Evolutionary Computation in Brazil:
A Review of the Literature in Two Databases

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Abstract: Similar to what can be found all over the world, Evolutionary Computation (EC) has been receiving an increasing attention in Brazil in the last decade. It is possible to find several works on EC, both in theory and applications, produced by Brazilian researchers. In this paper, a review of the works on EC produced in Brazil indexed in two important databases until April 2006 is presented. The papers are classified, and the results are discussed. Most of works on EC produced in Brazil are applications, mainly in the areas where the use of optimization methods is traditional. The EC terminology employed in Brazil is discussed in this paper too. One can observe that different terms are used to describe the same elements of EC.

Keywords: evolutionary computation, genetic algorithms, evolution strategies, evolutionary programming, artificial intelligence, optimization.

1 INTRODUCTION

Nature has been very efficient in the solution of several complex problems and challenges. Inspired on this efficiency, several computational techniques have been proposed in the last decades [139]. Among these sources of biological inspiration, we can cite the nervous system, as is the case of Artificial Neural Networks (ANN) [372], from real ant colonies, as in the case of Ant Colony Optimization (ACO) [156], the behaviour of flocks, which is the fundamental concept of Particle Swarm Optimization (PSO) [227], the immune system, simulated by Artificial Immune Systems [140] and Genetics and Natural Evolution, which has originated the research area of Evolutionary Computation [288].

Evolutionary Computation (EC) has been successfully applied to an increasing number of optimization and machine learning problems in recent years. In EC, algorithms inspired by the optimization process performed by Natural Evolution, known as Evolutionary Algorithms (EAs), are employed to search for optimal solutions over a search space composed of candidate solutions. In the literature, one can find works where EAs have been successfully applied in many areas, like Computation, Engineering, Medicine, Chemistry, Physics, and Biology. Important publications, like Evolutionary Computation and IEEE Transactions on Evolutionary Computation, and conferences, like the Genetic and Evolutionary Computation Conference (GECCO) and the IEEE Congress on Evolutionary Computation (CEC), in the EC have been created on last decades.

Like in many parts of the world, EC has been receiving an increasing attention in Brazil in the last decade. One can find several papers on EC, both in theory and practice, produced by Brazilian researchers. Applications of EC on the most diverse areas can be found.

In this paper, a review of the works on EC produced by Brazilian researchers indexed, until April 2006, in two important databases is presented. This text is organized as follows. The next section (Section 2) briefly introduces the main EAs found in the literature. In

Section 3, the EC terminology employed in Brazil is discussed. A survey of published works on Evolutionary Computation by Brazilian researchers indexed in databases ISI Web of Science and Compendex is presented in Section 4. Finally, the paper is concluded in Section 5.

2   EVOLUTIONARY ALGORITHMS

EAs are a class of meta-heuristic algorithms employed in optimization and machine learning which are inspired by the principles of Natural Evolution and Genetics. The basic idea behind EAs is to create a set of candidate solutions to a given task and to evolve them using some mechanisms of selection and reproduction inspired by those found in Natural Evolution [203]. In the EC terminology, the candidate solutions are known as individuals, strings or chromosomes and the set of individuals is known as population.

Algorithms 1 and 2 present the pseudocode of the basic structures of an EA. In these algorithms, $\mathbf{P}_t$ denotes the population of individuals in the iteration t, also known as generation [285], [34]. In the function *"initializePopulation"*, the individuals of the initial population are usually initiated with random solutions obtained from a uniform distribution. In the generational scheme, a new population is formed entirely by offspring generated from parents of the previous generation, while in the steady-state scheme, only a few individuals are replaced at each generation [288].

Algorithm 1 Basic Structure of an Evolutionary Algorithm (Generational)

1: $t \leftarrow 1$
2: initializePopulation($\mathbf{P}_t$)
3: evaluatePopulation($\mathbf{P}_t$)
4: **while** (stop criteria are not satisfied) **do**
5:    $\mathbf{P}_{t+1} \leftarrow$ selection($\mathbf{P}_t$)
6:    transformPopulation($\mathbf{P}_{t+1}$)
7:    evaluatePopulation($\mathbf{P}_{t+1}$)
8:    $t \leftarrow t + 1$
9: **end while**

Algorithm 2 Basic Structure of an Evolutionary Algorithm (Steady State)

1: $t \leftarrow 1$
2: initializePopulation($\mathbf{P}_t$)
3: evaluatePopulation($\mathbf{P}_t$)
4: **while** (stop criteria are not satisfied) **do**
5:    $\mathbf{Q}_t \leftarrow$ transformPopulation($\mathbf{P}_t$)
6:    evaluatePopulation($\mathbf{Q}_t$)
7:    $\mathbf{P}_{t+1} \leftarrow$ selection($\mathbf{P}_t \cup \mathbf{Q}_t$)
8:    $t \leftarrow t + 1$
9: **end while**

EAs differ from traditional optimization techniques mainly because [203]:

- EAs work with a population of candidate solutions rather than with only one candidate solution. The use of a population of candidate solutions usually reduces the probability of being trapped in local optima, mainly in the initial steps of the optimization process.

- Like Simulated Annealing and other random search methods, EAs use probabilistic transition rules, instead of deterministic rules.

- EAs employ only the objective function information to guide the optimization process, and not the derivatives or other auxiliary knowledge. This characteristic makes the use of EAs very promising in problems where it is difficult, or impossible, to compute the derivatives and other auxiliary knowledge. However, it usually makes the optimization process slower, as little information is available to guide the optimization process.

- The optimization can occur with a coding of the candidate solutions rather than with themselves. In spite of the use of coding in the candidate solutions, this can be an advantage in some problems and a disadvantage in others [99].

