Revisiting the Contributions Involving Artificial Intelligence Reported on the First 25 Years of the Journal of Microwaves, Optoelectronics and Electromagnetic Applications

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***Abstract*— This paper reviews all artificial intelligence contributions presented in the first 25 years of the JMOe. The 36 articles showing intersection with the area were selected, and it was observed that the most significant contributions were made in optics and electromagnetism & microwaves, with 15 contributions in each area. It was also noticed that the most used techniques are genetic algorithms, particle swarm optimization, and multilayer perceptron artificial neural networks. There are opportunities to be explored, such as the use of optimization techniques with many goals, deep machine learning techniques with implicit pattern extraction to handle raw data directly, and the use of reinforcement machine learning techniques.**

***Keywords*— Optics, Electromagnetism, Microwave, Artificial Intelligence, Machine Learning, Optimization**

I. INTRODUCTION

Artificial intelligence [1] has attracted much attention in the last decades, and it has become more intense in the last years. The main reason is the availability of data and computational resources to create models and techniques to solve data-based problems. Artificial intelligence has been applied in several areas, including industry [2], telecommunications [3], agriculture [4], oil & gas [5], and medicine [6], among others. These applications generate automation processes in many science, technology and innovation areas. Because of this, we have a massive impact on jobs and labor [7]. The area of artificial intelligence comprehends the sub-areas of Machine Learning (ML), intelligent optimization using evolutionary computing and swarm intelligence, and fuzzy logic.

The ML area, despite having its roots in the 1940s, is the one that has been currently used to solve most engineering problems. It is mainly because, in its various subfields, ML can solve problems of pattern recognition, anomaly detection, classification, clustering, multivariate regression, and time series prediction. The main machine learning paradigms are supervised learning [8], unsupervised learning [9], and semi-supervised learning [10]. Supervised machine learning algorithms need humans or external processes to provide the required labels for the systems' outputs as a function of the input examples and provide feedback on the prediction accuracy in the training process. Unsupervised learning approaches contrast with supervised learning approaches because they do not need labels to identify classes, typically looking for similarities between examples to identify patterns. Reinforcement learning approaches use quality indicators as a reference to evolve the system with a reward system.

The field of intelligent optimization has its history starting around the 1970s, with the emergence of evolutionary algorithms [11]. The most famous of the algorithms are the genetic algorithms (GA) [12], which use concepts of crossover, mutation, and natural selection. Other approaches have been proposed throughout history to address deficiencies in GAs in some problems, such as Differential Evolution (DE) for optimizing continuous variables. In the 1990s, algorithms inspired by the behavior of groups of animals emerged, called swarm intelligence [13]. The most famous of these algorithms is Particle Swarm Optimization (PSO) [14].

The third branch of artificial intelligence is called Fuzzy logic. It is associated with membership functions with semantic variables that can smooth behaviors and transitions. It has been widely used for control since it embodies human-like thinking in practical systems [15].

This article aims to portray the use cases of artificial intelligence techniques in JMOe editions published in the last 25 years. The remainder of the paper is organized as follows. Section II describes the methodology to review all the contributions concerning artificial intelligence published in JMOe. Section III summarizes the contributions of the 36 papers selected in the review. Section IV presents a discussion and possible trends and opportunities for the future.

II. METHODOLOGY

We verified all articles from all editions published until July 7th, 2022, and all articles in which some use, development, or application of artificial intelligence techniques appears. As a result, we selected 36 articles. Figure 1 shows the number of papers according to the year of publication. The first papers were published in 2002. These two papers [16][17] deal with more theoretical aspects of computing and are not related to the topics most addressed by the JMOe. In the first decade of this century, few articles were published involving artificial intelligence, only eight articles in sparse years. On the other hand, an increase in the number of publications can be seen in the second decade of this century, showing a greater interest from the community in using artificial intelligence techniques for the purpose areas covered by the JMOe.

It was also the object of analysis of this paper to assess which Brazilian institutions most published scientific articles in the JMOe using artificial intelligence. Figure 2 shows the number of occurrences of these institutions as the affiliation of the authors of the analyzed papers. The biggest highlight is UFPA with seven appearances, followed by UPE and UFRN with four appearances. With three appearances, we list UTFPR, UFPE, UFMG, and UFES. We could map 30 institutions as affiliations of authors of articles published in JMOe using Artificial Intelligence.

As the JMOe aims to be an international publication, we evaluated the number of occurrences of publications from foreign countries in scientific papers in the JMOe using Artificial Intelligence. Figure 3 presents the number of occurrences by country. Nine countries participate in this list, with emphasis on India, with three occurrences.

