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https://doi.org/10.5109/6793672

出版情報：Evergreen. 10 (2), pp.1120-1126, 2023-06. 九州大学グリーンテクノロジー研究教育センター
バージョン：

Design and Implementation of Machine Learning Modelling through Adaptive Hybrid Swarm Optimization Techniques for Machine Management

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(Received February 1, 2022; Revised May 14, 2023; accepted May 14, 2023).

Abstract: Because of the billions of transactions that take place every day, the volumes of information is always growing. There are a plethora of categorization techniques accessible for extracting usable information from the massive quantity of information obtained. Swarm optimization methods, as well as hybridizations of these techniques, are now playing a significant role in classifications, and they do so in a very efficient way. An introduction and thorough comparison of many swarm optimization techniques & hybrid swarm optimization techniques that have been published in the academic journals are presented in this article. Bio-inspired computing is a fascinating field of machine learning that investigates how natural occurrences may serve as a rich source of motivation for the development of clever processes that can be turned into strong algorithms in the future. In categorization, prediction, & optimization issues, several of these methods have been utilised effectively. In the field of optimization, swarm intelligence techniques are a kind of microbially algorithm that has been proven to be very effective for quite some time. However, in order for these algorithms to function at their peak levels, the starting variables must be adjusted correctly by a skilled user who knows what they're doing. The development and expansion of machine management are aided greatly by the use of efficient machinery and equipment. Different research investigations are engaged in the execution of the study and reviewers have concluded that machine learning technologies are the most effective means of supporting this expansion of the research. In order to better understand machine learning technologies and machine learning algorithms, the majority of implementations are investigated using swarm intelligence optimization techniques. As a result, they may be used as an essential judgement tool in the manufacturing industry.

Keywords: Machine Learning, Swarm Optimization, Intelligence, PSO, Techniques, Model, Algorithms, Hybrid methods, Etc.

1. Introduction

Swarm intelligence and optimization techniques have piqued the scientific group's interest in past few decades owing to their remarkable flexibility to cope their technique to complicated situations. These methods are classified as microbially computational models seen in environment because they imitate the aggregated behaviour of people engaging in their surroundings[1)]. Many of these processes, including genetic algorithms, differential evolution, ant colony system, & particle swarm optimization, were becoming popular approaches, and they remain at the forefront of major research in the optimal control area[2)]. Swarm intelligence & optimisation techniques operate as a smart-flow, iteratively applying gained information to create near-optimal solutions[3)]. The developmental approach of these methods is mostly determined by the initial parameter setup, which is crucial for the successful development of the search process and, as a result, the successful discovery of high-quality alternatives[4)].

Swarm optimization methods, a kind of evolutionary algorithm, utilise feature extraction, rule finding, or exception exploration to make classification easier[5)]. Nowadays, intelligence decision support systems (IDSS) are extensively utilised in businesses, transportation, protection of the environment, as well as other fields[6)]. It is essential in practise and helps to the advancement of mankind. Machine management is riddled with issues. Following a thorough examination of these issues and machine learning algorithms, it is concluded that appropriate swarm intelligence optimization techniques should be employed to better allow machine learning algorithms to solve difficulties. Due to inherent characteristics of machine learning & swarm intelligence algorithms, the present approach, with a lack of accuracy or being completely incorrect, may elicit severe mistakes. The limits of machine learning will be divided into two parts: finding answers and improving swarm intelligence optimization algorithms so that issues may be solved easily and logically[6]. Because of technological advancements, most machine management depends on the machine learning algorithms, which has been suggested by using environmental information as training examples to determine the ideal futures. Among the technologies are k-nearest neighbour, artificial neural network, and genetic algorithm, among others[7].

2. Optimization of Swarms

Swarm optimization (SO) is a computer technique for optimising an issue by continuously enhancing a candidate solution in relation to a specified measure of quality. Particle Swarm Optimization (PSO), Cat Swarm Optimization (CSO), Ant Colony Optimization (ACO), and artificial bee colony algorithm (ABC) are only a few of the swarm optimization methods that have been developed in the previous[8].

