-Cantón
Valentín Alonso-Novelo
Luis Martín Barrera-Ramírez
https://doi.org/10.37572/EdArt_2508226379

CAPÍTULO 10 133

MEMÓRIA DE AFETOS: CULTURA E REVOLUÇÃO NO RECIFE DOS ANOS DE CHUMBO

José Antonio Spinelli Lindoso

https://doi.org/10.37572/EdArt_25082263710

CAPÍTULO 11 153

TRAÇAR UMA REDEFINIÇÃO DO CONCEITO DE ECONOMIA: UMA APROXIMAÇÃO

Rúsbel Freddy Ramos Serrano
Raúl Eleazar Arias Sánchez

https://doi.org/10.37572/EdArt_25082263711

INVESTIGAR NO FEMININO

CAPÍTULO 12 161

CONTROLOGIA: DESENVOLVIMENTO HARMONIOSO DO CORPO E DA MENTE

Thaís Medeiros da Costa Dias
Fabiana Vieira de Medeiros

https://doi.org/10.37572/EdArt_25082263712

CAPÍTULO 13 165

O ESPETÁCULO DO CORPO DA MULHER NEGRA E AS MARCAS HISTÓRICAS DA HIPERSEXUALIZAÇÃO E DA OBJETIFICAÇÃO: UM OLHAR PARA O CASO DE SARA BAARTMAN (XIX) E PARA O CASO DA CANTORA DE *FUNK* BRASILEIRA, JOJO MARONTTINNI (XXI)

Dayse Alfaia

https://doi.org/10.37572/EdArt_25082263713

CAPÍTULO 14 184

CARACTERIZACIÓN SOCIOECONÓMICA DE INTEGRANTES DE LA ASOCIACIÓN DE MUJERES (APRIMUJER) PARA ESTIMAR POTENCIALIDADES EN EL TERRITORIO DEL ÁREA RURAL DE SAN VICENTE DE CHUCURÍ, SANTANDER, COLOMBIA

Miguel Arturo Lozada Valero
Ángela María Andrade Ulloa
Mónica María Pacheco Valderrama
Héctor Julio Paz Díaz
Rafael Calderón Silva

Leidy Andrea Carreño Castaño
Cristian Giovanny Palencia Blanco
Irina Alean Carreño
Shirley Lizeth Mancera
Daniel Augusto Buitrago Ibañez
Ana Milena Salazar Beleño
Dally Esperanza Gáfaro Álvarez
https://doi.org/10.37572/EdArt_25082263714

INFORMAÇÃO: UM INSTRUMENTO TRANSVERSAL

CAPÍTULO 15 202

STATISTICAL ANALYSIS OF CONVERGENCE FOR NON-LINEAR OPTIMIZATION ALGORITHMS IN CALL CENTERS PROBLEMS

Ángel Rubén Barberis
Lorena Elizabeth del Moral Sachetti
https://doi.org/10.37572/EdArt_25082263715

CAPÍTULO 16 215

LOS DECENIOS DE ACCIÓN PARA LA SEGURIDAD VIAL: RECAPITULACIÓN GENERAL Y REFLEJO EN COSTA RICA

Carlos Contreras-Montoya
https://doi.org/10.37572/EdArt_25082263716

CAPÍTULO 17 228

ACOMPANHAMENTO ARQUEOLÓGICO E MÉTODO. CONTRIBUTO PARA O SEU ENQUADRAMENTO LEGAL

Iva João da Silva Teles Morais Botelho
https://doi.org/10.37572/EdArt_25082263717

SOBRE OS ORGANIZADORES 248

ÍNDICE REMISSIVO 249

CAPÍTULO 15

STATISTICAL ANALYSIS OF CONVERGENCE FOR NON-LINEAR OPTIMIZATION ALGORITHMS IN CALL CENTERS PROBLEMS

Data de submissão: 15/05/2022
Data de aceite: 10/06/2022

Ángel Rubén Barberis
Facultad de Ciencias Exactas de la Universidad Nacional de Salta
Doctor de la Universidad de Buenos Aires en Ciencias de la Computación
Magister de la Universidad de Buenos Aires en Simulación Numérica y Control
Licenciado en Análisis de Sistemas
Salta-Capital, Argentina

Lorena Elizabeth del Moral Sachetti
Sede Regional Orán de la Universidad Nacional de Salta
Especialista en Psicopedagogía Institucional de la Universidad Nacional de Salta
Licenciada en Análisis de Sistemas
San Ramón de la Nueva Orán-Salta Argentina

ABSTRACT: Call center optimization is not an easy problem to solve, due to the complexity of the mathematical models that derive from Erlang formulas. This complexity is transferred to optimization models, which in most cases, conform to non-linear, non-convex and non-derivable objective functions. As in all areas of Operations Research, solving these problems demands efficient, fast and accurate algorithms. In most nonlinear optimization problems with constraints, the researcher is faced with the difficulty of verifying and validating the correct functioning of the algorithm. In many cases, computational complexity makes it difficult to estimate the result by brute force. The usual way is to have a set of similar problems or well-defined equivalents, and with known results metrics with which it can be contrasted. The problem is that you don't always have these repositories. The need to have a strategy to validate the convergence and precision of a numerical sequence generated by an optimization algorithm becomes imperative. This work describes a statistical method to quickly evaluate the convergence and accuracy of algorithms that generate numerical sequences in the approximation of a result.
KEYWORDS: Non-linear optimization. Convergence of optimization algorithms.Integer Nonlinear Optimization. Call Center Optimization.

