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ROLE OF MACHINE LEARNING IN FIELD OF SWARM INTELLIGENCE

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ABSTRACT

One aspect of artificial intelligence is swarm intelligence (SI). It is becoming more and more popular as complexity forces less-than-ideal solutions into the picture. It belongs to the machine learning (ML) field. A few SI methods have applications in machine learning. These algorithms either work alone or in combination with other algorithms. SI serves as the foundation for machine learning, fine-tuning the parameters of the model. The collective behaviour of a group of animals is known as swarm intelligence. Swarms can be seen in a variety of settings, such as ant colonies, fish schools, and flocks of birds. which describe the biology of ants, their activities, and how they help birds overcome obstacles. The Bee Colony Optimization monitors and investigates bee behaviour, connections, mobility, and swarm interactions. This study investigates the issues of swarm intelligence and swarm intelligence-based algorithms like ACO, PSO, GA, and FA in the field of machine learning.

KEYWORDS: Swarm Intelligence (SI), Machine Learning (ML), Genetic Algorithms, Optimization, Particle Swarm Optimization, Ant Colony Optimization, Firefly Algorithm.

1. INTRODUCTION

The term "swarm intelligence" was coined to describe the way in which "clusters of basic agents," such as ants, bird flocks, and bees, communicate with one another and with their surroundings. Because of their innate power and adaptability, these nature-inspired algorithms are good architectural models for challenging engineering issues. ACO and PCO were first developed using swarm intelligence. Numerous more algorithms have been published, along with some well-known ones as the Artificial Bee Colony, Firefly, and Bat algorithms (Abraham, A. et al 2006) and (Ahmed et. el, 2020) and (Aydoğdu, İ., 2012).

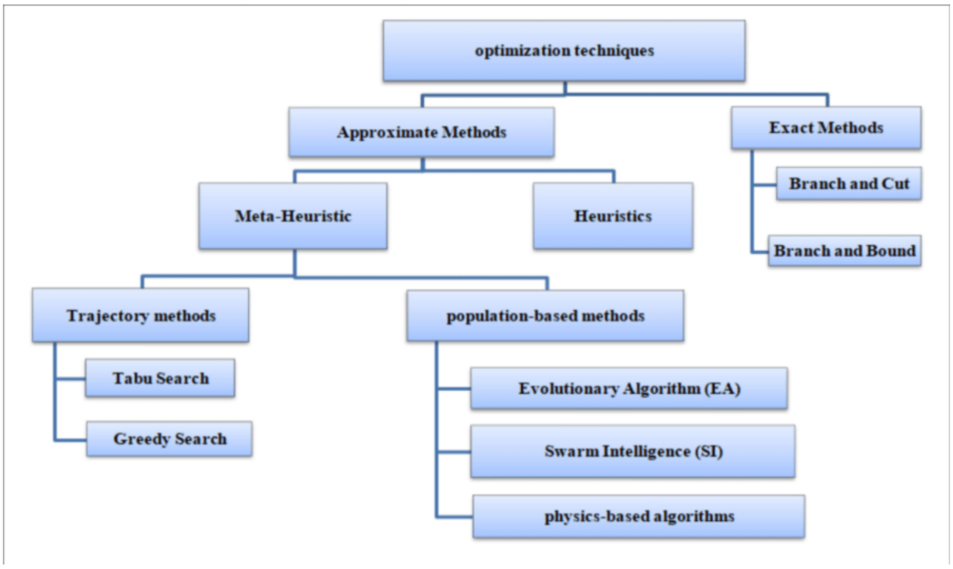

Figure 1: Classification of optimum techniques[4]

2. MOST COMMON ALGORITHMS FOR SWARM INTELLIGENCE

2.1 GENETIC ALGORITHMS

Genetic algorithms founded on the fundamental idea of natural evolution, initially presented by John Holland in 1970.Biology's field of genetics was modified by GA. Using this method, viable model behavior is encoded into "genes" (Abraham, A. et al 2006) and (Ahmed et. el, 2020). Selection and modification are the two main processes that make up a genetic algorithm. The method of selection involves choosing an individual to produce the next generation, and manipulation involves using crossover and mutation procedures to construct the next generation from the chosen person (Ahmed et. el, 2020) and (Aydoğdu, İ., 2012).SI paradigm for addressing issues with optimization. It draws inspiration from biological phenomena including swarming, flocking, and vertebrate herding.

2.2 PARTICLE SWARM OPTIMIZATION

Kennedy and Eberhart created the PSO algorithm.By taking advantage of a person's inclination to compete with the achievements of others in the group, PSO mimics social behavior in conjunction with the group. The foundation for PSO is a bird without quality or size known as a particle that moves across a D-dimensional space, shifting its position in search space according to its own ability and that of its neighbors (B. Niu et al, 2007) and (Beni G et al, 1993).A swarm is a collection of random particles (or solutions) that are used to start the search for the optimal solution. There is an optimal fitness function for every particle. The result of the fitness function is used to identify the issue. Particle motion determines both their position and velocity. Through updating its three primary properties—inertia (personal experience), best location identified by group (social exchange), and its best position (personal experience)—particles adopt the dynamic environment for seeking for the optimal solution.PSO use both local and global search techniques to strike a balance between exploration and exploitation (Beni G et al, 1993) and (CH. V. Raghavendran, 2013).