The three main areas of research in EAs are Genetic Algorithms (GAs), Evolution Strategies (ESs), and Evolutionary Programming

(EP) [288]. The idea that the principles of Natural Evolution can be employed as an optimization tool was explored in the independent proposition of these algorithms mainly by Rechenberg (ESs), Fogel, Owens, Walsh (EP), and Holland (GAs) in the 1960s [34]. GAs are the most explored of the three techniques, while ESs are very popular in Europe, where it was initially developed. It is important to observe that the difference between these three areas is decreasing in the last years, as a growing number of research in each area is adopting concepts from the other areas.

In GAs, which can be found in the generational or steady-state form, a candidate solution of the problem is usually encoded in a vector composed of binary numbers, despite other representations can be found. This vector is known as chromosome, and only one is usually used per individual, i. e., the individuals are usually haploid. GAs use selection and reproduction to evolve the individuals of the population. First, individuals of the current population are selected, according to a given criteria, to compose the next population. Fitness-proportionate selection (e. g., the roulette wheel sampling), where the expected number of times an individual will be selected is proportional to its fitness, is one of the most employed selection methods. Rank and tournament selection are interesting alternatives to the use of fitness-proportionate selection mainly to reduce the problem of premature convergence and the computational cost.

After selection, the genetic operators of reproduction are applied. The most popular are crossover (or recombination) and mutation, despite several others have been proposed. When crossover is applied, components of the chromosome of two individuals are exchanged with a crossover probability rate, known as crossover rate. After crossover, each component of the chromosome of an individual is mutated with a mutation probability rate known as mutation rate. When binary encoding is used, the flip mutation, where the value of the bit is flipped, is employed. Other representations have other mutation types.

In the beginning of 1990s, Koza proposed Genetic Programming (GP) to evolve Lisp programs for automatic programming based on the form of the GA [231], [288]. Since then, GP has become very popular, and some researchers point out that it represents a new area of research in EC.

The initial form of EP, where candidate solutions were initially represented by finite-state machines, was an attempt to create artificial intelligence inspired by the principles of Natural Evolution [184]. In the initial form of EP, the state-transition diagrams of the machines that represent the evolving individuals are randomly mutated, and the individuals with the best fitness are selected. In recent years, other EP representations have appeared what resulted in algorithms similar to ESs.

ESs were proposed to optimize candidate solutions composed of real-valued parameters [47]. In the (μ, λ)-ES, which represents one of the most used ESs, a population of μ parents creates $\lambda > \mu$ offspring using recombination and mutation. The best μ offspring are then selected to compose the new population. In another way, in the $(\mu + \lambda)$-ES, the new population is composed of the best μ individuals obtained from the union of the μ parents and offspring (see Algorithm 2). One can observe that while the $(\mu + \lambda)$-ES is elitist, i. e., it always preserves the best individuals from one generation to the next one, the (μ, λ)-ES is not elitist. In the mutation, each component of the chromosome is changed by a random value obtained from a normal distribution with zero mean and standard deviation σ, which can be adapted during the evolutionary process [34]. The recombination can be discrete, like in GAs, or intermediary, where arithmetic averaging is the most frequent type.

3 TERMINOLOGY

In EC, many biological terms are employed to define entities inspired by real biological ones. It is important to observe that such EC entities are much simpler than the biological ones [288], what has been generating a lot of

misuse. The same problem can be observed in Brazil, where multiple definitions of EC entities can be found and where, sometimes, terms are translated from English without verifying the existence of biological terms.

The use of some EC terms in Portuguese is discussed below.

- **Evolutionary Computation:** Two terms can be found to EC (see last section): *"Computação Evolutiva"* (e. g., [76]) and *"Computação Evolucionária"* (e. g. [93]). Both adjectives *"Evolutivo (relativo a evolução)"* [175] and *"Evolucionário (relativo a evoluções)"* [175] can be found in Portuguese dictionaries. However, *"Evolutivo"* is usually employed in Biology (e. g., *"Biologia Evolutiva")* [388].

- **Evolutionary Algorithms:** Two terms are used (see last section and last term): *"Algoritmos Evolutivos"* (e. g., [76]) and *"Algoritmos Evolucionários"*.

- **Evolution Strategies:** ESs (see last section) are called: *"Estratégias de Evolução"* (e. g., [76]), *"Estratégias Evolutivas"* (e. g., [105]), or *"Estratégias Evolucionárias"* (e. g., [93], [129]).

- **Evolutionary Programming:** EP (see last section) is called: *"Programação Evolutiva"* (e. g., [105]) or *"Programação Evolucionária"* (e. g., [93], [129]).

- **Genetic Programming:** GP (see last section) is called *"Programação Genética"* (e. g., [76], [105]).

- **Genetic Algorithm:** GA (see last section) is called *"Algoritmo Genético"* (e. g., [76], [373]).

- **Recombination:** The process by which the genes of two or more parents are combined to generate the genes of one or more offspring. The recombination can be discrete, which is usually known as crossover, or intermediary, which is used in the real representation and where arithmetic averaging is the most used type [34]. In the Brazilian works on EC written in Portuguese, recombination has been traslated

as *"Recombinação"* (e. g., [105], [441]) or *"Cruzamento"* (e. g., [355]), which is used for crossover too. In Biology, the term *"Cruzamento"* is used to denote the sexual crossing of organisms [388], which has a similar meaning in EAs with diploid codification [288].

- **Crossover, Crossing-Over:** The discrete recombination is called crossover (or crossing-over) in the EA terminology (see recombination). In crossover, genes of the two parents are exchanged to generate offspring. In the Brazilian works on EC written in Portuguese, crossover is called *"Cruzamento"* (e. g., [76], [411]) or "crossover" (e. g., [59], [373]). In Biology, the term "crossing-over" is not translated to Portuguese [68].