1 INTRODUCTION

Optimizing operational resources in Call Center problems is a difficult process to solve accurately, mainly due to the complexity of Erlang's models, especially when trying

to approximate reality. Although the mathematical formulations for the Erlang-A queue models (M/M/n + G) are available, they are too complicated to derive analytical and algorithmic solutions for Call Center problems. Therefore, solving issues such as estimating the additional number of operators needed when the volume of incoming calls is doubled, or determining the sensitivity of the model when there are errors in the estimation of patience (Zeltyn et al., 2005), among others, is usually a difficult task.

The optimal administration of Call Center pursues, mainly, two opposing objectives: 1) Optimal operational dimensioning, which seeks to minimize the cost in hiring personnel; and 2) Maximum service levels, which seeks to maximize user satisfaction. The first goal is achieved by solving integer linear optimization problems. Under conditions of convexity for functions there is a robust theory in the literature that guarantees the global solution of problems, as well as a wide development of efficient algorithms (Robbins et al., 2010; Ingolfsson et al., 2010). Achieving the second goal involves solving an integer nonlinear optimization problem. Most engineering and applied science problems involve optimization models with non-convex and non-derivable functions, resulting in complex resolution due to the existence of multiple local optimums. This requires the creation of procedures to deal with these difficulties during the search for good solutions that may not be optimal but satisfactory. To say that a solution is satisfactory implies the realization of a set of previous activities that guarantee that the algorithm converges to a limit point, and that its approximation is in an acceptance interval. Validating the reliability of the algorithmic result of a restricted, non-convex, non-derivable nonlinear problem is a complex task, especially if you do not have in the literature well-defined problem repositories, with known results metrics with which it can be contrasted. Consequently, several researchers use simulation as a comparison tool, supported by confidence intervals (Kim et al., 2011). In order to use simulation in convergence analysis, statistical theory is used to extract from it, some concepts such as Residual Analysis and Empirical Rule 68-95-99. The evaluation of kurtosis is incorporated into the analysis for sample data that follow a normal distribution. Simulation is used as a valid frame of reference for the generation of empirical residual samples on which the new method is developed.

The present work shows a statistical procedure that allows to quickly study the convergence and precision of results obtained by algorithms that approximate a solution to non-linear problems. Section 2 describes the conceptual framework considered for the development of the method. Section 3 describes the rapid convergence validation process. Finally, in section 4, the conclusions are presented.

2 CONCEPTUAL REFERENCE FRAMEWORK

2.1 RESIDUAL ANALYSIS

The *residual analysis* is the tool used to evaluate the suitability of a linear regression model against a set of experimental data by defining residuals and verifying statistical assumptions through the analysis of residual plots (Topp et al., 2004; Asuero et al., 1989).

The main statistical assumptions regarding the regression model that are verified with the residuals plot are (Black, 2010; Massart et al., 2003):

1. The generation of residuals must have a random behavior and be independent and identically distributed.
2. All residuals must have the same variance. This means that the variance must be constant throughout the dynamic concentration range of the residuals. This property is known as *homoscedasticity*.
3. All residuals must be random variables with (approximately) normal distribution with mean 0, therefore the expected value of residuals must be 0.

The verification of properties, such as being independent and identically distributed, leads to the fulfillment of other implicit assumptions (Korner-Nievergelt et al., 2015).

Once the residual *independence is* verified, it implies the fulfillment of assumptions such as: ***a)*** the residuals are not correlated with any other variable included or not in the model; ***b)*** The residuals are not grouped (i.e., the sample means of any set of residuals should all be equal); ***c)*** The residuals are not autocorrelated (i.e., no temporal or spatial autocorrelation exist).

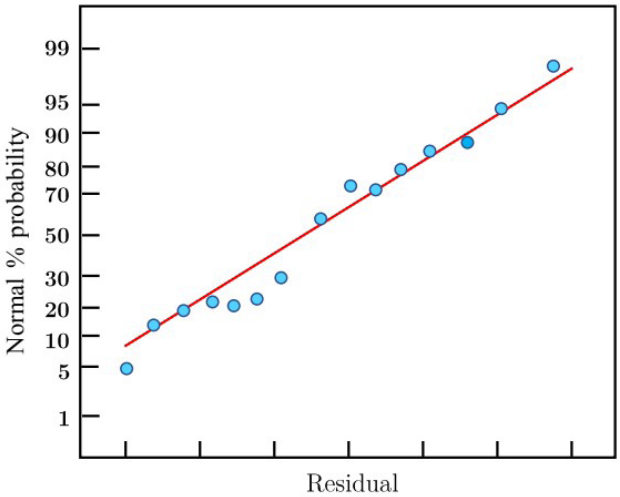
On the other hand, to say that the residuals are *identically distributed* means that: ***a)*** All the residuals come from the same distribution. In the case of a linear regression, it is assumed that they all come from the same normal distribution; ***b)*** The residual variance is homogeneous, that is, the homoscedasticity property is fulfilled; ***c)*** The mean of the residuals is zero throughout the range of predictor values. When numerical predictors (covariates) are present, it implies that the relationship between the independent and dependent variable can be adequately described by a straight line in the plane.

