REVISTA DE GESTÃO E SECRETARIADO
MANAGEMENT AND ADMINISTRATIVE PROFESSIONAL REVIEW
ISSN: 2178-9010

Revista GeSec
São Paulo, SP, Brasil
v. 14, n.3, p. 3348-3367, 2023

DOI: http://doi.org/10.7769/gesec.v14i3.1809

Scientific research trends about metaheuristics in process optimization and case study using the desirability function

Tendências de pesquisa científica sobre meta-heurística na otimização de processos e estudo de casos usando a função de desejabilidade

Ronald Palandi Cardoso[1]
José Salvador da Motta Reis[2]
Dayana Elizabeth Werderits Silva[3]
Maria da Glória Diniz de Almeida[4]
José Glenio Medeiros de Barros[5]
Nilo Antonio de Souza Sampaio[6]

Abstract

This study aimed to identify the research gaps in Metaheuristics, taking into account the publications entered in a database in 2015 and to present a case study of a company in the Sul Fluminense region using the Desirability function. To achieve this goal, applied research of exploratory nature and qualitative approach was carried out, as well as another of quantitative nature. As method and technical procedures were the bibliographical research, some literature

[1] Mechanical Engineering Undergraduate, Universidade do Estado do Rio de Janeiro, Rod. Pres. Dutra, km 298, Polo Industrial, Resende - RJ, CEP: 27537-000. E-mail: ronaldpalandi0805@gmail.com
[2] Master in Production Engineering, Universidade do Estado do Rio de Janeiro, Rod. Pres. Dutra, km 298, Polo Industrial, Resende - RJ, CEP: 27537-000. E-mail: jmottareis@gmail.com
[3] Master in Environmental Technology, Universidade do Estado do Rio de Janeiro, Rod. Pres. Dutra, km 298, Polo Industrial, Resende - RJ, CEP: 27537-000. E-mail: daywerder@gmail.com
Orcid: https://orcid.org/0000-0003-2397-4396
[4] Master in Environmental Technology, Universidade do Estado do Rio de Janeiro, Rod. Pres. Dutra, km 298, Polo Industrial, Resende - RJ, CEP: 27537-000. E-mail: gloria_uerj@yahoo.com.br
Orcid: https://orcid.org/0000-0002-0645-8907
[5] Doctor of Mechanical Engineering, Universidade do Estado do Rio de Janeiro, Rod. Pres. Dutra, km 298, Polo Industrial, Resende - RJ, CEP: 27537-000. E-mail: glenio.barros@gmail.com
Orcid: https://orcid.org/0000-0002-6902-599X
[6] PhD in Mechanical Engineering, Universidade do Estado do Rio de Janeiro, Rod. Pres. Dutra, km 298, Polo Industrial, Resende - RJ, CEP: 27537-000. E-mail: nilo.samp@terra.com.br

review, and an adopted case study respectively. As a contribution of this research, the holistic view of opportunities to carry out new investigations on the theme in question is pointed out. It is noteworthy that the identified study gaps after the research were prioritized and discriminated, highlighting the importance of the viability of metaheuristic algorithms, as well as their benefits for process optimization.

Keywords: Statistical Software. Optimizer. Modeling. Desirability Function.

Resumo

Este estudo teve como objetivo identificar as lacunas de pesquisa em Metaheurística, levando em conta as publicações inseridas em um banco de dados em 2015 e apresentar um estudo de caso de uma empresa na região do Sul Fluminense utilizando a função Desejável. Para atingir este objetivo, foram realizadas pesquisas aplicadas de caráter exploratório e qualitativo, bem como outra de caráter quantitativo. Como método e procedimentos técnicos foram a pesquisa bibliográfica, alguma revisão bibliográfica e um estudo de caso adotado, respectivamente. Como contribuição a esta pesquisa, é apontada a visão holística das oportunidades para realizar novas investigações sobre o tema em questão. É notável que as lacunas de estudo identificadas após a pesquisa foram priorizadas e discriminadas, destacando a importância da viabilidade dos algoritmos metaheurísticos, bem como seus benefícios para a otimização de processos.

Palavras-chave: Software Estatístico. Otimizador. Modelagem. Função de Desejabilidade.

Introduction

Algorithm development began in the 1960s and the rate of introduction of new Algorithms has been increasing steadily ever since. The sharp increase in the last decade indicates a growing number of researchers contributing to the research area (Rajpurohit et al., 2021). Algorithms that solve optimization problems consist of finding the best combination of a set of variables to improve a function, usually called the objective function or cost function (Mitić et al., 2015; Mohamed et al., 2017). These problems can be divided into three categories: variables with real values, variables with discrete values, and variables that mix integer and continuous values (Gomes, Pereira, Silva, et al., 2019; Rafieerad et al., 2017).

The current trend is to use nature-inspired metaheuristic algorithms to solve difficult problems, and metaheuristics have been shown to be very efficient (Askarzadeh, 2016).

Optimization methods are widely used to solve multiobjective optimization problems with objectives that generate conflicts. Reasonable tradeoffs between different objectives are considered (Gomes, Pereira, Marins, et al., 2019; Kalra & Singh, 2015). Combinatorial optimization is one of the most studied fields in artificial intelligence, optimization, logistics and other applications. Many scientific papers are published every year in this field, both in journals and conferences, as well as in books. There are different types of problems within this type of optimization, including routing problems as one of the most attractive (Osaba et al., 2016).

Considering the above, the research question that guided the realization of this work is: what are the main scientific gaps and research trends in metaheuristics to optimize mathematical systems? The objective of this work is to identify the existing scientific gaps on the subject, which will serve as a guide for future studies contributing to the advancement of this field of knowledge, show the connection of this subject with Design of Experiments (DOE) and show a case study using the Desirability function. Initially, the article addresses the concepts of different metaheuristic methods. In the sequence, the results and discussions of the proposed objectives are presented, and an application carried out with data from a company in the Sul Fluminense region is presented. Finally, the conclusion suggests future studies.

Theoretical Referential

Metaheuristic techniques are used in solving task scheduling problems, allowing an optimal allocation of resources among given tasks in a finite time to achieve the desired quality of service within the stipulated deadline. The scheduling problem involves tasks that must be scheduled on resources subject to some constraints to optimize objective functions **(ABDULLAHI ET AL., 2020; KALRA & SINGH, 2015)**. The Traveling Salesman Problem (TSP) and the Asymmetric Traveling Salesman Problem (ATSP) are two of the most well-known and widely studied problems throughout history in computer science and operations research. Like many other combinatorial routing and optimization problems, both problems are considered NP-hard. This is the main reason for their great scientific interest. Thus, TSP and all its variants are used in many research works every year as benchmarking problems (Osaba et al., 2016).

Particle Swarm Optimization (PSO) is an evolutionary computational technique introduced by Kennedy and Eberhart in 1995, motivated by the social behavior of particles

(Abdullahi et al., 2020; Kalra & Singh, 2015). Ant Colony Optimization (ACO) is inspired by the behavior of real ants that find the shortest path between their colonies and a food source. ACO is a technique based on swarm intelligence, proposed by Dorigo et al. for solving combinatorial problems. The ACO algorithm is originally inspired by the biological behavior of ants and specifically their mode of communication. This inspiration comes from the ability of real ants to find short paths in their movements to and from their nests when searching for food sources. However, ants do not communicate with each other directly (Kalra & Singh, 2015; Tolabi et al., 2016).