- **Mutation:** The process by which genes are randomly changed is called *"Mutação"* (e. g., [76], [373]) in Portuguese.

- **Selection:** The process by which individuals of the current population are selected to compose the next population is called *"Seleção"* (e. g., [59]) in Portuguese.

- **Population:** The set of candidate solutions is called *"População"* ([76], [373]).

- **Chromosomes:** The vector that encodes the candidate solution is called *"Cromossomo"* (e. g., [76], [59]).

- **Search Space:** Two terms have been used to define the space of all candidate solutions: *"Espaço de Busca"* (e. g., [76], [59]) and *"Espaço de Soluções"* (e. g., [105], [411]).

- **Gene:** The functional block of a chromosome, which can be a component or a subset of components of the vector that encodes the candidate solution, is called *"Gene"* (e. g., [76], [105]).

- **Fitness Function:** Four terms can be found to define the objective function of the optimization process in EC: *"Função de Aptidão"* (e. g., [76]), *"Função de Adequação"* (e. g., [105]), *"Função de fitness"* (e. g., [373]), and *"Função de Adaptação"* (e. g., [173]).

4 REVIEW OF PUBLISHED WORKS ON EVOLUTIONARY COMPUTATION BY BRAZILIAN RESEARCHERS

This section presents the references of works on EC produced by Brazilian researchers obtained in April 2006 in two databases through the search of the terms: "genetic algorithm", "evolutionary algorithm", "evolution strategy", or "genetic programming". The databases returned the references where the field "topics" contained at least one of the previous terms and the term "Brazil" appeared in the field "country" of at least one of the authors. In this way, only the references from researchers associated with a Brazilian institution were returned. The first database employed to generate the list of references are the Institute for Scientific Information (ISI) Web of Science, which covers over 22000 journals [2]. The second database is the Compendex, which covers over 5000 journals and proceedings of conferences, mainly in the engineering area [1]. It is important to observe that the references that are not present in these two databases were not cited in this work. Thus, works in proceedings of national conferences and other sources that are not covered by those two databases were not cited. The results obtained in the searches were preprocessed through the removal of the inconsistent and redundant data.

Table 1 presents the references obtained, classified according to the algorithm employed. In the papers classified as "Miscellaneous", two or more different EAs are covered. The papers where a substantially modified GA, ES, or GP algorithm is used are classified as "Miscellaneous" too. Due to the small number of publications, papers where EP is employed were still classified as 'Miscellaneous". The percentage of papers for each algorithm is displayed in Figure 1.

TABLE 1: Survey of works on EC by Brazilian researchers - Algorithms.

Algorithm	Reference
Genetic Algorithms	[446], [82], [3], [182], [151], [429], [33], [249], [122], [239], [38], [405], [345], [167], [169], [236], [128], [334], [126], [11], [431], [210], [406], [193], [163], [343], [410], [246],[435], [378], [448], [55], [238], [32], [121], [166], [323], [404],[319], [264], [208], [244], [428], [152], [376], [117], [389], [235],[96], [256], [279], [65], [200], [212], [342], [305], [66], [251], [453], [297], [135], [281], [237], [316], [232], [189], [434], [42], [444], [81], [69], [451], [199], [280], [307], [339], [375], [255], [94], [219], [409], [302], [385], [104],[95], [390],[290], [254], [70], [83], [31], [420], [202], [72], [168], [324], [21], [16], [241], [411], [337], [49], [127], [436], [45],[366], [6], [14], [415], [273], [421], [399], [327], [423], [93], [315], [270], [338], [194], [326], [60], [417], [8], [261], [18], [267], [353], [347], [371], [416], [245], [276], [425], [119], [333], [118], [233], [218], [401], [85], [450], [185], [380], [158], [164], [13], [400], [424], [209], [355], [172], [262], [335], [396], [419], [90], [407], [242], [124], [84], [222], [229],[91], [26], [71], [108], [178], [272], [381], [216], [360], [89], [301], [379], [286], [364], [165], [393], [125], [19], [282], [382], [87], [248], [289], [44], [447], [58], [77], [30], [9], [250], [107], [228], [10], [320], [161], [12], [278], [240], [314], [43], [437], [271], [24], [15], [291], [48], [155], [445], [196], [329], [363], [433], [92], [440], [138], [181], [226], [430], [439], [103], [207], [221], [427], [356], [377], [39], [112], [57], [220], [78], [25], [183], [402], [73], [442], [4], [368], [268], [136], [418], [176], [269], [17], [79], [174], [162], [392], [115], [365], [197], [114], [357], [234], [266], [98], [299], [328], [37], [311], [296], [201], [177], [159], [358], [130], [294], [432], [132],

TABLE 1: Survey of works on EC by Brazilian researchers - Algorithms.

Algorithm	Reference
Genetic Algorithms	[349], [391], [359], [413], [150], [171], [211], [170], [213], [313], [275], [5], [22], [438], [369], [36], [310], [110], [137], [387], [223], [259], [408], [352], [325], [370], [120], [330], [336], [51], [383], [247], [344], [100], [260], [64], [129]
Evolution Strategies	[331], [106], [101], [206], [346]
Genetic Programming	[52], [20], [54], [153], [274], [7], [56], [191], [306], [304], [154], [180], [303], [300], [308], [35], [277], [455], [257], [258], [309], [350], [29], [298], [53], [332], [28], [160], [312], [367], [422]
Miscellaneous	[105], [204], [287], [144], [123], [295], [23], [243], [253], [74], [322], [62], [40], [341], [217], [252], [179], [41], [143], [198], [293], [340], [374], [456], [230], [190], [354], [63], [361], [61], [443], [452], [398], [215], [441], [157], [225], [146], [224], [195], [283], [386], [75], [449], [86], [384], [80], [426], [149], [111], [50], [192], [412], [205], [148], [214], [147], [102], [403], [188], [284], [187], [414], [351], [133], [145], [348], [263], [321], [394], [142], [97], [186], [113], [131], [46], [265], [318], [292], [362], [134], [67], [397], [27],[88], [109], [395], [141],[317], [116], [454]

Table 2 presents the obtained references classified as application or theory. The percentage of papers in each class is displayed in Figure 1. One can observe that more than 80 % of papers are applications.