The difference between the observed values of the dependent variable (y) and the values predicted by the model ($\hat{y}$) is called *residual* (e) (Martin et al., 2017). Also known as *error.* That is:

$$Residuals\ (e) = Observed\ values\ (\hat{y}) - values\ predicted\ by\ the\ model\ (y) \Rightarrow e = y - \hat{y}$$

Where $\sum e_i = 0$ and $\overline{e} = 0$ provided that the statistical assumptions are fulfilled.

Figure 1: Residuals with normal distribution.

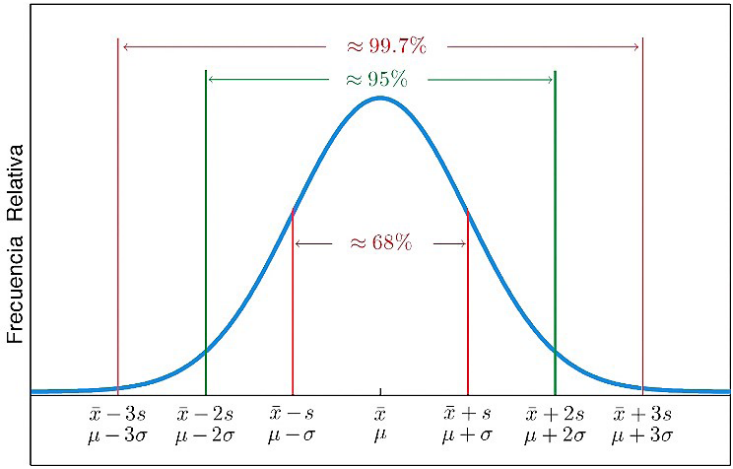


A residual plot shows the residuals on the vertical axis and the independent variable on the horizontal axis. When the points on the graph are randomly scattered around the horizontal axis, the linear regression model is considered appropriate for the data. A quick way to check the assumption of normality is to analyze the trend of the graph. If the residuals are drawn approximately along or over the straight line as in figure 1, then the normality assumption is fulfilled (Myers et al., 2009), which implies immediately satisfying the assumptions of implication mentioned above. From the conceptual point of view, the analysis of residuals constitutes a simple tool that facilitates the detection of errors and the verification of the degree of approximation between an empirical or theoretical equation with experimental results (Tomàs et al., 2006).

2.2 EMPIRICAL RULE OR 68–95–99

Using a central estimate such as the mean or median along with a measure of variation (such as the standard deviation or interquartile range) in a sampling distribution is a good way to describe the values or behavior of a population. In case that the relative frequency histogram of the data has the shape of a bell (or has an approximately normal distribution), the population mean and the standard deviation are the appropriate combination to study variability or dispersion, and a special rule links them to obtain fairly detailed information about the general population. This rule is the so-called *empirical rule*, also known as the 68–95–99 rule (Rumsey, 2016).

Figure 2: Empirical Rule. Percentage data according to distance from the mean.