ANT COLONY OPTIMIZATION

ACO is an algorithm that uses meta-heuristics. A colony of native ants collaborates to find solutions to challenging issues. Its purpose is to mimic the foraging behavior of wild ant colonies by determining the quickest way to find food.

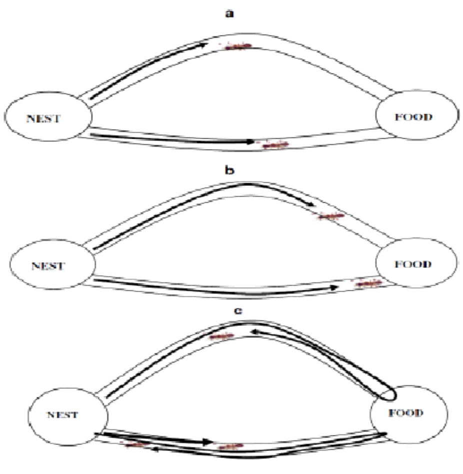

Figure 2: Basic of Ant routing[5]

The ants use a substance they generate called pheromone to deposit the food source. Pheromones serve as a communication channel between the ant colony and its food supply.

The consistency and quantity of the diet determine how much chemical is stored. Insects use their pheromones to trace a route between their place of residence and the food supply. With a group of ants on a specific path, there was an increase in the likelihood that they would look for food and pursue one of several alternative routes (Deng, W., 2019) . Through the stemmery process, the artificial ants coordinate and communicate in an indirect manner. This organic stemmery is transformed into the ACO meta-heuristic optimization.The basis of an ACO algorithm is a parameterized probabilistic model called the pheromone model. The pheromone trail is linked to the elements of solutions and increases the likelihood of the solutions related to a particular issue. It generates a search space filled with different options. The pheromone trail is initialized using various ant types and values. Pheromones update artificial ant power by altering the pheromone rule after developing a solution(Engelbrecht, A. P., 2007).

By increasing the sample size of a good solution that is comparable to those built previously, this update aims to focus the worldwide search for high-quality solutions(Engelbrecht, A. P., 2007) and (Fister, I, 2013).

2.3 FIREFLY ALGORITHM

In 2007, researchers at Cambridge University developed firefly algorithms (FA), which were inspired by the way butterflies flap their wings to entice potential mates(Gandomi, A. H. et al, 2011) and (M. Dorigo,et al, 2007) and (M. Ghazavi et al, 2011). It is a population-based stochastic search technique that draws inspiration from fireflies' luminosity, absorption, and mutual attraction. Blinking lights are as visible as they are attractive, and brightness is a target feature that needs to be both increased and decreased. One might think of the optimal solution as being proportionate to the lighting of an ideal problem (M. Ghazavi et al, 2011) and (M. JangaReddy et al, 2011). The firefly starts by initializing its population, where each firefly symbolizes a potential fix for the problem. The population size determines the solution space's volume. Every firefly or potential solution's light intensity is evaluating its overall health. The brightness, wavelength, and coefficient of absorption of light can be used to characterize the amount of light and its components, which in turn determines how appealing nearby fireflies are. The firefly's natural walk, present location, and beauty all influence its movement. A firefly's position and, more importantly, its ability to attract other fireflies are directly correlated with its brightness(M. JangaReddy et al ,2020) and (O. Hasançebi et al, 2013). Fireflies use their appearance and light to their advantage to shift their position and reach the highest global altitude. This ability divides the community into smaller groups, each of which revolves around a local optimum. This allows for the simultaneous determination of local optima by vast populations. Firefly attraction regulates how far a group of fireflies can see from a neighbouring group on a quantitative level. Because of these advantages, A is significantly nonlinear and appropriate for modality optimization problems (O. Hasançebiet al, 2013).

3. CHALLENGES OF SWARM INTELLIGENCE

One of the primary problems with swarm intelligence is that its behavior cannot be predicted by individual rules.SI is more sensitive when little changes to the fundamental guidelines result in different behaviors at the group level. The understanding of an agent's function was incomprehensible.PSO's performance is heavily impacted by the parameters that are chosen, some of which have an impact on its shortcomings. the weight of inertia for occurrence increases the speed of particles, allowing for more exploration and less manipulation.32The identification of the problem determines the value of inertia (S. Kareem et al, 2019). The PSO and ACO lack a robust mathematical foundation for research, particularly with regard to

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operational algorithms for convergence conditions and approaches for estimating basic parameters. Regarding the "dark side" of swarm intelligence, some questions remain. On the social front, the rivalry between the two future swarm intelligence domains—army management and biomedical—is intensifying (S. W. Kareem et al, 2020).

4. CONCLUSIONS

The word "optimization" has a plethora of applications. Because of the complexity of the optimization problems that engineers must solve, traditional computing may not be able to handle the best answers. As a result, engineers' primary focus has been on developing more scalable and efficient meta heuristic algorithms. Optimization plays a key role in optimal resource management by solving problems in an effective and efficient manner. Swarm intelligence is the field of meta-heuristic optimization with the greatest potential. The stochastic, population-based meta-heuristics used by the swarm intelligence techniques are inspired by a range of natural events. Ant socialization is modeled after the naturally occurring self-organization of swarms of bees, wasps, and other birds to maximize productivity.Swarm-based optimization techniques promote self-organization by examining the cooperative behavior of these basic entities. Iterations also offer a chance to learn new things. When handling huge optimization issues, the review paper revealed a number of optimization algorithms; these basic agents calculate more quickly because they are comparable to one another.

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