The main application of the papers classified as application is presented in Tables 3 and 4, and Figure 2. These papers are classified in one of the following categories:

Figure 1: Works on EC by Brazilian researchers: algorithm (left) and type (right).

- Agriculture: GAs were employed to investigate the process of optimization in the process of partitioning in the growing of plants [132], and in the identification of leaves in images of canopies [313];

Figure 2: Works on application of EC by Brazilian researchers (ps: Power Systems; cs: Control Systems; fz: Fuzzy Systems; nn: Artificial Neural Networks; ha: Hardware; pl: Planning; fs: Feature Selection; ph: Physics; ml: Machine Learning; ip: Image Processing; ee: Electrical Engineering; me: Mechanical Engineering; tl: Telecommunication; ot: Others).
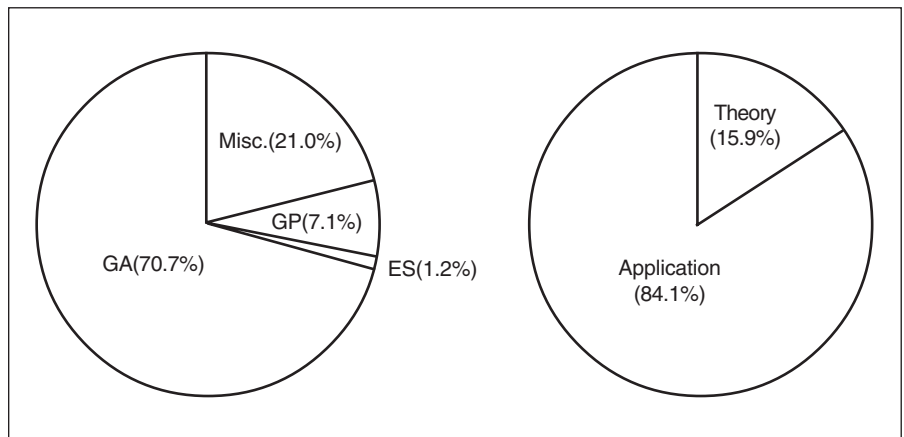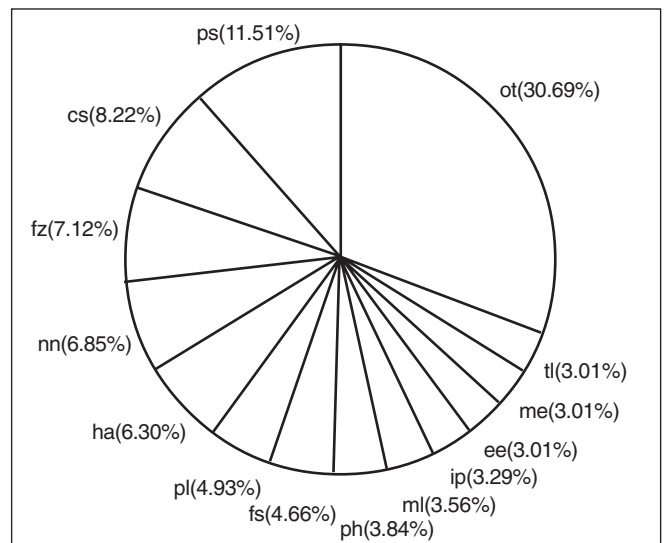
TABLE 2: Survey of works on EC by Brazilian researchers - Type.

Type	References
Application	[446], [82], [3], [182], [429], [33], [249], [122], [239], [405], [345], [167], [169], [236], [128], [334], [126], [11], [431], [210], [406], [193], [163], [343], [410], [246],[435], [378], [448], [55], [238], [32], [121], [166], [323], [404],[319], [264], [208],[428], [152], [376], [117], [389], [235],[96], [256],[279], [65], [200], [212], [342], [66], [297], [135], [281], [237], [232], [189], [42], [81], [69], [451], [199], [307], [317], [375], [255], [94], [219], [409], [302], [385], [104],[95], [390],[290], [70], [83], [420], [202], [72], [168], [324], [21], [16], [241], [411], [337], [49], [127], [436],[45],[366], [6], [14], [415], [273],[421], [399], [327], [423], [93], [315], [270], [338], [194], [326],[60], [417], [8], [261], [18], [267], [353], [347], [371], [416], [245], [276], [425], [119], [333], [118], [233], [218], [401], [85],[185], [380], [158], [164], [13], [400], [424], [209],[172], [262], [335], [339], [419], [90], [407], [242], [84],[222], [229],[91], [26], [71], [108], [178], [272], [381], [216], [360], [89], [301], [379], [286], [364], [393], [125], [19], [282], [382], [87], [248], [289], [44], [447], [58], [77], [30], [9], [107], [228], [320], [161], [12], [278], [240],[314], [43], [437], [271], [24], [15], [291], [48], [155],[329], [363], [92], [440], [138], [226], [430], [439], [103], [207], [221], [377], [78], [25], [402], [73], [442], [4], [368], [268], [136], [418], [176], [269], [17], [79], [174], [162], [392], [365], [197], [114], [234], [266], [98], [299], [328], [311], [74] [296], [201], [177], [159], [358], [130], [294], [432], [132], [349], [391], [359], [413], [141], [171], [211], [170], [213], [313], [275], [5], [22], [438], [369], [36], [310], [110], [137], [387],[223], [259], [408], [352], [325], [370], [120], [330], [336], [51], [383], [247], [344], [100], [260], [64], [129], [150], [106], [101],[346], [52], [20], [54], [153], [274], [7], [56], [191], [306], [304], [154], [180], [303], [300], [308], [35], [277], [455], [257], [258], [309], [298], [53], [332], [28], [160], [105], [204], [287], [144], [123], [295], [23], [243], [116], [62],[341], [217], [179], [41], [143], [198], [293], [340], [456], [230], [190], [63], [361], [61], [452], [398], [215], [441], [157], [146], [224], [195],[386], [75], [86], [384], [149], [111],[412], [205], [148],[147], [102], [403], [351],[348], [263], [394], [97], [186], [113], [131], [318], [362], [67], [397], [27],[109], [395]
Theory	[151], [38], [331], [244], [253], [305], [251], [453], [316], [434], [444], [322], [40], [280], [252], [254], [374], [31], [354], [443], [225], [450], [449], [80], [426], [396],[124], [165], [50], [192], [206], [214], [250], [10], [188],[284], [445], [196], [433], [181], [414], [427],[356],[39], [112], [57], [220], [183], [283], [187], [133],[145], [321],[350], [29], [115], [357], [142], [312], [367], [422], [46], [265], [292], [134], [88], [454], [355], [37]