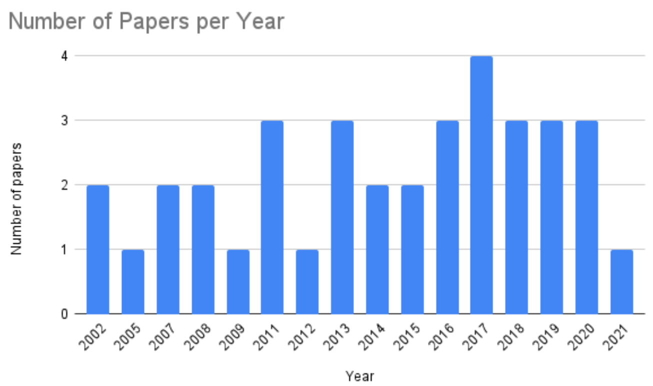

Fig. 1. Number of scientific papers published in the JMOe using Artificial Intelligence according to the years of publication.

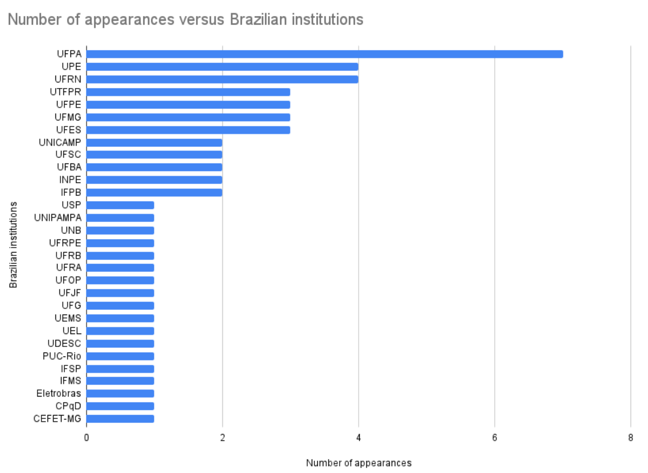

Fig. 2. Number of appearances by Brazilian institutions in scientific papers published by authors affiliated within the JMOe papers using Artificial Intelligence.

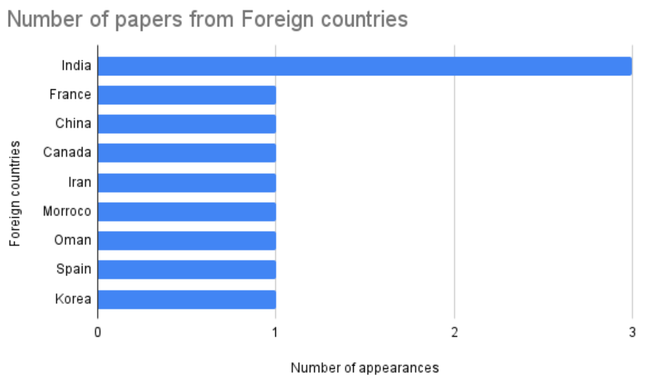

Fig. 3. Number of occurrences of participation of authors based in foreign institutions in scientific articles published by authors affiliated to the JMOe using Artificial Intelligence.

Regarding the technical profile of these articles, a survey was carried out, and it was observed that almost 70% of the articles involved simulation or modeling activities. A quarter of the articles involve experimental activities, and only 5.6% of the articles are theoretical in artificial intelligence.

Regarding the application of artificial intelligence, we could see that the two areas that predominate in the selected articles were optics and electromagnetism/microwaves/antennas, each with 15 occurrences. It was also possible to observe applications in other areas, such as power systems, telecommunications, and biomedical engineering, as seen in Figure 4.

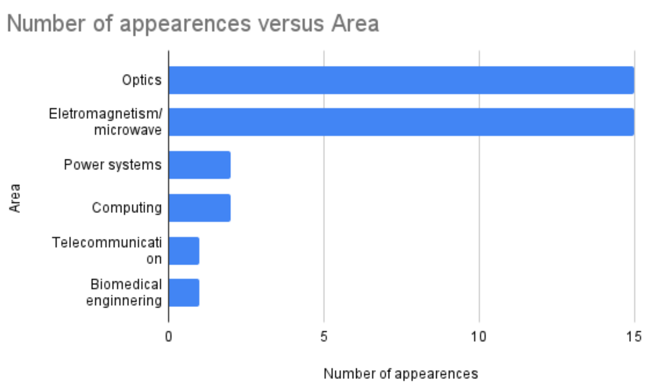

Fig. 4. Number of occurrences by area of application in engineering in scientific papers published by authors affiliated to JMOe using Artificial Intelligence.