The Crow Search Algorithm (CSA) uses two adjustable parameters flight length and awareness probability. In CSA, the awareness probability parameter is directly used to control the diversity of the algorithm (Askarzadeh, 2016). Bats found in the wild come in various sizes, from microbats of 1.5-2g to giant bats that weigh up to 1kg. Echolocation is a technique used by bats to navigate and locate prey. Bats use frequency-modulated signals to sense distance, where each pulse lasts a few thousandths of a second (8-10 ms) within the frequency range of 25-100 KHz. Typically, bats emit 10-20 such pulses per second. However, when hunting, they can emit more than 200 pulses per second in the form of short bursts (Adarsh et al., 2016).

The exploratory and exploitative phases of the proposed HHO were modeled, inspired by the exploration of a prey, the surprise attack, and the different attack strategies of Harris's hawks. HHO is a population-based, gradient-free optimization technique; therefore, it can be applied to any optimization problem subject to a suitable formulation (Xu et al., 2019).

Determining a process improvement is typically complex due to variations in customer demand and technological advances. Generally, multiple responses must be considered to achieve an overall process improvement. It is important to note that an optimization process does not necessarily imply the determination of optimal operating conditions since it is practically impossible to establish the optimal point due to the large number of variables that impact a process. Instead, what can be determined are the improvement conditions from the selection of maximum points determined within a predetermined search space (Alketbi et al., 2022; Ding et al., 2020; Laidani et al., 2020; Rathod et al., 2020).

According to Pesteh et al., 2019, simultaneous optimization of multiple responses has been a priority in many branches of industry, and much effort has been directed toward researching alternative methods for efficiently determining a process tuning that achieves a given goal. Multi-response optimization problems often involve conflicting objectives, making them difficult to solve (Muniswamaiah et al., 2020), for example, the minimization of production time versus the minimization of equipment cost in manufacturing processes or the maximization of biomass production versus the minimization of substrate consumption in biotechnological processes. Currently, the most widely used process optimization method in scientific work is the joint employment of the Desirable agglutination method with the mathematical search method Generalized Reduced Gradient (GRG) (Bell et al., 2020; Goffe et al., 2020; Karthikeyan et al., 2020; Lebron et al., 2020).

A viable explanation for this fact is that this combination is present in the Minitab® software's Optimizer function, which would facilitate the execution of this method (Cardoso et al., 2023; Gomes, Pereira, Marins, et al., 2019). DOE is a structured and organized method used to determine the relationship between different process input and output factors, involving the definition of the set of experiments, in which all relevant factors are systematically varied. By analyzing the obtained results, one can determine the degree of influence on the response variable of each used factor, as well as the interactions between the factors and the optimum conditions (Chen et al., 2020; Korolchenko & Minaylov, 2020; Setiawati & Yusuf, 2020; Yang et al., 2020).

In processes with multiple responses, you should model each of the responses you wish to optimize by a function which describes the so-called Response Surface, i.e., which allows you to estimate the value of the response within the range of variation defined by the variables involved in the study. These functions (multiple regression equations) are usually obtained from the analysis of the results of experiments designed by Box-Behnken, Central Composite Design or three-level factorial designs, and are usually second-order equations which characterize these models and state that the Central Composite Design (CCD) model is the most widely used (Handoyono et al., 2020; Rajesh Ruban et al., 2020; Wang et al., 2020). A factor ignored by many studies using Design of Experiments (DOE) for process optimization, especially those involving multiple responses, is the individual quality of the models obtained (Derringer & Suich, 1980).

In many cases, one or more models end up having a low degree of fit. The success of the optimization process is closely linked to the robustness of the models (Gomes, Pereira, Silva, et al., 2019). When the optimization procedure involves more than one response, it is not possible to optimize each of them in one because a series of solutions equal to the variables under study would be gathered. In the optimization of a process or an analytical method, the global solution must be included in an optimal region, leading to a certain degree of compliance with the proposed criteria for each variable of the system; namely, a compromise solution must be found (Del Castillo et al., 1996; Natarajan et al., 2011; Ortiz et al., 2004; Vera Candioti et al., 2014).

2.1 Desirability Method

One of the most used techniques for simultaneously optimizing multiple responses is to transform the equations that model each of these responses into individual utility functions, and then proceed to optimize an overall utility function, known as Total Desirability (D), which is described as in terms of the individual utility functions. The simultaneous optimization of multiple responses thus becomes the optimization of a single function. The main drivers of this approach were Derringer and Suich (1980), and a benchmark for other methods in terms of the results it provides remains. This function is based on the idea that the quality of a product or process that has many characteristics is completely unacceptable if one of them falls outside a "desirable" limit. Its goal is to find the operating conditions that ensure that the criteria of all involved responses are met and, at the same time, provide the best value trade-offs in the desirable joint response. Furthermore, its easy interpretation and implementation motivated the method to be described and its performance (Cardoso et al., 2023; Gunst et al., 1996, 2011; Vera Candioti et al., 2014).

Scientific Method

Scientific research can be classified as to its nature, approach, objectives, and procedures. Regarding its nature, this work is characterized as applied research because it has practical interest so that the results can be applied and/or used in the solution of real problems. As for the objectives, this research is descriptive and exploratory (Alvarenga et al., 2021; Kothari & Garg, 2019; Reis et al., 2022; Reis et al. 2023; Silva et al., 2021).

Descriptive because it allows the description of the characteristics of the phenomenon observed in concerning the delimitation made in this project, and exploratory because it will provide the greater familiarity of the researcher with the research problem to provide greater contact/familiarity in loco with the elements to be studied, with a qualitative and quantitative approach (Araujo et al., 2021; Espuny et al., 2022; Reis et al., 2021; Sales et al., 2022). In March 2022, the data was processed, and the theoretical framework was found in the Scopus database, and the quantitative data analysis was made in January 2023.

Results and Discussions

The result section is divided in the step where the results of research trends in the topic are presented and, in another step, where a study with the Desarability function is performed.

4.1 Research Trends

The papers used in this investigation were ranked according to the citation index per title, which can be identified in Table 1. It should also be noted that the study gaps identified after the literature review were also listed. The most prominent paper according to the number of citations is "A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm", published in 2016 by Computers and Structures (ISSN 0045-7949) and was cited 432 times up to the time of data collection. Next comes "Symbiotic Organism Search optimization-based task scheduling in cloud computing environment", published in 2016 by Future Generation Computer Systems (ISSN 0167-739X) which has been cited 156 times up to the time of data collection.