A. Ant Colony Optimization (ACO)

An algorithmic represents a decision rule as a collection of attribute-value pairs in a computer programme. It is necessary to feed artificial ants the complete training set in order for them to find a rule set. Ants begin to build rules based on the provided training set by gradually attaching words (attribute-value pair) to a partly formed rule that has already been formed. There are two criteria that must be met before terms may be added to a partly built rule[9]. These are as follows:

a) When a new word is introduced, the rules must encompass the smallest number of possible instances.

b) In order for a rule to be valid, the characteristic that is going to be added to it must have been before contained in any other word. Therefore, the rules would be ridiculous.

It is clear that the Ant-Miner algorithms implements the Michigan method since each cycle of the algorithms produces one greatest standard, and at the conclusion of the process, we get a selection of the top regulations to choose from. It differs from traditional decision tree algorithms in that it calculates the probability of a feature, while traditional decision tree algorithms compute the probability of an attribute-value pair[10]. This unpredictability is integrated into the system via the use of a heuristic function. The complexity measurement is the sole criteria in use for tree construction, while the entropy measure and pheromone upgrading are both utilised in the instance of Ant-Miner, that is another point of differentiation. Figure 1 shows the ant colony optimization flow chart.

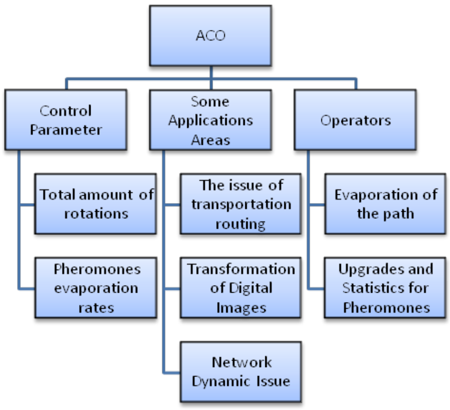

Fig 1. Ant Colony Optimization (ACO)

B. Particle Swarm Optimization (PSO)

PSO is an evolutionary method that was influenced by birds swarming and that, like some other darwinian techniques, is based on the notion of fitness[11]. PSO is created by imitating social behaviour and analysing the results. In order to better balance domestic and global searching, a new measure known as persistence weight (w) was introduced to the classic PSO algorithm in order to enhance the outcomes generated by the PSO algorithm. In its initial form, PSO was intended to address real-world problems of significance[12]. Figure 2 shows the particle swarm optimization process.

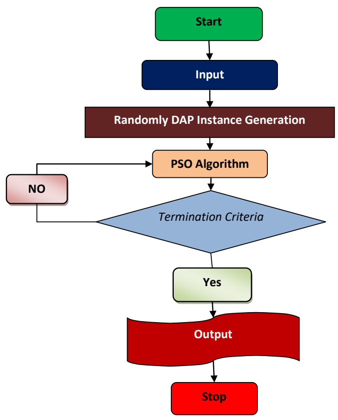

Fig 2: Particle Swarm Optimization (PSO)

It was necessary to expand the classic PSO into Discontinuous space in order to deal with the discrete issue in which speed was squished to use the exponential functional.[13] The use of both binaries and continuously representations of Particle Swarm Optimization (PSO) in categorization has been presented, and the outcomes of the classification are significantly improved as a consequence. In the first phase of the study, three PSO versions decided to name Discrete Particle Swarm Optimizer (DPSO), Linear Decreasing Weight Particle Swarm Optimizer (LDWPSO), & Constricted Particle Swarm Optimizer (CPSO) were especially in comparison with Genetic Algorithm (GA) and the Tree Induction Algorithm (J48) and the results were positive (CPSO) [14]. Second, the PSO version is improved in terms of characteristic type support or temporal complexities in the second phase of the study. PSO is competitive with evolving techniques as well as tree induction methods, according to experimental findings[15].

C. Cat Swarm Optimization (CSO)

CSO is yet another optimization technique that is inspired by the behaviors of felines. Despite the fact that cats are superb hunters, they also exhibit greater awareness even while at resting[16] There are two different modes that may be used to characterise their behaviour: searching phase and monitoring phase. It is unique to each cat in terms of its location and speed (direction of movement). Several researchers have claimed that the searching performance of CSO is superior to that of PSO[17], since the locations are represented dots in D dimensions, and the speeds for each dimensions alter the values of the these points. Figure 3 shows the cat swarm optimization process.