- Analysis of Algorithms: EAs were used to analyze the complexity of algorithms [131].

- Artificial Networks: EAs were applied in Artificial Neural Networks mainly in architecture design (e. g., [319]) and synaptic

weight adjustment (e. g., [446]).

- Bioinformatics: EAs were applied to search special regions in sequences of amino acids (e. g., [439]), RNA, or DNA (e. g., [418]). EAs were still applied to predict structures of proteins [136] and to docking problems [268].

- Biology: EAs were applied to predict species distribution in Ecology [223], [348].

- Chemistry: the main applications were in chemical process control (e. g., [125]) and molecular simulation (e. g., [369]). The reference [129] presents a survey of chemistry applications of GAs.

- Civil Engineering: the main applications were in the optimization of water distribution systems (e. g., [186]) and of structures (e. g., [169]).

- Combinatorial Mathematics: EAs were applied to set theory [264], [41] and to find minimal arithmetic chains [311], [296].

- Computer Networks: GAs were applied to find optimal paths in computer networks [67].

- Control Systems: several works produced by Brazilian researchers where EAs are applied to control systems can be found. The use of EAs is traditional in the control system area, mainly to tune control parameters (e. g., [410]) and to design optimal and robust controllers (e. g., [232]). In the works produced by Brazilian researchers, several papers in the use of EAs to design

TABLE 3: Survey of works on EC by Brazilian researchers - Applications.

Main Application	References
Agriculture	[132], [313]
Analysis of Algorithms	[131]
Artificial Neural Networks	[446], [287], [319], [279], [23], [219], [72], [277], [417], [267], [224], [333], [86], [178], [286], [248], [102], [278], [15], [193], [456], [233], [234], [27], [194]
Bioinformatics	[256], [366], [439], [268], [136], [418], [269], [438]
Biology	[348], [223]
Chemistry	[14], [125], [394], [369], [395], [344], [129]
Civil Engineering	[169], [83], [97], [186]
Combinatorial Mathematics	[264], [41], [311], [296]
Computer Networks	[67]
Control Systems	[105], [3], [122], [345], [167], [431], [210], [153], [410], [121], [7], [212], [281], [232], [42], [409], [106], [390], [202], [415], [93], [8], [353], [185], [172], [58], [161], [155], [174], [352]
Data Mining	[20], [342], [66], [221], [78], [79], [332], [370], [260]
Distributed Systems	[116]
Electrical Engineering	[243], [127], [338], [261], [245], [386], [9], [4], [359], [387], [100]
Feature or Subset Selection	[179], [6], [347], [380], [91], [379], [393], [282], [382], [107], [327], [197], [328], [177], [130], [137], [336]
Fuzzy Systems	[429], [163], [166], [235], [217], [70], [168], [315], [146], [18], [371], [425], [164], [90], [71], [89], [149], [87], [148], [147], [430], [368], [114], [171], [211], [170]
Geophysics	[21], [384], [314], [349], [391], [413], [22]
Hardware	[297], [306], [304], [62], [451], [307], [303], [300], [308], [16], [61], [378], [272], [301], [320], [291], [377], [309], [17], [298], [299], [28], [310]
Hydraulics	[26], [363], [362]
Image Processing	[405], [126], [404], [94], [45], [270], [209], [455], [447], [403], [95], [365]
Information Retrieval	[440]
Machine Learning	[180], [198], [290], [326], [218], [222], [138], [103], [25], [263], [113], [325], [150]
Materials Science	[135], [262], [381], [201], [109], [408], [383]
Mechanical Engineering	[376], [423], [85], [424], [108], [360], [111], [437], [448], [98], [110]
Medical Informatics	[52], [54], [274], [53], [330], [51]
Music	[294]

fuzzy controllers can still be found (e. g., [415]). The paper [105] presents an overview of EAs applications in identification and control of industrial processes.

- Data Mining: the main applications were in mining sequential data (e. g., [20]) and to pattern recognition in large sets of data (e. g., [78]).

- Distributed Systems: GAs were applied to the multiprocessor scheduling problem [116].

Table 4: Survey of works on EC by Brazilian researchers - Applications (continuation).