Considering the main areas of artificial intelligence, most of the selected articles use evolutionary computing techniques and swarm intelligence (72.2%). Another 22.2% of the articles use machine learning techniques, and only 5.6% use fuzzy logic. It is an exciting finding, as machine learning techniques have historically been used more for engineering problems than bio-inspired metaheuristics.

An analysis was also made of the most used techniques in the applications. Figure 5 shows the number of occurrences per the base algorithm of artificial intelligence in scientific articles published by authors affiliated with the JMOe using Artificial Intelligence. Wide use of genetic algorithms (13 occurrences), particle swarm optimization (9 occurrences), and multilayer artificial neural networks (9 occurrences) can be observed. Furthermore, it can be observed that some authors used lesser-known techniques but with exciting applications, such as differential evolution, artificial immune systems, evolutionary strategies, bat-based optimization algorithms, fuzzy logic, and KNN.

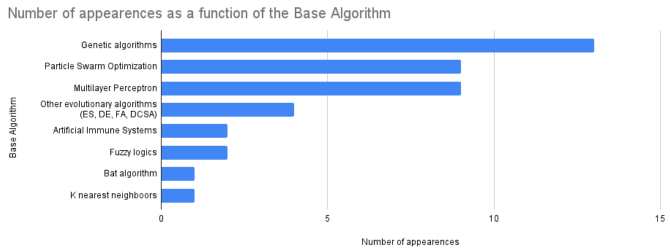

Fig. 5. Number of occurrences by base algorithm of artificial intelligence in scientific papers published by authors affiliated to JMOe using Artificial Intelligence.

III. Applications of Artificial Intelligence in Different Fields Reported on JMOe

This section presents the application of artificial intelligence reported in the selected papers. We divided it into three subsections to better organize the description of the use cases: optics, electromagnetism/microwave/antennas, and applications in other fields.

A. Applications in Optics

We could observe many applications of evolutionary and swarm-based approaches for optimization in optics. Bastos-Filho et al. [18] proposed optimizing Raman amplifiers with multiple pumping lasers using a swarm intelligence technique, MOPSO-CDR, to define the wavelength and power of pumping lasers to achieve a wide and flat gain spectrum profile. Santana et al. [19] deployed the improved chaos particle swarm optimization (IC-PSO) for power allocation in PON-OCDMA systems. Rocha et al. [20] used a genetic algorithm to optimize the DDO-OFDM parameters with three modulation schemes in an optical system. Miranda et al. [21] deployed a genetic algorithm together with graph techniques to improve routing processes in optical networks considering the cross-phase modulation impairment. Lima et al. [22] proposed novel boolean logical operators to improve the performance of an optimization process based on the NSGAII algorithm and applied the proposal to the topology optimization problem of optical networks. Silva-Santos [23] deployed artificial immune systems to optimize the structure of optical multiplexers and demultiplexers. Sisnando et al. [24] proposed using genetic algorithms and artificial immune systems to optimize planar waveguide couplers. Souza et al. [25] performed a comparative study of three encoding methods for optimizing Fiber Bragg Gratings (FBG) using Evolutionary Strategies. Negri et al. [26] deployed the differential evolution algorithm for the experimental reconstruction of FBG profiles to a previously proposed model. Carvalho et al. [27] used a genetic algorithm to optimize the parameters of FBG to design optical filters. Silva et al. [28] proposed using a genetic algorithm to optimize a holey fiber design in two situations, with two and three cores. Pereira da Silva [29] deployed the Particle Swarm Optimization to determine regression coefficients in the characterization of otto chips based on surface plasmons.

We also found three applications of machine learning techniques in optics. Bastos-Filho et al. [30] deployed artificial neural networks to create regression models of optical amplifiers' performance metrics, aiming to create lightweight models for practical management of the amplifiers. Kamizi [31] used a set of artificial neural networks for preprocessing signals from different FBGs and detecting patterns together with a neural network for decision-making on the impact of structures. Barino et al. [32] deployed two different artificial neural network architectures to discriminate the complex and non-linear behavior of the transverse load applied to the LPG detection system.