Table 1. Identification of the gaps in the 50 most cited papers

Title	Author (year)	Scientific gaps	Citations
A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm	A. Askarzadeh (2016)	Analyze the advantages that the meta-optimizer heuristic raven search algorithm provides	432
Symbiotic organism search optimization based task scheduling in cloud computing environment	Abdullahi et al. (2016)	Analyze the advantages of the symbiotic organism search algorithm scheduling	156
A review of metaheuristic scheduling techniques in cloud computing	Kalra and singh (2015)	Identify the applicability of the meta-heuristic scheduling algorithm for cloud environments	149
An improved discrete bat algorithm for symmetric and asymmetric traveling salesman problems	Osaba et. Al (2016)	Propose a descriptive reversal of the improved discrete bat algorithm for optimization of processes	139
A social spider algorithm for global optimization	Yu and li (2015)	Identify the feasibility of the swarm intelligence algorithm inspired by the social nature of spiders in optimization processes	134
Economic dispatch using chaotic bat algorithm	Adarsh et al. (2016)	Propose a comparison of chaotic sequences for optimization problems	127
Harris hawks optimization: algorithm and applications	Heidari et al. (2015)	Propose the use of the harris hawks optimizer method for problem solving	124
Simultaneous reconfiguration, optimal placement of dstatcom, and photovoltaic array in a distribution system based on fuzzy-aco approach	Tolabi, ali and rizwan (2015)	Evaluate the feasibility of combining a multiobjective fuzzy effect with the optimization of ant colony optimization	118
A modified flower pollination algorithm for global optimization	Nabil (2016)	Propose an improved variant of the flower pollination algorithm in solving optimization problems	106

Hybrid artificial intelligence approach based on neural fuzzy inference model and metaheuristic optimization for flood susceptibilitgy modeling in a high-frequency tropical cyclone area using gis	Bui et al. (2016)	Identify the advantages of artificial intelligence based on fuzzy neural inference system in process optimization	95
Optimal integration and planning of renewable distributed generation in the power distribution networks: a review of analytical techniques	Ehsan and yang (2018)	Propose the use of artificial intelligence to optimize the planning and distribution of renewable energy	93
Hybrid methods for fuzzy clustering based on fuzzy c-means and improved particle swarm optimization	Silva filho et al. (2015)	Evaluate the viability of hybrid methods in the optimization of processes with multiple output variables	92
A new feature selection method to improve the document clustering using particle swarm optimization algorithm	Abualigah et al. (2018)	Evaluate the benefits of bayesian calibration for building energy simulation	91
Chaotic fruit fly optimization algorithm	Mitić et al. (2015)	Implementing new algorithm method and optimization of fruit fly in studies practical studies	83
Spotted hyena optimizer: a novel bio-inspired based metaheuristic technique for engineering applications	Dhiman and kumar (2017)	Systematize the new metaheuristic algorithm called spotted hyena optimizer and identify new applications	80
Emperor penguin optimizer: a bio-inspired algorithm for engineering problems	Dhiman and kumar (2018)	Identify the difficulties when implementing emperor penguin optimization algorithm optimizer in engineering problems	73
Computational intelligence techniques for hvac systems: a review	Ahmad et al. (2016)	Systematize the benefits of using computational intelligence to optimize problems in heating, ventilation and air-conditioning systems and air-conditioning systems	71
An algorithm for many-objective optimization with reduced objective computations: a study in differential evolution	Bandyopadhyay and mukherjee (2015)	Implementing the algorithm for many-objective optimization in practical studies	67
A survey of multiobjective evolutionary clustering	Mukhopadhyay, maulik and Bandyopadhyay (2015)	Describe the evolutionary clustering techniques in the optimization of processes with multiple output variables	67
An improved opposition-based sine cosine algorithm for global optimization	Elaziz, oliva and xiong (2016)	Identify the possibilities of applicability of the sine cosine algorithm based on opposition	66
An efficient chaotic water cycle algorithm for optimization tasks	Heidari, abbaspour and jordehi (2017)	Identify the benefits in optimizing processes with multiple output variables by implementing the water cycle algorithm	66
Metaheuristics in structural optimization and discussions on harmony search algorithm	Saka, hasançebi and geem (2016)	Describe the benefits of applying meta-heuristic algorithms to the optimization of everyday problems	66
Optimization of fuzzy controller design using a new bee colony algorithm with fuzzy dynamic parameter adaptation	Caraveo, valdez and castillo (2016)	Analyze and describe the techniques of multi-agent systems for optimization of climatization systems	65
Water cycle, mine blast and improved mine blast algorithms for discrete sizing optimization of truss structures	Sadollah et al. (2015)	Propose the implementation of the fuzzy bco method	65
Parameters identification of photovoltaic models using hybrid adaptive nelder-mead simplex algorithm based on eagle strategy	Chen et al. (2015)	Propose the operation of an adaptive Nelder-Mead simplex enhanced with the metaheuristic of the artificial bee colony on different types of systems	64
Use of meta-heuristic techniques in rainfall-runoff modelling	Chau (2017)	Analyze and describe the benefits of using meta-heuristic modeling techniques for rainfall	63
A power efficient cluster-based routing algorithm for wireless sensor networks: honeybees swarm intelligence based approach	Ari et al. (2016)	Identify the benefits of the cluster-based cluster-based routing protocol called abc- sd	63
Smart artificial firefly colony algorithm-based support vector regression for enhanced	Chou and pham (2015)	Proposing a new support vector regression based on the firefly algorithm in process optimization	62

forecasting in civil engineering			
A comparison of recent metaheuristic algorithms for crashworthiness optimisation of vehicle thin-walled tubes considering sheet metal forming effects	Karagöz and yildiz (2017)	Map the best performing algorithms for process optimization	59
A genetic algorithm for energy-efficiency in job-shop scheduling	Salido et al. (2016)	The application refers exclusively to the use of clusters for application-specific consumption in sensors	59
Algorithmic design issues in adaptive differential evolution schemes: review and taxonomy	Al-dabbagh et al. (2018)	Identify the benefits of algorithmic design schemes that have been used in variants of differential evolution	58
Capacitor placement in distribution systems for power loss reduction and voltage improvement: a new methodology	Askarzadeh (2016)	Identify applications for the newly developed meta-heuristic, crow search algorithm	57
High-dimensional feature selection via feature grouping: a variable neighborhood search approach	García-torres et al. (2016)	Identify the applicability of the neighborhood search algorithm in processes with multiple output variables	57
Particle swarm optimization algorithm for capacitor allocation problem in distribution systems with wind turbine generators	Ramadan, bendary and nagy (2017)	Map the new applications for the particle swarm optimization method	54
Design of a cost-effective wind/photovoltaic/hydrogen energy system for supplying a desalination unit by a heuristic approach	Maleki, pourfayaz and ahmadi (2016)	Implement a model of a hybrid photovoltaic, wind and hydrogen desalination system desalination system to increase the availability of fresh water	54
A modified symbiotic organisms search algorithm for large scale economic dispatch problem with valve-point effects	Secui (2016)	Identify as weaknesses the symbiotic organisms modified search algorithm	54
Adaptive dimensional search: a new metaheuristic algorithm for discrete truss sizing optimization	Hasançebi and azad (2015)	Identify the weaknesses of the adaptive dimensional search algorithm	53
Toward improved mechanical, tribological, corrosion and in-vitro bioactivity properties of mixed oxide nanotubes on ti–6al–7nb implant using multi- objective PSO	Rafieerad et al. (2017)	Identify the applicability of the particle swarm optimization algorithm in multiple output variable processes	51
Glossary of metaheuristic algorithms	Rajpurohit et al. (2017)	Systematize the algorithms that can be applied to processes with multiple output variables	51
A destroy and repair algorithm for the bike sharing rebalancing problem	Dell`amico et al. (2016)	Identify the applicability of the destroy and repair algorithm in process optimization	51
Computational intelligence approaches for energy load forecasting in smart energy management grids: state of the art, future challenges, and research directions	Fallah et al. (2018)	Systematize main intelligent computational methods in forecasting energy load in smart grids	50
Ant lion optimization algorithm to control side lobe level and null depths in linear antenna arrays	Saxena and kothari (2016)	Identify the benefits of the ant lion optimization algorithm in electromagnetics	50
A new rooted tree optimization algorithm for economic dispatch with valve-point effect	Labbi et al. (2016)	Identify the applicability of the root tree optimization algorithm in process optimization	49
Design optimization of real world steel space frames using artificial bee colony algorithm with levy flight distribution	Aydoğdu, akin and saka (2016)	Identify the applicability of the artificial bee colony algorithm in multiple output variable processes	49
A research survey: review of ai solution strategies of job shop scheduling problem	Çaliş and bulkan (2015)	Map the main causes of job shop scheduling problems	49
A novel approach for multispectral satellite image classification based on the bat algorithm	Senthilnath et al. (2016)	Identify the applicability of the bat algorithm in processes with multiple output variables	46
Cuckoo optimization algorithm with penalty function for combined heat and power economic dispatch problem	Mellal and williams (2015)	Identify the applicability of the cuckoo optimization algorithm in processes with multiple output variables	46