Main Application	References
Nuclear Technology	[343], [238], [96], [237], [154], [375], [339], [341], [340], [240]
Oil Industry	[11], [48], [213]
Optical Technology	[81], [416], [119], [118], [158], [5], [397]
Physics	[249], [293], [421], [398], [276], [49], [257], [258], [392], [358], [275], [36], [247], [64]
Planning	[82], [117], [189], [199], [302], [436], [216], [364], [44], [30], [228], [74], [207], [73], [389], [159], [141], [317]
Power Systems	[144], [123], [128], [334], [406], [246], [55], [323], [428], [152], [200], [204], [266], [143], [385], [420], [241], [411], [273], [452], [215], [441], [399], [60], [195], [75], [401], [13], [400], [335], [419], [407], [242], [229], [19], [205], [12], [271], [346], [442], [283], [162]
Reliability	[35], [239], [236], [295], [101], [84]
Robotics	[435], [190], [412] , [104], [92], [432]
Simulation	[182], [56] , [230], [43], [402]
Software Engineering	[65], [176], [160]
Signal Processing	[191], [69], [337], [63], [77], [226]
Telecommunication	[33], [208], [255], [324], [289], [24], [329], [351], [259], [120], [32]
Vehicle Routing	[157], [318]

- Electrical Engineering: EAs were mainly applied to the identification and analysis of electric machines (e. g., [245]) and to the optimal design of equipments (e. g., [359]).

- Feature Selection: EAs were applied to select attributes in pattern recognition problems (e. g., [379]), what is important to remove the inconsistent and/or redundant data and, as a consequence, to improve the performance of the classifier.

- Fuzzy Systems: EAs were mainly applied to optimize the parameters of fuzzy systems, such as fuzzy rules (e. g., [163]) and/or membership functions (e. g., [149]).

- Geophysics: EAs were mainly applied to optimize models used in geology (e. g., [22].

- Hardware: EAs were employed to design optimal and robust hardware (e. g., [304]).

- Hydraulics: the applications were in the optimization of water supply networks, e. g., looking for the best configuration for control valves [26], [363] and operational points in multi-reservoirs [362].

- Image Processing: EAs were mainly applied to optimize quantization tables [126], image restoration [455], and range image segmentation (e. g., [209]). Some works on pattern recognition in vision systems (e. g., [94]) can still be found.

- Information Retrieval: in [440], a GA was employed to adapt an agent that retrieves documents from web information sources.

- Machine Learning: EAs were mainly applied to optimize machine learning systems, e. g., cellular automata [326], N-tuple classifiers [198], and clustering methods (e. g., [218]).

- Materials Science: EAs were applied to identify constants of composite materials (e. g., [135]), to set production parameters (e. g., [381]), to determine the structural composition of materials [262], and to design conducting polymers [201].

- Music: GAs were applied to music composition ([294]).

- Mechanical Engineering: the main applications were of vibration reduction (e. g., [423]), optimization (e. g., [360]), and modeling in mechanical systems (e. g., [85]).

- Medical Informatics: EAs were mainly applied to knowledge discovery in medical data sets (e. g., [54]), computer-aided diagnosis (e. g., [330]), and to predict survival of patients [53].

- Nuclear Technology: EAs were mainly applied to nuclear reactor core design optimization (e. g., [343]), to reliability of nuclear equipments (e. g., [238]), to fuel management (e. g., [96]), and to maintenance (e. g., [240]).

- Oil Industry: GAs were employed to optimize production scheduling (e. g., [11]) and to identify reservoir heterogeneities [213].

- Optical Technology: EAs were mainly applied to the design of optical devices (e. g., [5]) and to route optimization [158].

- Physics: EAs were mainly employed in molecular conformation analysis (e. g., [293]), spectroscopy data analysis (e. g., [421]), semiconductor design (e. g., [49]), and high energy physics (e. g., [257]).

- Planning: EAs were mainly applied to classic planning and scheduling problems (e. g., [82]), to multiprocessor scheduling tasks [117], to test scheduling optimization [199], to minimize the number of late jobs in workflow systems [436], and to specification of cellular manufacturing systems (e. g., [228]).

- Power Systems: the area with more works on EAs applications produced by Brazilian researchers is the power systems area, a traditional area where several optimization methods have been applied all over the world. Several works from Brazilian researchers where EAs were applied to optimization in distribution systems (e. g., [144]), transmission (e. g., [200]), and gene-

ration of energy (e. g., [246]) can be found.

- Reliability: EAs were applied to generate optimum surveillance tests policies (e. g., [239]), to preventive maintenance planning [236], to fault diagnosis [295], to perform reliability analysis [101], and to availability optimization [84].

- Robotics: the use of EAs was proposed to control mobile robots (e. g., [435]) and nanorobots [92], to navigation planning [432], and to optimize coordinating strategies in cooperative robots [104].

- Simulation: EAs were employed in simulators of the coevolution between an artificial immune system and a set of antigens [182], in adjusting parameters in simulation models (e. g., [230]), and in the simulation of complex systems (e. g., [402]).

- Software Engineering: GAs were applied to test data generation for path testing (e. g., [65]).

- Signal Processing: EAs were applied to sound synthesis (e. g., [69]), optimization of microwave oscillators [63] and phase equalizers [77], and to set filter parameters in the simulation of electroencephalographic (EEG) signals [226].

- Telecommunication: EAs were applied to optimize the design and the location of antennas [33], to optimize telecommunication equipments (e. g., [32]), to define the coverage areas and the design of telecommunication networks (e. g., [208]), and to routing (e. g., [324]).

- Vehicle Routing: the applications covered classical and period vehicle routing problems (e. g., [157]).