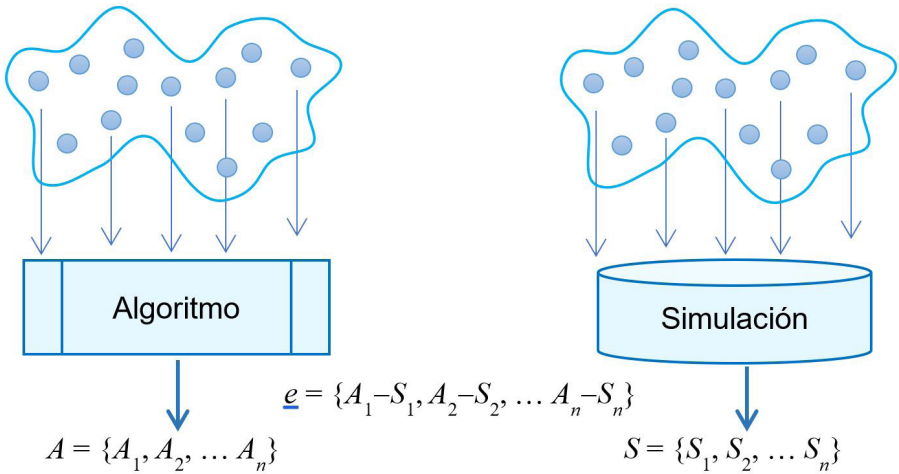


The empirical rule is a general rule that is used to indicate the approximate percentage of sample values that are found within the interval formed by the standard deviations with respect to the sample mean, when these are normally distributed (Black, 2010). The rule is generally applied to a random variable that follows a normal distribution, with mean μ and standard deviation σ. An important characteristic expresses that, if the distribution of the data is more or less symmetric, unimodal and follows a normal law or an approximation to it, then approximately 68.27% of the data are concentrated within the range $\mu \pm \sigma$; 95.45% within $\mu \pm 2\,\sigma$, and 99.73% within $\mu \pm 3\,\sigma$. Figure 2 illustrates the three intervals of the 68–95–99 rule. An important point to keep in mind is that the empirical rule does not apply to data sets with very asymmetric distributions.

2.3 RESIDUAL EMPIRICAL VALIDATION PROCESS

The objective is to know if the optimization algorithm executed with different initial points from the decision space converges to the same limit point, and if this is close to the solution of the problem under study or not. The conclusions are developed from statistical comparisons between the outputs of a simulation process and the deterministic results obtained by the objective algorithm.

Figure 3: Residuals Sample formation process.



The procedure consists in generating observations from the results of the algorithm which are obtained from *m* executions with *m* different starting points from the decision space. The simulation processes are also started with the *m* different points used by the algorithm, see the diagram in figure 3. If A_i is the observed value obtained as a result of the algorithm executed in the *i*-th experiment, and S_i the estimation of the same study variable obtained by simulation in the *i*-th process, then the residues $r_i = A_i - S_i$, $\forall i = 1 \ldots m$, form the residual random variable *R*. Thus, if $A_i \to E(S_i)$ then $E(R) \to 0$. After generating the sample, the residuals analysis is performed to ensure fulfillment of the statistical assumptions. Failure to comply with some of the assumptions implies increasing simulation times and generating a new sample of simulation observations using the process of the alternative not chosen. If some of the statistical assumptions of the analysis of residuals were to fail again, then the hypothesis that the algorithm converges to the solution of the problem under study is rejected. In the case that all the assumptions are verified, it is considered that the algorithm tends to converge to a limit point that may or may not be close to the solution of the target problem. The next step is to analyze the degree of concentration of the residues around the central measure. The estimate is obtained from the Kurtosis indicator, which measures the degree of flatness or tailedness of the shape of the sample distribution with respect to the normal curve (Khurshid et al., 2007). In the comparison with the normal distribution curve, if the kurtosis indicator is greater than 0, the sample distribution will be Leptokurtic; if it is equal to 0 it will be Mesokurtic, (it indicates that it has a normal distribution); however, if the indicator is less than 0, the distribution will be

Platykurtic (Chissom, 1970, Pearson, 1905). For a successful application of the empirical rule, a kurtosis indicator larger or equal to 0 is desirable. This will give rise not only to a successful validation of the algorithm's convergence, but also to a convergence with an acceptable degree of precision.

Once the kurtosis condition is satisfied, the results derived from the Standard Deviation (σ) will be studied in its three values: σ, 2σ and 3σ , according to the *68-95-99 empirical rule*. It is desirable that 100% of the algorithmic results are within an acceptable approximation range around the solution. As it is a statistical study, it will be sought that at least a certain percentage of the algorithmic results have an acceptable precision, which implies setting an upper bound of 2σ or 3σ, which will depend on the type of problem to be solved. Thus, for example, for the case study described in section 3.2, which seeks to determine the optimal distribution policy of working shifts for the operators of a Call Center, which maximize service levels (SL), requires that 2σ or 3σ be less than 1 – since, the SL is quantized in the real range (0, 1] – to ensure that at least 95% of the algorithmic results are within the precision range.

3 RAPID CONVERGENCE VALIDATION PROCESS

The validation of the algorithm, aims to give reliability in stability and convergence towards a satisfactory result, considering certain precision. The method consists of 7 steps, of which the first 5 corresponds to the study of convergence towards a limit point; and the last 2, to the study of the proximity of the limit point to the solution of the optimization problem.