Binary grasshopper optimisation algorithm approaches for feature selection problems	Mafarja et al. (2019)	Identify the applicability of the grasshopper optimisation algorithm in processes with multiple output variables	45
Whale optimization algorithm based optimal reactive power dispatch: a case study of the algerian power system	Medani, sayah and bekrar (2018)	Identify the applicability of the whale optimization algorithm in processes with multiple output variable processes	45

From the analysis of Table 1, it can be seen the grouping of scientific gaps into four categories, namely: "Analyze the advantages of a metaheuristic optimizing algorithm" (10 notes); "Identify the applicability of metaheuristic algorithms" (19 notes); "Propose optimizations for metaheuristic algorithms" (8 notes) and "Identify the feasibility of use for metaheuristic algorithms" (13 notes). These categories, with their respective authors, can be better observed in Table 2.

Table 2. Opportunities for Metaheuristics Research

RESEARCH OPPORTUNITIES	AUTHORS
Analyze the advantages of a metaheuristic optimizing algorithm	Abdullahi et al. (2016); Abualigah et al. (2018); Al-dabbagh et al. (2018); Ari et al. (2016); Askarzadeh (2016a); Chau (2017); Heidari etal. (2017); Karagöz and Yildiz (2017); Saka et al. (2016); Tien Bui et al. (2016).
Identify the applicability of metaheuristic algorithms	Abd elaziz et al. (2017); Askarzadeh (2016b); Aydoğdu et al. (2016); Bandyopadhyay and Mukherjee (2015); Dell׳amico et al. (2016); Dhiman and Kumar (2018); Ehsan and Yang (2018); Fallah et al. (2018); García-torres et al. (2016); Heidari et al. (2019); Kalra and Singh (2015); Labbi et al. (2016); Mafarja et al. (2019); Maleki et al. (2016); Mitić et al. (2015); Rafieerad et al. (2017); Rajpurohit et al. (2017); Ramadan et al. (2017); Sadollah et al. (2015).
Propose optimizations for metaheuristic algorithms	Adarsh et al. (2016); Caraveo et al. (2016); Chou and Pham (2015); Faris et al. (2018); Nabil (2016); Osaba et al. (2016); Salido et al. (2016); Senthilnath et al. (2016).
Identify the feasibility of use for metaheuristic algorithms	Ahmad et al. (2016); Bagheri Tolabi et al. (2015); Çaliş and Bulkan (2015); Chen et al. (2016); Dhiman and Kumar (2017); Hasançebi and Azad (2015); Medani et al. (2018); Mellal and Williams (2015); Mukhopadhyay et al. (2015); Saxena and Kothari (2016); Secui (2016); Silva Filho et al. (2015); Yu and li (2015).

According to the analysis in Table 2, the two categories that presented the highest number of scientific gaps related to the theme were: "Identify the applicability of metaheuristic algorithms" (19 notes) and "Identify the feasibility of using metaheuristic algorithms" (13 notes), thus demonstrating the lack of studies in the highlighted areas, which highlights propositions for future studies to be able to fill these identified scientific gaps.

4.2 Case Study

The results obtained from the data of a company in the Sul Fluminense Region are summarized in Table 3 (Experimental Design) and refer to variables x1 (Paint Level), x2

(Paint Concentration), and x3(Paint Temperature). The Response Variables are Paint Quality (Y1), Paint Density (Y2), 400 Modulus (Y3), and Paint Strength (Y4). The Response Variables follow the following Constraints: 100 < Y1, 950 < Y2, 350<Y3<550, 65<Y4<78. An analysis was performed using Minitab statistical software, which is one of the most widely used for statistical analysis today. A SURFACE RESPONSE TYPE experiment, which is the most appropriate for these 4 response variables, was created using 20 runs, 1 block and 6 replicates at the center point (Derringer & Suich, 1980).

Table 3. Experimental Planning

A	B	C	Y1	Y2	Y3	Y4
-1	-1	-1	103	495	650	62,5
1	-1	-1	118	862	420	65
-1	1	-1	115	805	580	77,5
1	1	-1	145	1100	392	72
-1	-1	1	103	905	450	65,8
1	-1	1	130	1280	295	67
-1	1	1	135	1325	420	78
1	1	1	195	2594	250	75,5
-1,68179	0	0	108	790	500	78
1,681793	0	0	152	1600	287	72
0	-1,68179	0	95	750	545	65
0	1,681793	0	165	1500	390	95
0	0	-1,68179	115	2100	522	68
0	0	1,681793	150	1789	250	72
0	0	0	130	1350	385	79
0	0	0	132	1320	390	69,5
0	0	0	145	1140	435	70
0	0	0	140	1098	480	72
0	0	0	142	1267	397	65
0	0	0	148	1349	398	75

With the Analysis of the Responsive Surface Experiment, a result was obtained for each value of Y. The results for each Mathematical Model and each Pareto Graph are in Equations (1),(2),(3), and (4) and Figures 1,2,3, and 4.