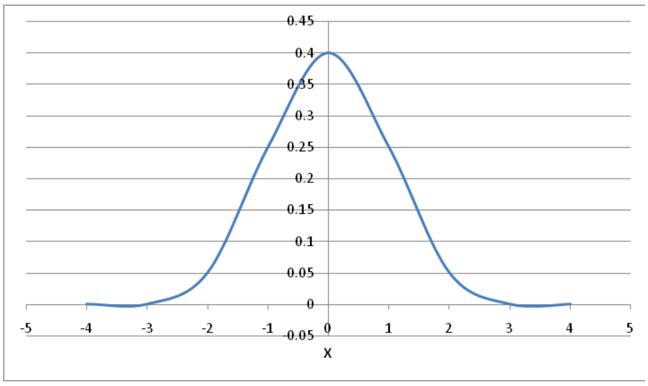

Fig 3: Cat Swarm Optimization (CSO)

3. Using Swarm Optimization For Classifications

There is a huge quantity of study on classification utilizing swarm optimization methods that has been done. As a result of their extensive international search capabilities, several progressive search methods (PSO), which fall under the category of nature-inspired machine learning algorithms, have been employed to get the optimum selection of features. Meta-heuristic algorithms, such as the genetic algorithm (GA) & particle swarm optimization (PSO), are used to resolve the optimization problems by following search processes. Through the use of natural evolution simulation, the GA is able to address optimization issues[18]. In PSO, each alternative is regarded as a particle, and the machine learning algorithms looks for the optimal solution by taking into account the experiences of all objects in the solution space. Several additional optimization methods, including such ant colony optimization (ACO), artificial bee colony algorithm (ABC), or cat swarm optimization, have indeed been suggested in recent decades (CSO). These algorithms tackle the optimization issue by observing how intelligently ants swarm for food-finding & data sharing with the aid of pheromones behave and then optimizing their behavior accordingly. The ABC algorithms were developed as a result of studying the food-finding behavior of a swarm of bees. The search performance of CSO outperforms that of PSO in most cases. CSO, on the other hand, necessitates lengthy calculation periods in order to find the optimal solution (Orouskhani, 2013). Enhanced Cat Swarm Optimization (ICSO) is a method modified from a method in, as well as the total efficiency of the ICSO algorithm in selecting features has been assessed utilizing support vector machines (SVM). A novel hybrid ant colony optimization algorithm (ACOFS) combines the benefits of wrappers and filtering methods to optimize ant colony formation and growth.

A. Classification methods based on hybrid swarm optimization techniques

In this paper, we propose a hybrid ant colony optimization method that combines the benefits of wrappers or filter techniques by choosing a subset of prominent characteristics from a smaller collection of main characteristics[19]. The distinction between ACOFS and current algorithms may be explained by the fact that it has two unique characteristics: First and foremost, ACOFS is concerned with not only the selection of a handful of prominent characteristics, but also the achievement of a smaller number of these features. Second, ACOFS employs a hybrid search method for choosing important characteristics, which combines the benefits of both the wrappers & filter techniques in order to maximise efficiency. Artificial bee's colony optimization and excessive randomized adaptive filtering method are combined to form a hybrid DABC-GRASP by merging their respective characteristics. The suggested techniques have been compared to other techniques such as tabu search, GA, PSO, ACO, and GRASP, and the findings show that the proposed method is more accurate. A hybrid GA-ACO method in which the deceased people of the GAs population are replaced by new people of the ACO population.[20] Compared to current methods, the findings of the study indicate that GA-ACO is comparable. When it comes to classification results, the hybrid ACO-RF algorithm outperformed the competition. The characteristics of ACO & TOFA (Trace Oriented Feature Analysis) are combined in this technique, which may improve accuracy of classification for massive amounts of information by shrinking the feature space to a considerably lower dimension.[21]

For classification accuracy, the following table-1 summarizes the differences between different hybrid swarm optimization methods used in the study.