The main topic of the papers classified as theory is presented in Table 5 and in Figure 3. These papers are classified in one of the following categories:

- Analysis: the modeling of the migration step in distributed GAs was investigated in [316], an exhaustive study to set the best operation types and parameters of three different GAs in a benchmark problem

TABLE 5: Survey of works on EC by Brazilian researchers - Theory.

| Topic	References
Analysis	[316], [444], [250], [284], [312]
Comparison	[244], [192]
Dynamic Optimization	[434], [433]
Heuristics	[322]
Hybrid Algorithms	[254], [374], [225], [80],[165], [50], [188], [445], [181], [414], [361], [321], [29], [46], [292], [88], [454]
Implementation	[305]
Multiobjective Optimization	[151], [31], [443], [449], [355], [426], [396], [10], [57], [265]
New Operators	[453], [450], [206], [214], [196], [427], [356], [183], [115], [367], [134]
Parameter Tuning	[354], [124], [422]
Penalty Scheme	[38], [251], [37]
Representation	[331], [253], [40], [280],[252], [39], [112], [220], [187], [133], [145], [350], [357], [142]
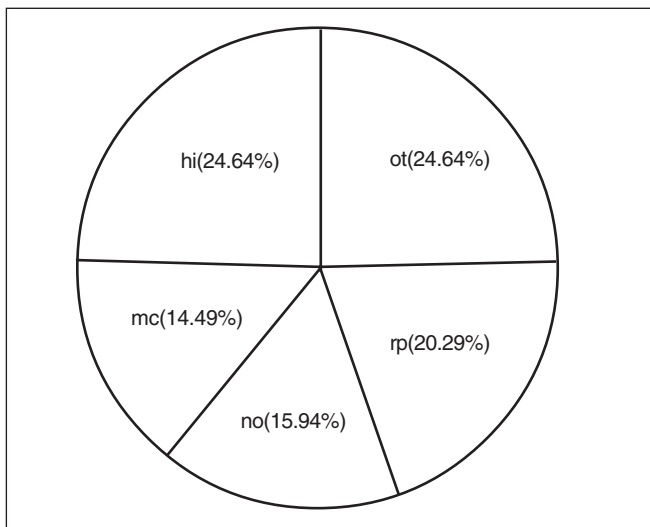
Figure 3: Works on theory of EC by Brazilian researchers (hi: Hybrid Algorithms; mo: Multiobjective Optimization; no: New Operators; rp: Representation; ot: Others).

was performed in [444], the adaptation of a GA that models a regulatory gene network was investigated in [250], the fitness landscape for a single machine scheduling problem is analysed in [284], and the evolutionary process in GP was investigated in [312].

- Comparison: EAs were compared to Fuzzy Sets in general problems [244] and to local search methods in the problem of attribute interaction in data mining [192].

- Dynamic Optimization: when EAs are applied to dynamic optimization, the fitness function and the constraints of the problem are not fixed, which can cause a premature convergence of the optimization process. In [434], random immigrants and self-organization were employed to increase the diversity level of the population and in [433], a GA with gene dependent mutation probability was proposed.

- Heuristics: Problem-specific heuristics can be employed to improve the performance of EAs. In [322], heuristics were applied to fitness definition in pattern sequencing problems.

- Hybrid Algorithms: several approaches where EAs are combined to other techniques, in general local optimization methods, can be found in literature. In the works produced by Brazilian researchers, several algorithms were investigated where EAs were combined: to fuzzy logic [254], [374], to local search methods [225], [188], [29], to decision trees [80], to fuzzy decision trees [165], to deterministic methods [445], [50], [181], [88], to artificial immune systems [414], to Bayesian methods [361], to clustering search [321], to probabilistic

reasoning [46], to statistic models [292], and to simulated annealing [454]. One can observe in Figure 3, that the hybrid algorithms area is the one with more works on EA theory.

- Implementation: in [305], an architecture for hardware implementation of GAs was proposed.

- Multiobjective Optimization: problems involving different optimization requirements are difficult to solve by standard EAs, what resulted in the proposition of new strategies. Among the strategies to deal with multiobjective optimization, Brazilian researches have proposed the use of four new GAs: the constructive GA [265], the non-dominated sorting GA [151], a non-generational GA [57], and the niched pareto GA [449]. Brazilian researches still proposed: the combination of EAs with local search [31] and scatter search techniques [443], new crossover operators [355] and ranking strategies [396], the use of group properties of the intermediate Pareto-set estimates to generate a consistent final estimate [426], and the use of the energy minimization method for fitness evaluation [10].

- New Operators: several operators have been proposed to improve the performance of EAs, usually in specific problem domains. Brazilian researchers have proposed: transformation operators for GAs based on local search [453], [450], [427], [356], the use of a Cauchy-based mutation rather than the classical Gaussian Mutations for ESs [206], replacement operators for GAs [214], mutation inspired by the simulated annealing technique in GAs [196], operators to transform an integer constrained problem into an unconstrained one [183], a new heuristic hypermutation operator to increase the diversity level of the population in a GA [115], the use of context free-grammar to define the structure of the initial population of GP algorithms [367], and the use of cultural algorithms operators to a new quantum-inspired EA [134].

- Parameter Tuning and Control: the values of the parameters have a major influence in the performance of EAs. There are two main strategies to set the parameters in EAs. In the first, called parameter tuning, the parameters of the EA are fixed in the beginning of the run. Examples of parameter tuning can be found in [354] and [124], where Logistic Regression and Factorial Design were, respectively, employed for parameter tuning in EAs. The second strategy is parameter control, where the parameters are controlled during the run of the EA. As an example, in [422], the population size in a GP is controlled by the GA approach known as parameter-less.

- Penalty Scheme: in constrained optimization problems, the definition of the penalties for poor solutions has a major influence on the performance of the optimization process. In [38], [251], and [37], a parameter-less adaptive penalty scheme for GAs was proposed and investigated

- Representation: several works in the literature deal with the problem of representation of the solutions in EAs. In the works published by Brazilian researchers, new representations were proposed: to graphs [253], [252], [40], [145], [142], to smooth fitness landscapes in ES [331], to automatically satisfy a class of cardinality constraints [39], to assignment problems [112], [187], to reduce the number of parameters defined by the user in GAs [280] and GP [350], to data mining applications [220], to physics [357], and to numerical optimization problems [133].