(1) Regression Equation in Uncoded Units

Y1 = 139,49 + 15,08 A + 18,58 B + 10,31 C - 3,32 A*A - 3,32 B*B - 2,43 C*C + 6,00 A*B + 5,25 A*C + 7,25 B*C

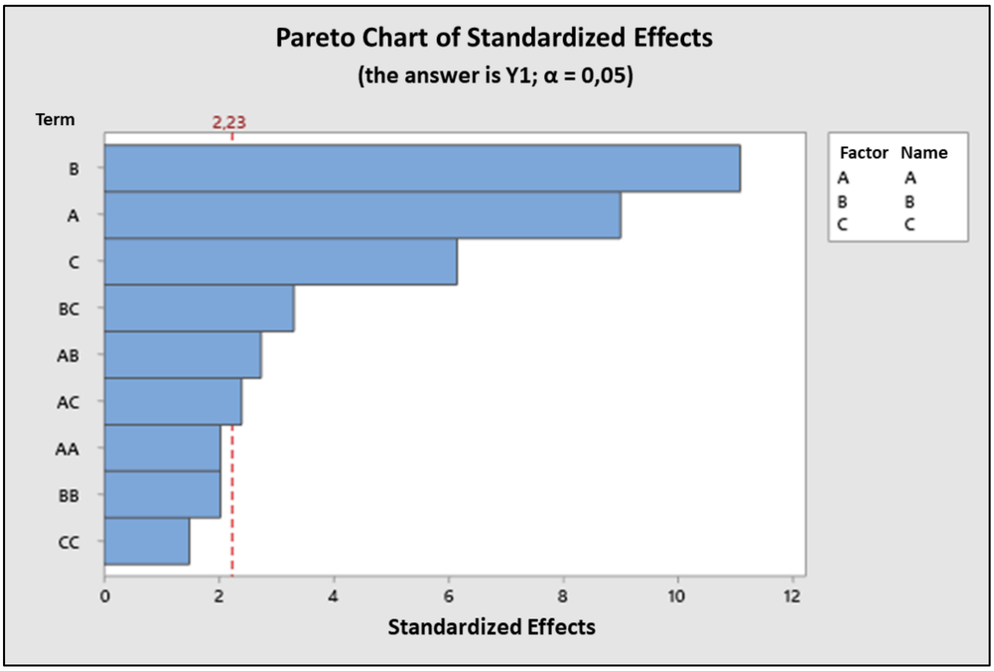

Figure 1. Pareto Chart for Response Y1

(2) Regression Equation in Uncoded Units

Y2 = 1262+ 268,6 A+ 259,5 B+ 169,8 C- 75,9 A*A- 100,7 B*B+ 189,1 C*C + 103 A*B+ 123 A*C + 148 B*C

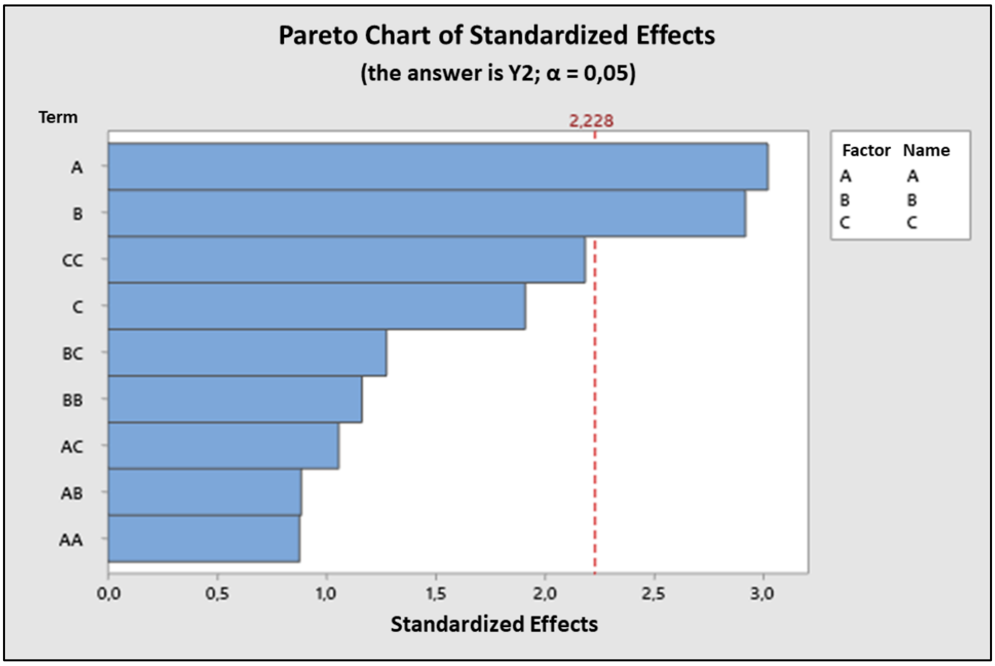

Figure 2. Pareto chart for Response Y2

(3) Regression Equation in Uncoded Units

Y3 = 413,6 - 80,64 A - 31,76 B - 79,41 C - 3,85 A*A + 22,31 B*B - 6,50 C*C + 3,4 A*B + 11,6 A*C + 2,9 B*C

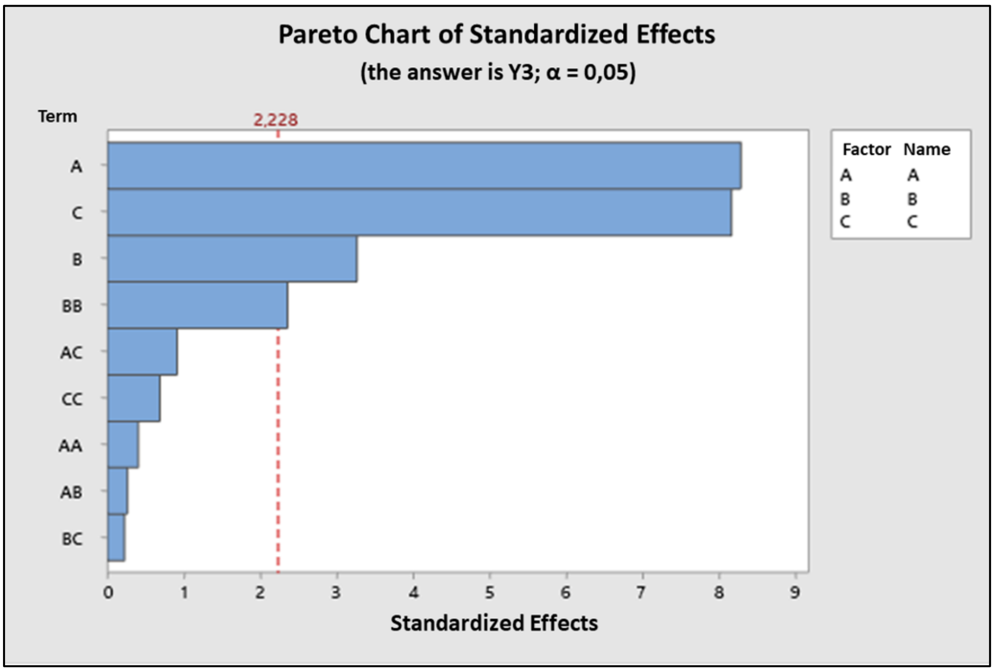

Figure 3. Pareto chart for Response Y3

(4) Regression Equation in Uncoded Units

Y4 = 71,90 - 1,05 A + 6,82 B + 1,17 C + 0,14 A*A + 1,91 B*B - 1,63 C*C - 1,46 A*B + 0,21 A*C - 0,16 B*C

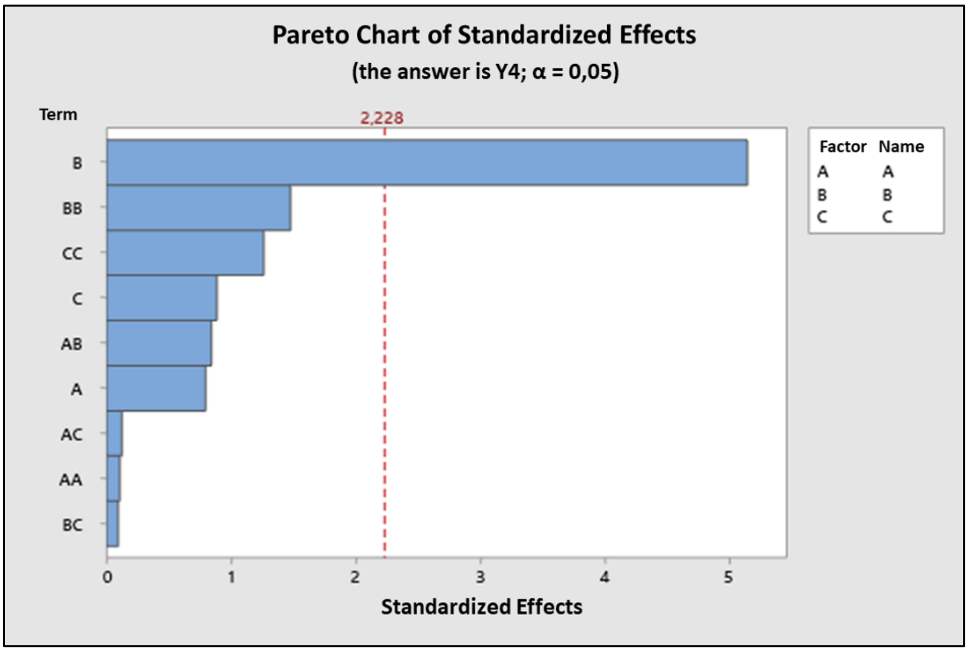

Figure 4. Pareto chart for Response Y4

The big challenge is that while one variable is optimized to meet the conditions required by the problem, the others are outside the required optimal conditions, that is, a conflicting behavior occurs, and it becomes difficult to meet the targets proposed for solving the problem. The solution is to transform this set of four answers (Y1, Y2, Y3 and Y4) into a single answer. In the Minitab software, you use the Optimize Response function and enter the desired targets to obtain the desired Optimized Response.

VARIABLE	CONFIGURATION
A	0,009806
B	-0,141686
C	-1,137

ANSWER	ADJUST	EP OF ADJUSTED	95% IC	95% IP
Y4	67,50	2,36	(62,23; 72,77)	(55,38; 79,62)
Y3	500,0	17,3	(461,3; 538,7)	(411,1; 588,9)
Y2	1300	159	(947; 1653)	(487; 2113)
Y1	123,17	2,99	(116,51; 129,83)	(107,86; 138,48)

Table 4. Multiple Response Prediction

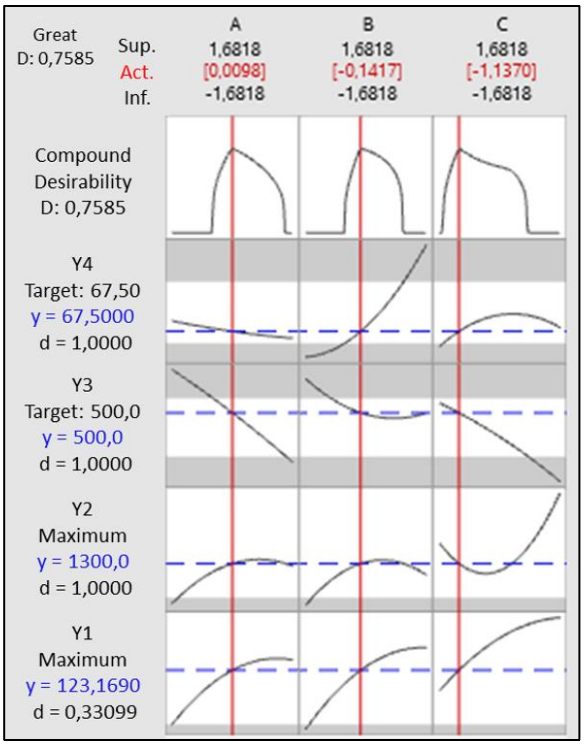

Figure 5. Optimized Response Graphs

The result of the optimization appears in Table 4 and the Figure 5. A simple analysis shows that the response variable Y1, which should obtain a minimum value of 120 and a maximum value of 170, found a value of 123.169 with an individual desirability (d1=0.33099). The response variable Y2 reached the optimal value of 1,300 with an individual desirability (d2=1). Variable Y3, which had a target of 500, obtained a value of 500 with an individual desirability (d3=1), and variable Y4, whose target was 67.5, reached the same value with an individual desirability (d4=1). It can be seen the adjustment values of the coded process variables to meet the optimal responses obtained were X1 (0.0098), X2(-0.1417), and X3(-1.1370), all within the ranges considered. It would now be enough to simply decode the variables to obtain the values that should be substitute those variables in the process.