Table 1. summarizes the differences between different hybrid swarm optimization methods used in the study.

The Fundamental Technique	*Hybridized Techniques*	*In comparison to*	*Perspectives*
GA	SVM (Support Vector Machine) with HGAPSO (Hybrid Genetic Algorithm And Particle Swarm Optimization)	• PSO+SVM • GA+SVM • HGAPSO+SVM	Techniques were compared. In respect of efficiency measures, HGAPSO+SVM outperforms some other methods compared.
PSO	PSO+SVM+ABC relying on endocrinology signals (Artificial Bees Colony Optimization)	• PSO-SVM • EPSO-SVM • ABC+SVM	EPSO+SVM+ABC outperforms other hybridised methods in terms of correctness while requiring less variables.
ABC	Co ABC Miner (Cooperative Rule Learning)	• C4.5Rules • SIA • CORE • ABCMiner	For categorization criteria, Co ABC Miner produces the best findings.
PSO	HPSO+LS (Local search)	• Simulated Annealing (SA) • Genetic Algorithm (GA) • Particle Swarm Optimization (PSO) • Ant Colony Optimization (ACO)	Additionally, the proposed technique for selecting features is examined. According to the findings of the experiments, HPSO + Local Search provides better performance with increased precision in very little period.

B. PSO Is Used For Classification.

Because adaptive search methods such as PSO have excellent global search capabilities, they have been utilised to get the optimum features selection for this problem. PSO for feature extraction utilising a filter-based method is shown. To assess the optimum extraction of attributes using just a nearest neighbour classifiers in this work, a wrapper method to features extraction was employed[22]. The fitness parameter was the reduction of class labels, which was achieved by minimising the classification errors. The classification efficiency is enhanced by using a smaller group of characteristics depending on PSO. The size of the original central aspect set and the training set is critical in order to get the optimum feature subset. The MultiSwarm PSO (MSPSO) algorithm was utilised to get the optimum feature subset. Along with feature selection, the parameters of the SVM are improved as well[23]. To enhance the categorization, MSPSO and support vectors with F-measure have been employed in conjunction. This method has been evaluated in comparison to other methods such as conventional PSO, grid search, and genetic algorithm in order to determine its efficacy (GA). MSPSO beats all of the other techniques in this comparison. The communication rules between various sub in MSPSO are complex. Because of the huge population and complex communication regulations, the calculation cost of MSPSO is higher than the cost of the other three techniques combined (see table). Given that lack of precision or uncertainties can be dealt with simply by rough sets, a features choice technique depending on PSO and rough set theory has been suggested[24]. The results of the experiments demonstrate that PSO is an effective method for rough set minimization. For feature reductions, binary particle swarm optimization (PSO) along with a crude set concept is used[26]. However, there is a disadvantage to using rough set theories in attribute selection troubles: rough set theory takes the majority of the available computing time. On the basis of two different data measurements, two new techniques were created. On the foundation of the BPSO and data theory, the optimized feature group choice is determined. Figure 4 shows the classification using PSO