3.1 GENERATION OF INDEPENDENT AND IDENTICALLY DISTRIBUTED SAMPLES

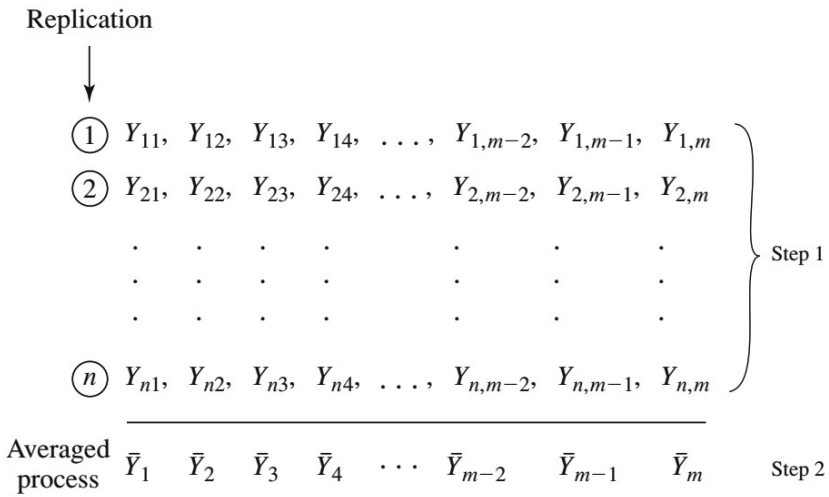
Each point of the decision space of the optimization problem is the starting point of the algorithm that concludes with a result. It is convenient to design a grid of points that covers the total area of the decision space. The objective algorithm will generate as many results as there are points in the grid. In an ideal convergence scenario, all the results given by the algorithm for a particular optimization problem must be exactly the same. The algorithmic process is numerical and the results should be at least approximately equal for successful validation. The numerical reference series can come from a deterministic or stochastic numerical process and are approximately equal with acceptable precision as much as you want. In case any of the numerical series comes from a stochastic process a new sample is selected with one of the two alternatives:

1) Perform *n* different executions of the simulation and extract from them a subset of *m* ($m < n$) results of the study variable, preferably those with the greatest variability. This will lead to *m* observations. Or,

2) Form *n* groups of *m* different simulation executions, with *n* different seeds for the generation of pseudo-random numbers (each group uses the same seed for the *m* simulations). Each group of *m* simulation results forms a row of the matrix of size $n \times m$. Then, a new random sample is designed by averaging the values of each column of the matrix, as shown in figure 4, thus generating, m values observed, with characteristics of being independent (Law et al., 2000).

From either alternative, m independent observations are obtained, identically distributed, and approximately normal, very convenient for the generation of residuals.

Figure 4: Sample formation process from simulations.



3.2 VERIFICATION OF THE ASSUMPTION OF NORMALITY. RESIDUALS GRAPHIC

The result of the previous step does not guarantee that the residual sample is independent and identically distributed when both numerical series come from deterministic processes. It is sought in all cases, that the residuals sample has a distribution, at least approximately normal. A rapid verification of the normal assumption is to analyze the normal probability graph of residuals. In the graph, they will show the residuals on the vertical axis and the independent variable on the horizontal axis. If the points in the residual graphic are randomly dispersed around the horizontal axis, then the normality assumption is verified, since the residuals is approximately along or on the line of trend. Once the assumption of normality is fulfilled, it implies immediately satisfying the

assumptions of Step 1. From the conceptual point of view, the residuals analysis forms a simple tool that facilitates the detection errors and the verification of the degree of approximation between an empirical or theoretical equation with results with results with results experimental.

3.3 NORMALITY VALIDATION IN THE RESIDUALS SAMPLE

Step 2 can be considered subjective, since it depends on the estimates and details sought by the observer. Therefore, rapid validation to demonstrate that the residuals are distributed (approximately) normal is to verify that $\sum e_i \rightarrow 0$ and $\overline{e} \rightarrow 0$.

3.4 AUTOCORRELATION TEST IN THE RESIDUALS SAMPLE

The independence of residuals values with each other is key to demonstrating that residual is randomly distributed according to a normal distribution. To demonstrate the existence or not of autocorrelation, the Durbin-Watson indicator (Durbin et al., 1950) is used, whose expression is shown in Figure 5, which takes value 2 when the residual is completely independent, from the theoretical point of view.

Figure 5: Durbin-Watson indicator.

$$DW = \frac{\sum_{i=2}^{n} (e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \quad ; \quad 0 \leq DW \leq 4$$

A *DW*< 2 indicates positive autocorrelation, and a *DW* >2 a negative autocorrelation. In practice when *DW* is between 1.5 and 2.5 it is considered that there is independence. To calculate this, the *DW* statistic is compared with critical values according to the level of significance α. These values are tabulated for the critical estimators d_L and d_U (Durbin et al., 1951).

The null hypothesis H_0 is contrasted against the alternative H_a, where H_0 = *The residuals are not autocorrelated* and H_a = *The residuals are autocorrelated*. The null hypothesis H_0 is not rejected if the result $DW \in [d_U ; 4 - d_U]$.

3.5 TEST DE HOMOSCEDASTICITY

To demonstrate homoscedasticity, the *Bartlett Test* is used (Bartlett, 1937). This defines the null hypothesis, H_0 that the variances of *k* independent samples of a

population are equal, versus the alternative hypothesis that at least two are different. The statistic is shown in Figure 6. The test statistic *T* has a distribution which is approximately χ^2_{k-1}. Due to this, the null hypothesis is rejected if *T* > $\chi^2_{k-1,\alpha}$ with a significance level α.