B. Application in electromagnetism, microwaves and antennas

Banookh and Barakati [33] proposed the optimization performed by a Particle Swarm Optimization algorithm of Stub Microstrip filters. The fitness function is calculated by a multilayer perceptron artificial neural network deployed as a surrogate model. Mouna [34] applied the Particle Swarm Optimization algorithm to optimize a microwave absorber structure. Lacouth et al. [35] proposed to optimize microwave circuits using a Particle Swarm Optimization variation. They compared the results with the genetic algorithm and the original Particle swarm optimization approach, confirming that they had obtained better results. Neto et al. [36] proposed a new multi-objective and bio-inspired hybrid optimization technique, associating a General Regression Neural Network (GRNN) to MOBA, applied to the design and modeling of a Frequency Selective Surface (FSS) with diamond-shaped patch elements for mm-Wave filtering applications, specifically, in the IEEE 802.15.3c standard. Perdiz and Lebensztajn [37] compare some multi-objective optimization algorithms to solve three problems: the design of a die press model, the design of superconducting magnetic energy storage (SMES), and the design of a reluctance motor. Four multi-objective optimization algorithms were analyzed: Weighted Sum Method, Non-dominated Sorting Genetic Algorithm (NSGA), Strength Pareto Evolutionary Algorithm (SPEA), and Pareto Archived Evolutionary Strategy (PAES). Surrogate functions were used for fitness assessment with reduced computational effort. The electromagnetic field calculation was performed by the finite element method, and the Kriging models were used as surrogate functions to approximate the objective functions of the problems. Liu et al. [38] use a genetic algorithm to recover the shape and conductivity of an imperfectly conducting cylinder illuminated by an EM wave. Batista et al. [39] proposed a mono-objective algorithm based on the Distributed Clonal Selection Algorithm (DCSA) to optimize electromagnetic devices. The proposed algorithm is compared with two other known methods for solving microwaves and electromagnetism benchmark problems.

Patidar [40] proposed to optimize a linear antenna using a Quantum based Particle Swarm Optimization. The results were compared with FA and showed promising for wide frequency ranges. Wakrim [41] deployed the genetic algorithm and particle swarm optimization to design the ground plane geometry of a multiband PIFA antenna with large bandwidth. Yoshimoto and Heckler [42] proposed an optimization procedure based on the Firefly Algorithm (FA) for synthesizing non-uniformly spaced linear antenna arrays and for a uniformly spaced planar microstrip array. Dantas et al. [43] used a hybrid multi-objective Evolutionary Algorithm to design microwave filter topologies. Two objective functions are defined to allow for an exchange ratio: (1) an error measurement based on circuit performance evaluated through a frequency domain circuit simulator; and (2) the measurement of structural size based on the circuit topology — the size of the circuit, given by the number of nodes. Avila et al. [44] used a multi-objective genetic algorithm to design a reconfigurable satellite antenna. Rama et al. [45] presented a method to design a multi-function antenna array with 25 elements performed with machine learning techniques with RBFNN.

Travessa and Carpes [46] developed a regression model using RMLP (Artificial Neural Network, multilayer perceptron with Real backpropagation learning algorithm) to accelerate optimizer convergence applied to quasi-3D tracing. Cavalcanti et al. [47] introduced an approach for error correction of analytical models aiming to estimate LTE signal losses in urban environments using artificial neural networks.

C. Application in other fields

We found two applications in power systems. The first one presents an architecture definition for IoT systems focused on energy management using fuzzy logic [48]. The second one presents a multiclass classification system of electrical discharges in insulators using MLP-type artificial neural networks [49]. Another exciting application is using fuzzy logic for routing in ad-hoc networks using UAVs as infrastructure [50]. There is an interesting application of the machine learning KNN technique for Characterization of Bone Tissue applying microwaves [51].

IV. POSSIBILITIES FOR THE FUTURE AND FINAL REMARKS

It can be observed in this review that most contributions related to artificial intelligence in JMOe are linked to optimization processes using metaheuristics, mainly genetic algorithms, and Particle Swarm Optimization. Several applications of multi-objective algorithms were observed, which is expected, since most engineering problems, including optics and electromagnetism, present conflicting relationships involving at least cost and performance. Despite the various reports, there are currently more modern techniques using decomposition and convergence using indicators (such as hypervolume) [52] that did not appear in these articles. It was also noticed that none of the publications presented optimization approaches with many objectives (with more than four conflicting fitness functions) [53].

In addition, despite all the success of deep machine learning techniques in several areas, none of the publications present applications for this set of techniques that is increasingly frequent in artificial intelligence scientific reports. These techniques allow patterns not easily recognized by humans to be implicitly extracted and used in an integrated way for classification, regression, and prediction tasks [54]. Furthermore, the use of reinforcement learning techniques [55] in the publications was also not found.

It is worth mentioning that only two articles reported the use of fuzzy logic, and few studies related to the exploration of data characteristics using modern data science techniques [56] were reported. We conclude by pointing out that there is considerable potential for applying artificial intelligence techniques to solve the various complex problems related to fields as relevant as optics, microwaves and electromagnetism.

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