Conclusion

This study aimed to identify the existing scientific gaps in the papers with the highest number of citations on the subject that are indexed in SCOPUS, considering the publications entered in this database since 2015. For this goal to be achieved, applied research of exploratory nature and qualitative approach was conducted. The adopted method and technical procedures were, respectively, the bibliographic research and the literature review. The contribution of this research is the holistic view of opportunities to carry out new investigations on the theme in question. It is noteworthy that the study gaps identified after the research were prioritized and listed in Table 1, highlighting the importance of the viability of metaheuristic algorithms, as well as their benefits for process optimization. The second objective was to perform an application of the Desirability Function to evaluate a process with multiple response variables, which was also achieved by showing the correct coded values of the input variables to achieve the best values of the output variables for the process constraints.

References

Abdullahi, M., Ngadi, M. A., Dishing, S. I., Abdulhamid, S. M., & Usman, M. J. (2020). A survey of symbiotic organisms search algorithms and applications. *Neural Computing and Applications*, *32*(2), 547–566. https://doi.org/10.1007/s00521-019-04170-4

Adarsh, B. R., Raghunathan, T., Jayabarathi, T., & Yang, X. S. (2016). Economic dispatch using chaotic bat algorithm. *Energy*, *96*, 666–675. https://doi.org/10.1016/j.energy.2015.12.096

Alketbi, K., Elmualim, A., & Mushtaha, E. S. (2022). Investigating the Factors Influencing the Tqm Implementation on Organizations Performance. *International Journal for Quality Research*, *16*(3), 733–748. https://doi.org/10.24874/IJQR16.03-05

Alvarenga, A. B. C. de S., Espuny, M., Reis, J. S. da M., Silva, F. D. O., Sampaio, N. A. de S., Nunhes, T. V., Barbosa, L. C. F. M., Santos, G., & Oliveira, O. J. de. (2021). The Main Perspectives of The Quality of Life of Students In The Secondary Cycle: An Overview of The Opportunities, Challenges and Elements of Greatest Impact. *International Journal for Quality Research*, *15*(3), 983–1006. https://doi.org/10.24874/IJQR15.03-19