Figure 6: Bartlett statistic.

$$T = \frac{(N-k)\ \ln(S_p^2) - \sum_{i=1}^{k}(n_i-1)\ \ln(S_i^2)}{1+\frac{1}{3(k-1)}\left\{\left(\sum_{i=1}^{k}\frac{1}{n_i-1}\right)-\frac{1}{N-k}\right\}} \quad donde \quad N=\sum_{i=1}^{k} n_i \quad ; \quad S_p^2 = \frac{\sum_{i=1}^{k}(n_i-1)\ S_i^2}{N-k}$$

The non-verification of some of steps 2 to 5 implies that the numerical sequence generated by the objective algorithm does not converge to a limit point, so the validation process is interrupted with a negative conclusion. Otherwise we proceed with steps 6 and 7.

3.6 KURTOSIS ANALYSIS

The next step is to analyze the degree of accuracy of the convergence. To do this, the degree of tailedness of the approximately normal distribution of the residuals sample is measured, which is achieved with the kurtosis indicator. The Joanes Kurtosis Indicator is proposed, which is unbiased for normal distributions (Joanes et al., 1998). The expression is shown in Figure 7, where *S* denotes the standard deviation.

Figure 7: Joanes Kurtosis Indicator.

$$K = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_j-\bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

For a successful application of the empirical rule, an indicator of kurtosis *K* greater than or equal to zero is desirable, which will lead not only to a successful validation of the convergence of the algorithm, but also to a convergence with an acceptable degree of precision.

3.7 ANALYSIS BY EMPIRICAL RULE → DEGREE OF PRECISION

Considering the previous result, and by application of empirical rule *68-95-99,* it is known that 99.7% of the observations are concentrated in the range either in [$\bar{x}$ –3σ; $\bar{x}$ +3σ] or in [μ –3σ; μ +3σ]. Therefore, to statistically estimate the degree of proximity of the limit point to the solution of the optimization problem, it is necessary to set an upper

bound for 3σ. If the residual sample generates a value of 3σ greater than said bound, then it would be concluded that the limit point to which the algorithm converges does not have the desired proximity to the solution of the objective problem. Otherwise, the algorithm result is accepted as an approximate solution of the optimization problem.

4 CONCLUSIONS

The statistical method presented is a fast technique to demonstrate convergence and accuracy of the results by algorithms, which in their process, generate numerical series. Residual analysis is a statistical process used to study approximation characteristics in regression models. In this work, this process is shown as a key resource in the study of convergence of optimization algorithms in nonlinear problems. The combination of the kurtosis indicator with the empirical rule 68-95-99 made it possible to estimate the degree of similarity between the results obtained by the algorithm and those of simulation. The computational tests in which the technique was used, included non-linear optimization problems of small and medium size, up to dimension 1000. These tests included Call Center problems with constraints and non-linear, non-convex, non-derivable objective functions that do not configure quadratic models and on a discrete domain. The technique showed satisfactory and encouraging experimental results. It is risky and premature to establish conclusive and final conclusions of the general applicability of the technique in all areas of optimizations in the field of Operations Research, so it is necessary to extend the study for the generalization of the technique to other fields of knowledge. The Residual Empirical Validation technique could be a way to begin to discuss the convergence of optimization algorithms whose results are wrapped in a blanket of uncertainty.

REFERENCES

Asuero, A. G. and Gonzalez, A. G. (1989) Some observations on fitting a straight line to data. Microchemical Journal, 40 (2), 216-225.

Barberis, A. R. and Del Moral Sachetti, L. E. (2011) Modelización, Simulación y Optimización del personal operativo en la administración de Call/Contact Center. In: Simposio de Investigación Operativa 2011 - 40 JAIIO. Córdoba, Argentina: SADIO, pp. 103-120.

Barberis, A. R. and Del Moral Sachetti, L. E. (2019) Programación No Lineal Entera en la Planificación Óptima de Turnos para un Modelo de Call Center. In: VII Congreso de Matemática Aplicada, Computacional e Industrial - MACI 2019. S10-Métodos Numéricos: Algoritmos y Aplicaciones. Río Cuarto, Córdoba. Argentina: ASAMACI, Vol. 7, pp. 201-204.

Bartlett, M. S. (1937) Properties of Sufficiency and Statistical Tests. Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences, 160 (901), 268-282.

Black, K. (2010) Business Statistics: For Contemporary Decision Making. 6 ed. John Wiley. USA.

Chissom, B. S. (1970) Interpretation of the Kurtosis Statistic. The American Statistician, 24 (4), 19-22.

DeCarlo, L. T. (1997) On the meaning and use of kurtosis. Psychological Methods, 2 (3), 292-307.

Durbin, J. and Watson, G. S. (1950) Testing for Serial Correlation in Least Squares Regression: I. Biometrika, 37 (3/4), 409-428.

Durbin, J. and Watson, G. S. (1951) Testing for Serial Correlation in Least Squares Regression. II. Biometrika, 38 (1/2), 159-177.

Ingolfsson, A., et al. (2002) Accounting for time-varying queueing effects in workforce scheduling. European Journal of Operational Research, 139 (3), 585-597.