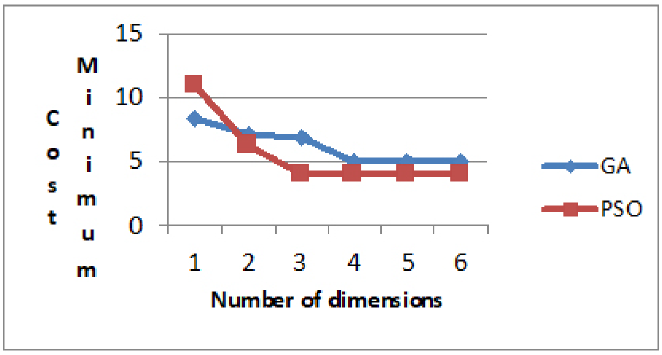

Fig 4: Classification using PSO

C. Classification based on the CSO

In part because of the intricacy of the two different modes of CSO, there is little research on categorization including CSO. The suggested CSO+SVM was used to assess the correctness of classification. The suggested method improves the efficiency of classification while maintaining a high level of correctness. It was presented in a fresh and enhanced CSO that standard classifications like as neural networks, Nave-Bayes classifiers, decision trees, and SVM were used. The idea of hyper-plane classification is used to data that is not linearly separable using SVM, which transforms input variables into a hyper-plane by adding a kernel functional to the input variables In the hyper-plane, the SVM determines the greatest distance among various data groups and separates them into 2 categories of information based on that distance between groups. This is accomplished via the use of the radial basis function (RBF)[27]. It was decided to adapt the ICSO algorithm from a method in, and the efficiency of the total ICSO algorithm in selecting characteristics was assessed using SVM. ICSO stands for Increased Cat Swarm Optimization, and it was modified from a method in. The ICSO procedure is divided into two phases: searching mode & tracking mode. For the enhanced searching mode, it has been suggested to use cat swarm optimization. There have been two techniques used to the searching mode in order to decrease the time needed to locate the optimum solution and to alter the location of the cats.

D. ACO is used for Classification.

A change to the Ant-Miner1 algorithm was proposed in the year 2002, which is now known as Ant-Miner2. So because choice of term is dependent on the heuristic function, the algorithms proposes a new method of computing the heuristic function and, therefore, a new method of selecting the term. A third variation of the aforementioned method, known as Ant-miner 3, has been developed. Specifically, Ant-Miner 3 suggested two new features:

a) A novel method of modifying the pheromones values of words that are utilised in rule building is introduced. Normalization, on the other hand, has the effect of decreasing the pheromone value of unneeded words.
b) The document also proposed a new transition rule, that is, a new rule for the choosing of words, as well.

In 2006, a new version of Ant-Miner[28)], which is used for finding incomplete rule lists, was released. Previous ant-mining algorithms were successful in discovering an organized rule list. The latest iteration found an unordered rule set, which is a collection of rules that do not have to be implemented to test data in the same sequence in which they were identified in the previous version. Several modifications to the high-level algorithms, heuristics function, and pheromone update were necessary to make this feasible. Simultaneous Ant Miner method presented some parallel processing in the Ant-Miner algorithm. Rather than finding consequents, we set the consequents and then identify antecedents that match to them later on. The ants in this grouping dig classification model in parallel with comparable subsequent sections, creating parallelism and giving rise to the term "parallel Ant-Miner" (parallel Ant-Miner). A large number of ants now explore the whole area in parallel to find categorization rules, and they then interact with the other ants in their own organization as well as the best from other members to keep the pheromone of words up to current.

4. Model with a Hidden Markov Chain

HMM is for hidden Markov model, and it is a paradigm that enables one to infer components of the Markov chain that are not immediately visible, or hidden (Naranjo 2020), based on the observations of some apparent state. When states change, it is believed that a Markov chain is used to move between them. The Markov chain may be described by a probabilities vector at the start of the chain and a transition matrix A at the end of the chain. In each concealed state, observable elements O are released in accordance with a predetermined distribution, and these components are recorded in the emissions matrix B (Nagendra, 2019). There are three primary duties that an HMM is responsible for completing as shown in Table 2.:

Table 2: Primary duties of HMM

Learning	We study the HMM's characteristics A and B given a series of observations O and a collection of phases.
Decoding	Calculate the optimum series of concealed states Q based on the parameters A, π, and B, as well as the observable information O.
Probability	Suppose you have an HMM $\lambda = (A, B)$ and a series of observations O; compute the probability that those data belong to the HMM, denoted by the symbol $P(O\|\lambda)$.

5. Conclusion

The investigation of swarm methods for categorization in a variety of areas is gaining momentum. Swarm optimization methods are optimization techniques that are particularly well suited for big datasets, such as databases. Machine learning, data mining, artificial intelligence, and pattern matching are just a few of the application fields available. When implemented to the aforementioned application domains, hybrid swarm optimization methods have the potential to provide more effective and precise solutions. Based on a comprehensive review and evaluation of different hybrid swarm optimization algorithms for classification, it is concluded that this field of research is still underexplored and that there is significant potential for the hybridization of swarm optimization techniques, in addition to the already established hybridised swarm optimization approaches, to be explored further in the future. And lastly in this paper we examine the model with a hidden markov chain.

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