Figure 4 presents the number of publications on EC by Brazilian researchers in each year. The data from year 2006 are not presented. One can observe that more than 100 papers were published in the year 2004. It is important to observe that this survey relates only paper inserted in the databases until April 2006. Paper inserted after this date are not cited, what can explain the smaller number of paper in 2005 when compared to 2004.
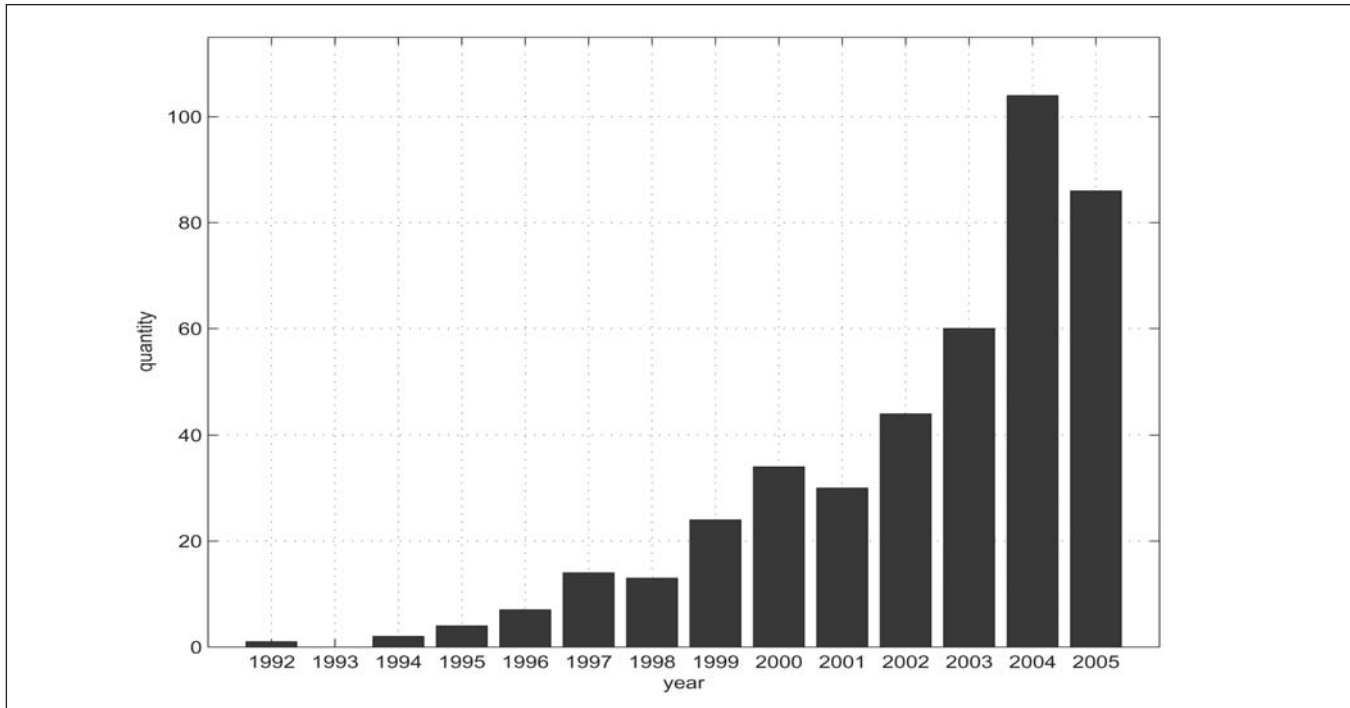
Figure 4: Year of publication of works on EC by Brazilian researchers. The data from year 2006 are not shown.

5 CONCLUSIONS

In this paper, a review of the scientific works on EC by Brazilian researchers was presented. It is very important to observe that the papers cited here are only a fraction of the works from Brazilian researchers, i. e., the works contained in the two databases cited in last section. Many other papers on EC have been published in important sources that are not present in these databases, like the proceedings of events in Computer Science and Engineering. One can still observe that works on other population based heuristics, like Memetic Algorithms, Swarm Intelligence and Artificial Immune Systems, both with important contributions from Brazilian researchers, were not cited. However, a few interesting facts can be observed from the presented data.

Most of the papers published by Brazilian researchers are applications, mainly in the areas where the use of optimization methods is traditional, like power and control systems, although works on EC can be found in a large number of areas. When compared to the number of application works, few works on EC theory can be found. Another important obser-

vation is that the number of publications on EC by Brazilian researchers has increased very much in the last years (see Figure 4). Therefore, it is important that governmental scientific agencies, scientific communities, and institutions have policies to the EC area. An important step has been given when the First Brazilian Workshop on Evolutionary Computation was organized as one of the workshops of the VIII Brazilian Symposium on Artificial Neural Networks in 2004. The authors believe that this workshop should be organized again to incentivate research in this area and provide a forum where Brazilian researchers can discuss their work. It is also possible to see in the references that the Brazilian research in this area is well spread out over the different regions of the country. It is possible to find strong research groups in several different states.

The EC terminology employed in Brazil was discussed in this paper too. One can observe that different terms are sometimes used in Portuguese to describe the same elements. Despite the use of multiple terms is common in the international literature too due to the misuse of terms from biology, it is important to define a standard terminology for EC in

Portuguese. The authors suggest that a committee composed of EC researchers be should formed to discuss this terminology with the aid of biologists in future Computer Science or Engineering events.

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