Ingolfsson, A., et al. (2010) Combining integer programming and the randomization method to schedule employees. European Journal of Operational Research, 202 (1), 153-163.

Joanes, D. N. and Gill, C. A. (1998) Comparing measures of sample skewness and kurtosis. Journal of the Royal Statistical Society: Series D (The Statistician), 47 (1), 183-189.

Khurshid, A., et al. (2007) A note on finding peakedness in bivariate normal distribution using Mathematica. Pakistan Journal of Statistics and Operation Research, 3 (2), 75-86.

Kim, S.-M., et al. (2011) The Staffing Problem at the Call Center by Optimization and Simulation. IE Interfaces, 24 (1), 40-50.

Koole, G. and van der Sluis, E. (2003) Optimal Shift Scheduling with a Global Service Level Constraint. IIE Transactions, 35 (11), 1049-1055.

Korner-Nievergelt, F., et al. (2015) Chapter 6 - Assessing Model Assumptions: Residual Analysis. In: KORNER-NIEVERGELT, F., et al. (Eds.) Bayesian Data Analysis in Ecology Using Linear Models with R, BUGS, and STAN. Boston: Academic Press, pp. 75-94.

Law, A. M. and Kelton, W. D. (2000) Simulation Modelling and Analysis. (Series in Industrial Engineering and Management Science). 3 ed. McGraw-Hill Higher Education. New York, USA.

Martin, J., et al. (2017) Fitting Models to Data: Residual Analysis, a Primer - Chapter 7. In: HESSLING, J. P. (Ed.) Uncertainty Quantification and Model Calibration. Rijeka: IntechOpen, pp. 133-173.

Massart, D. L., et al. (2003) Chemometrics: a Textbook. (Data Handling in Science and Technology). Vol. 2. Elsevier Science B.V. Hungary.

Myers, R. H., et al. (2009) Response Surface Methodology: Process and Product Optimization Using Designed Experiments. (Wiley Series in Probability and Statistics). 3 ed. John Wiley & Sons, Inc. Hoboken, New Jersey, USA.

Pearson, K. (1905) Das Fehlergesetz und Seine Verallgemeinerungen Durch Fechner und Pearson. A Rejoinder (Skew Variation, a Rejoinde). Biometrika, 4 (1/2), 169-212.

Robbins, T. R. and Harrison, T. P. (2010) A stochastic programming model for scheduling call centers with global Service Level Agreements. European Journal of Operational Research, 207 (3), 1608-1619.

Rumsey, D. J. (2016) Statistics For Dummies. 2 ed. Wiley Publishing, Inc. Indianapolis, Indiana, USA.

Tomàs, X., et al. (2006) Introducción al Cálculo Numérico. Institut Químic de Sarrià (IQS). Departament d'Estadística Aplicada. Barcelona, España.

Topp, R. and Gómez, G. (2004) Residual analysis in linear regression models with an interval-censored covariate. Statistics in medicine, 23 (21), 3377-3391.

Zeltyn, S. and Mandelbaum, A. (2005) Call Centers with Impatient Customers: Many-Server Asymptotics of the M/M/n + G Queue. Queueing Systems, 51 (3), 361-402.

SOBRE OS ORGANIZADORES

Jorge José Martins Rodrigues é Economista. Licenciado, mestre e doutor em Gestão (ISCTE-IUL). Mestre e pós doutorado em Sociologia – ramo sociologia económica das organizações (FCSH NOVA). Professor coordenador no ISCAL – *Lisbon Accounting and Business School* / Instituto Politécnico de Lisboa, Portugal. Exerceu funções de direção em gestão (planeamento, marketing, comercial, finanças) no setor privado, público e cooperativo. É investigador integrado no Instituto Jurídico Portucalense. Ensina e publica nas áreas de empresa familiar e família empresária, estratégia e finanças empresariais, gestão global, governabilidade organizacional, marketing, planeamento e controlo de gestão, responsabilidade social e ética das organizações.

Maria Amélia Marques, Doutora em Sociologia Económica das Organizações (ISEG/ULisboa), Mestre em Sistemas sócio-organizacionais da atividade económica - Sociologia da Empresa (ISEG/ULisboa), Licenciada (FPCE/UCoimbra), Professora Coordenadora no Departamento de Comportamento Organizacional e Gestão de Recursos Humanos (DCOGRH) da Escola Superior de Ciências Empresariais, do Instituto Politécnico de Setúbal (ESCE/IPS), Portugal. Membro efetivo do CICE/IPS – Centro Interdisciplinar em Ciências Empresariais da ESCE/IPS. Membro e Chairman (desde 2019 da ISO-TC260 HRM Portugal. Tem várias publicações sobre a problemática da gestão de recursos humanos, a conciliação da vida pessoal, familiar e profissional, os novos modelos de organização do trabalho, as motivações e expectativas dos estudantes Erasmus e a configuração e dinâmica das empresas familiares. Pertence a vários grupos de trabalho nas suas áreas de interesses.