Araujo, M. J. F. de, Araújo, M. V. F. de, Araujo Jr, A. H. de, Barros, J. G. M. de, Almeida, M. da G. de, Fonseca, B. B. da, Reis, J. S. D. M., Barbosa, L. C. F. M., Santos, G., & Sampaio, N. A. D. S. (2021). Pollution Credit Certificates Theory: An Analysis on the Quality of Solid Waste Management in Brazil. *Quality Innovation Prosperity*, *25*(3), 1–17. https://doi.org/10.12776/qip.v25i3.1574

Askarzadeh, A. (2016). A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm. *Computers and Structures*, *169*, 1–12. https://doi.org/10.1016/j.compstruc.2016.03.001

Bell, S. O., Shankar, M., Omoluabi, E., Khanna, A., Andoh, H. K., OlaOlorun, F., Ahmad, D., Guiella, G., Ahmed, S., & Moreau, C. (2020). Social network-based measurement of abortion incidence: promising findings from population-based surveys in Nigeria, Cote d'Ivoire, and Rajasthan, India. *Population Health Metrics*, *18*(1), 1–15. https://doi.org/10.1186/s12963-020-00235-y

Cardoso, R. P., Reis, J. S. da M., Silva, D. E. W., Barros, J. G. M. de, & Sampaio, N. A. de S. (2023). How to Perform a Simultaneous Optimization with Several Response Variables. *Revista de Gestão e Secretariado*, *14*(1), 564–578. https://doi.org/10.7769/gesec.v14i1.1536

Chen, I. C., Chen, M. T., & Chung, T. W. (2020). Analysis of antioxidant property of the extract of saponin by experiment design methodology. *IOP Conference Series: Earth* *and Environmental Science*, *594*(1). https://doi.org/10.1088/1755-1315/594/1/012002

Del Castillo, E., Montgomery, D. C., & McCarville, D. R. (1996). Modified desirability functions for multiple response optimization. *Journal of Quality Technology*, *28*(3), 337–345. https://doi.org/10.1080/00224065.1996.11979684

Derringer, G., & Suich, R. (1980). Simultaneous Optimization of Several Response Variables. *Journal of Quality Technology*, *12*(4), 214–219. https://doi.org/10.1080/00224065.1980.11980968

Ding, X., Sun, W., Harrison, G. P., Lv, X., & Weng, Y. (2020). Multi-objective optimization for an integrated renewable, power-to-gas and solid oxide fuel cell/gas turbine hybrid system in microgrid. *Energy*, *213*, 118804. https://doi.org/10.1016/j.energy.2020.118804

Espuny, M., Reis, J. S. da M., Anaya, Y. B., Cardoso, R. P., Sampaio, N. A. de S., Barbosa, L. C. F. M., & Oliveira, O. J. de. (2022). Identification of Research Gaps on Municipal Solid Waste Management from Data Indexed in the SCOPUS Database. *Revista de Gestão e Secretariado*, *13*(4), 2388–2402. https://doi.org/10.7769/gesec.v13i4.1478

Goffe, L., Uwamahoro, N. S., Dixon, C. J., Blain, A. P., Danielsen, J., Kirk, D., & Adamson, A. J. (2020). Supporting a healthier takeaway meal choice: creating a universal health rating for online takeaway fast-food outlets. *International Journal of Environmental Research and Public Health*, *17*(24), 1–12. https://doi.org/10.3390/ijerph17249260

Gomes, F. M., Pereira, F. M., Marins, F. A. S., & Silva, M. B. (2019). Comparative study between different methods of agglutination in multiple response optimization. *Revista Gestão Da Produção Operações e Sistemas*, *14*(1), 95–113. https://doi.org/10.15675/gepros.v14i1.2080

Gomes, F. M., Pereira, F. M., Silva, A. F., & Silva, M. B. (2019). Multiple response optimization: Analysis of genetic programming for symbolic regression and assessment of desirability functions. *Knowledge-Based Systems*, *179*, 21–33. https://doi.org/10.1016/j.knosys.2019.05.002

Gunst, R. F., Myers, H., & Montgomery, D. C. (2011). American Society for Quality. *SpringerReference*, *38*(3), 285–286. https://doi.org/10.1007/springerreference_6379

Gunst, R. F., Myers, R. H., & Montgomery, D. C. (1996). Response Surface Methodology: Process and Product Optimization Using Designed Experiments. In *Technometrics* (Vol. 38, Issue 3). https://doi.org/10.2307/1270613

Handoyono, N. A., Suparmin, Samidjo, Johan, A. B., & Suyitno. (2020). Project-based learning model with real object in vocational school learning. *Journal of Physics: Conference Series*, *1700*(1). https://doi.org/10.1088/1742-6596/1700/1/012045

Kalra, M., & Singh, S. (2015). A review of metaheuristic scheduling techniques in cloud computing. *Egyptian Informatics Journal*, *16*(3), 275–295. https://doi.org/10.1016/j.eij.2015.07.001

Karthikeyan, C., Sreedevi, E., Kumar, N., Vamsidhar, E., Rajesh Kumar, T., & Vijendra Babu, D. (2020). Cost optimization in neural network using whale swarm algorithm with batched gradient descent optimizer. *IOP Conference Series: Materials Science and Engineering*, *993*(1). https://doi.org/10.1088/1757-899X/993/1/012047

Korolchenko, D., & Minaylov, D. (2020). Method of mathematical modeling for the experimental evaluation of fire retardant materials parameters. *IOP Conference Series: Materials Science and Engineering*, *1001*(1). https://doi.org/10.1088/1757-899X/1001/1/012075

Kothari, C. R., & Garg, G. (2019). Research methodology methods and techniques. In *New Age International* (4º). New Age International.

Laidani, Z., Tolokonsky, A. O., Abdulraheem, K. K., Ouahioune, M., & Berreksi, R. (2020). Modelling and simulating of a multiple input and multiple output system to control the liquid level and temperature by using model predictive control. *Journal of Physics: Conference Series*, *1689*(1). https://doi.org/10.1088/1742-6596/1689/1/012065

Lebron, Y. A. R., Moreira, V. R., Drumond, G. P., Gomes, G. C. F., da Silva, M. M., Bernardes, R. de O., Jacob, R. S., Viana, M. M., de Vasconcelos, C. K. B., & Santos, L. V. de S. (2020). Statistical physics modeling and optimization of norfloxacin adsorption onto graphene oxide. *Colloids and Surfaces A: Physicochemical and Engineering Aspects*, *606*(August), 125534. https://doi.org/10.1016/j.colsurfa.2020.125534

Mitić, M., Vuković, N., Petrović, M., & Miljković, Z. (2015). Chaotic fruit fly optimization algorithm. *Knowledge-Based Systems*, *89*(August), 446–458. https://doi.org/10.1016/j.knosys.2015.08.010

Mohamed, A. A. A., Mohamed, Y. S., El-Gaafary, A. A. M., & Hemeida, A. M. (2017). Optimal power flow using moth swarm algorithm. *Electric Power Systems Research*, *142*, 190–206. https://doi.org/10.1016/j.epsr.2016.09.025

Muniswamaiah, M., Agerwala, T., & Tappert, C. C. (2020). Approximate Query Processing for Big Data in Heterogeneous Databases. *Proceedings - 2020 IEEE International Conference on Big Data, Big Data 2020*, 5765–5767. https://doi.org/10.1109/BigData50022.2020.9378310

Natarajan, U., Periyanan, P. R., & Yang, S. H. (2011). Multiple-response optimization for micro-endmilling process using response surface methodology. *International Journal of Advanced Manufacturing Technology*, *56*(1–4), 177–185. https://doi.org/10.1007/s00170-011-3156-2

Ortiz, F., Simpson, J. R., Pignatiello, J. J., & Heredia-Langner, A. (2004). A genetic algorithm approach to multiple-response optimization. *Journal of Quality Technology*, *36*(4), 432–450. https://doi.org/10.1080/00224065.2004.11980289

Osaba, E., Yang, X. S., Diaz, F., Lopez-Garcia, P., & Carballedo, R. (2016). An improved discrete bat algorithm for symmetric and asymmetric Traveling Salesman Problems. *Engineering Applications of Artificial Intelligence*, *48*, 59–71. https://doi.org/10.1016/j.engappai.2015.10.006

Pesteh, S., Moayyed, H., Miranda, V., Pereira, J., Freitas, V., Simões Costa, A., & London, J. B. A. (2019). A new interior point solver with generalized correntropy for multiple gross error suppression in state estimation. *Electric Power Systems Research*, *176*(June), 105937. https://doi.org/10.1016/j.epsr.2019.105937

Rafieerad, A. R., Bushroa, A. R., Nasiri-Tabrizi, B., Kaboli, S. H. A., Khanahmadi, S., Amiri, A., Vadivelu, J., Yusof, F., Basirun, W. J., & Wasa, K. (2017). Toward improved mechanical, tribological, corrosion and in-vitro bioactivity properties of mixed oxide nanotubes on Ti–6Al–7Nb implant using multi-objective PSO. In *Journal of the*

Mechanical Behavior of Biomedical Materials (Vol. 69). Elsevier. https://doi.org/10.1016/j.jmbbm.2016.11.019

Rajesh Ruban, S., Jayaseelan, P., Suresh, M., & RatnaKandavalli, S. (2020). Effect of textures on machining of carbon steel under dry cutting condition. *IOP Conference Series: Materials Science and Engineering*, *993*(1). https://doi.org/10.1088/1757-899X/993/1/012143

Rajpurohit, S., Vrkoslav, V., Hanus, R., Gibbs, A. G., Cvačka, J., & Schmidt, P. S. (2021). Post-eclosion temperature effects on insect cuticular hydrocarbon profiles. *Ecology and Evolution*, *11*(1), 352–364. https://doi.org/10.1002/ece3.7050

Rathod, L., Poonawala, N. S., & Rudrapati, R. (2020). Multi response optimization in WEDM of H13 steel using hybrid optimization approach. *IOP Conference Series: Materials Science and Engineering*, *814*(1). https://doi.org/10.1088/1757-899X/814/1/012015

Reis, J. S. da M., Cardoso, R. P., Silva, D. E. W., Almeida, M. da G. D. de, Barros, J. G. M. de, Sampaio, N. A. de S., & Barbosa, L. C. F. M. (2023). The Titans Sustainability and Industry 4.0 Working for The Planet Earth. *Revista de Gestão e Secretariado*, *14*(2), 1953–1965.

Reis, J. S. da M., Espuny, M., Cardoso, R. P., Sampaio, N. A. de S., Barros, J. G. M. De, Barbosa, L. C. F. M., & Oliveira, O. J. De. (2022). Mapping Sustainability 4.0: contributions and limits of the symbiosis. *Revista de Gestão e Secretariado*, *13*(3), 1426–1438. https://doi.org/10.7769/gesec.v13i3.1417

Reis, J. S. da M., Espuny, M., Nunhes, T. V., Sampaio, N. A. de S., Isaksson, R., Campos, F. C. de, & Oliveira, O. J. de. (2021). Striding towards Sustainability: A Framework to Overcome Challenges and Explore Opportunities through Industry 4.0. *Sustainability*, *13*(9), 5232. https://doi.org/10.3390/su13095232

Sales, J. P. de, Reis, J. S. da M., Barros, J. G. M. de, Fonseca, B. B. da, Junior, A. H. de A., Almeida, M. da G. D. de, Barbosa, L. C. F. M., Santos, G., & Sampaio, N. A. de S. (2022). Quality Management in The Contours of Continuous Product Improvement. *International Journal for Quality Research*, *16*(3), 689–702. https://doi.org/10.24874/IJQR16.03-02

Setiawati, E., & Yusuf, W. A. (2020). The ulitization of durian wood (Durio zibethinus) and corn cob (Zea mays) biochar on corn yields in acid sulphate soil. *IOP Conference Series: Materials Science and Engineering*, *980*(1). https://doi.org/10.1088/1757-899X/980/1/012027

Silva, H. de O. G. da, Costa, M. C. M., Aguilera, M. V. C., Almeida, M. da G. D. de, Fonseca, B. B. da, Reis, J. S. da M., Barbosa, L. C. F. M., Santos, G., & Sampaio, N. A. de S. (2021). Improved Vehicle Painting Process Using Statistical Process Control Tools in an Automobile Industry. *International Journal for Quality Research*, *15*(4), 1251–1268. https://doi.org/10.24874/IJQR15.04-14

Tolabi, H. B., Hosseini, R., & Shakarami, M. R. (2016). A robust hybrid fuzzy-simulated annealing-intelligent water drops approach for tuning a distribution static compensator nonlinear controller in a distribution system. *Engineering Optimization*, *48*(6), 999–1018. https://doi.org/10.1080/0305215X.2015.1080579

Vera Candioti, L., De Zan, M. M., Cámara, M. S., & Goicoechea, H. C. (2014). Experimental design and multiple response optimization. Using the desirability function in analytical methods development. *Talanta*, *124*, 123–138. https://doi.org/10.1016/j.talanta.2014.01.034

Wang, C. N., Nguyen, N. A. T., & Dang, T. T. (2020). Solving order planning problem using a heuristic approach: The case in a building material distributor. *Applied Sciences (Switzerland)*, *10*(24), 1–21. https://doi.org/10.3390/app10248959

Xu, Y., Chen, H., Heidari, A. A., Luo, J., Zhang, Q., Zhao, X., & Li, C. (2019). An efficient chaotic mutative moth-flame-inspired optimizer for global optimization tasks. *Expert Systems with Applications*, *129*(April), 135–155. https://doi.org/10.1016/j.eswa.2019.03.043

Yang, L., Wang, J., Jiang, Y., & Zou, L. (2020). Oil–water flow splitting in eccentric annular T-junction tubes—Experimental and CFD analysis. *Chemical Engineering Science*, *228*. https://doi.org/10.1016/j.ces.2020.116000

Submetido em: 17.02.2023

Aceito em: 14.03.2023