ÍNDICE REMISSIVO

A

Acompanhamento Arqueológico 228, 229, 230, 231, 232, 233, 235, 236, 237, 244, 247
Administração 20, 23, 25, 33, 61, 62, 63, 66, 69, 71, 72, 73, 74, 76, 78, 79, 80, 157, 232, 235
Afetos 133, 149, 151, 244
American Depositary Receipts (ADRs) 1, 3
Apropiación Social 97, 186
Área Rural 184, 185, 186, 193, 199
Artigos 35, 43, 50, 61, 62, 68, 76, 78, 232
Autocracia 133, 139, 142

B

Bem-estar social 153
Biblioteca digital 35, 36, 39, 40, 42, 44
Bibliotecas do ensino superior 36
Biocompost 185, 186, 187, 188
B-on 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46

C

Call Center Optimization 202
Coeficiente de respuesta al resultado (CRR) 1, 3
Colonialismo 113, 165, 166, 168, 177, 179, 180, 181
Comandante das Operações de Socorro 19
Consejo de Seguridad Vial de Costa Rica - Cosevi 215
Contador Público 81, 82, 83, 84, 87, 90, 91
Contrologia 161, 162, 163, 164
Convergence of optimization algorithms 202, 212
Coreografias Didáticas 48, 49, 50, 52, 54, 57, 58, 59
Corpo da mulher negra 165, 166, 171, 177, 178, 179

D

Day 61, 62, 64, 66, 68, 70, 71, 72, 73, 74, 75, 76, 77, 78, 110
Decenios de Acción 215
Docencia 92, 93, 94, 98, 105, 106

E

Economia 7, 38, 67, 69, 88, 103, 107, 126, 138, 147, 149, 152, 153, 154, 155, 156, 157, 158, 159, 160, 187, 194
Educação Aberta 48, 49, 50, 51, 52, 59
Enquadramento Legal 228, 229, 234, 238
Equilíbrio corpo e mente 161
Estudo de utilizador 36
Ethos 110, 111, 112, 114, 116, 117, 118, 119, 120, 136
Ética Profesional 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91
Extensión 18, 92, 93, 94, 96, 97, 98, 103, 105, 108, 186, 188, 201, 216

G

Generación Milenio 125
Geração 68 133, 134, 137, 139, 144, 145, 146

H

Hipersexualização e objetificação 165, 166, 167
História do Pensamento Econômico 153
História econômica 153

I

Índice de mortalidad 215
Innovación 46, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 107, 108, 127, 132, 185, 187, 192
Integer Nonlinear Optimization 202, 203
Intervenções Estruturais 19, 21, 23, 24, 27, 28, 29, 30, 32, 33
Investigación 3, 4, 5, 8, 16, 81, 82, 86, 87, 89, 90, 92, 93, 94, 96, 97, 98, 99, 102, 103, 104, 105, 106, 108, 126, 185, 196, 200, 212, 224, 225

J

Junta de normas de contabilidad financiera en EE. UU. (FASB) 1

L

Liberdade de imprensa 110, 111, 112, 113, 114, 116, 117, 118, 120

M

Memória 25, 133, 135, 148, 149, 150, 151, 168, 177, 179, 229

Método 10, 54, 63, 79, 92, 94, 98, 110, 112, 117, 120, 155, 160, 162, 163, 164, 165, 167, 170, 172, 178, 228, 244, 246

N

Non-linear optimization 202, 212
Normas de contabilidad en EE. UU. (U.S. GAAP) 1
Normas Internacionales de Información Financiera (NIIF) 1, 2

O

Organización 83, 84, 88, 95, 105, 125, 128, 129, 216, 227

P

Pilates 161, 162, 163, 164, 165
Portugal 19, 20, 33, 35, 45, 46, 48, 50, 51, 60, 228, 229, 230, 231, 241, 245
Profesión Contable 81, 82, 83, 87, 88, 90
Pymes 125, 129

R

Rede Académica Internacional WEIWER® 48, 49, 50, 59
Relações de poder e autoritarismo 110
Residuos de cultivos 186
Retórica 61, 62, 63, 64, 66, 68, 72, 78, 79, 80, 116, 121

S

Segurança Contra Incêndio em Edifícios 19, 20, 33
Seguridad Vial 215, 216, 217, 218, 219, 221, 222, 225, 226, 227
Sostenibilidad 82, 92, 98, 105, 186

T

Tecnologias Educacionais em Rede 48, 49, 59
Tomada de Decisão 19, 22, 24, 26, 28, 29, 30, 32, 34, 159
Transformación 7, 94, 96, 102, 103, 105, 125, 131, 132, 190, 196, 198

U

Universidad 35, 46, 81, 82, 86, 90, 92, 93, 96, 97, 98, 100, 104, 106, 107, 125, 202

V

Valor de pertinencia 1, 3, 5, 6, 7, 8, 15, 16

W

Wikipédia 48, 49, 50, 51, 52, 54, 55, 56, 57, 58, 59, 60, 90, 173