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Classifying Nature-Inspired Swarm Algorithms for Sustainable Autonomous Mining

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Abstract

Over the resent decade, swarm-based algorithms have been utilized for automation in the mining industry. However, there is lack of understanding of their specific contributions at different stages of the mining process, in the broader sense. This paper classifies the optimization of mining lifecycle and swarm robotic systems based on reviewing nine nature-inspired algorithms for sustainable mining. Namely, the following swarm-based algorithms have been considered: Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Firefly Algorithm (FA), Bat Algorithm (BA), Krill Herd Algorithm (KHA), Grey Wolf Optimizer (GWO), Salp Swarm Algorithm (SSA) and Grasshopper Optimization Algorithm (GOA). In this study, we conduct a systematic review of their impact on spatial organization, navigation, and collective decision-making, which in their turn can help to improve exploration accuracy, mine planning precision, and transportation efficiency. This research highlights the utility of nature-inspired algorithms that can contribute to specific mining phases and operations and should allow to achieve a more efficient and targeted mine optimization, greater environmental sustainability and improved mine safety.

Keywords: Mining Lifecycle; Mining Optimization; Swarm Robotics; Nature-inspired Algorithm; Sustainable Mining

Introduction

Mining can be regarded as a global resource supply, supporting the gross domestic product (GDP) of various countries, and having a key role in their stable industrial and sustainable economic development [1]. As the human population increases and urbanization accelerates, the demand for resources is also growing rapidly. The mining industry needs to change to meet this demand by seeking innovation and advancement in mining technologies to increase efficiency in all stages of mining, and energy efficiency [2]. This goes beyond providing environmental sustainability and a safe work environment for miners to operate. Mining innovations are becoming more complex involving smart sensors, remote operations, advanced power systems, reliability and resilience, robots operating in harsh environments such as hot and humid underground tunnels, high topology, and desert climates [3]. The prime example of the application of the current revolution in the mining technologies is the Gudai-Darri iron ore mine in Pilbara, Western Australia, operated by Rio Tinto and known as the SMART Mine. Rio Tinto has implemented autonomous mining transport trucks, trains and drill rigs, there is no need for manual labour at this mine site, and all engineers and operators work remotely. Each operator can control up to eight trucks one of which is equipped with a combination joystick, at the Mining Control Station located at approximately 110 kilometres northwest of the Gudai-Darri, at Newman, Western Australia [4]. These innovative technologies have transformed traditional mining to automated robotic mining, integrating machine learning, robotics, and remote operations to maximize mine operational efficiency, reduce human safety risks and mitigate environmental sustainability. Innovation and transformation in the mining industry have increased iron ore production at the mine from 159 tons in 2000 to 836 tons in 2020 [5]. The Rio Tinto Financial report states that the integration of automation technology can not only increase productivity but also reduce operating and maintenance costs [5]. The success of this Rio Tinto operation has inspired further research into perfecting autonomous mining operations through fully automated remote control without the need for humans, while swarm robots can leverage nature-inspired swarm algorithms for decision-making and consensus building.

In this paper, nine nature-inspired swarm algorithms have been systematically analyzed through theoretical and mathematical models based on swarm behaviours and collaborations found in nature. The results from these analyses can contribute to the wider implementation of swarm robotics in mining and hence, achieving improved mining optimisation and operations. This research offers a structured and comprehensive framework of swarm robotics integrated mining that can be helpful for the further advancement of future mining technologies.

Analysis of Swarm-Based Bioinspired Algorithms

This section analyses theoretical and mathematical models of nine nature-inspired swarm algorithms, focusing on understanding how corresponding animal and insect models from nature collaborate, cooperate, and survive in large groups.

Ant Colony Optimization (ACO) Algorithm

The Ant Colony Optimization (ACO) algorithm is a meta-heuristic algorithm inspired by the foraging behavior of ants, and was proposed by Dorigo in 1992 [6,7]. The ACO algorithm illustrates the concept of stigmergy, utilizing indirect communication through ant pheromone experiments to imitate ants' pathfinding techniques, and uses a population-based approach in pheromone search experiments to solve optimization problems [8]. ACO schematic diagram [9] and finite state flow chart [10] includes initializing algorithm parameters and agents, building solutions through state transition rules, and refining these solutions through fitness-based evaluation, as shown in (Figure 1).

$$P_{ij}^{k} = \left(\tau_{ij}^{\alpha}\right)\left(\eta_{ij}^{\beta}\right) / \sum z \in \text{ allowed i}\left(\tau_{ij}^{\alpha}\right)\left(\eta_{ij}^{\beta}\right) \quad (1)$$

$$\tau_{ij} = \left(1-\rho\right)\tau_{ij} + \sum_{k}^{m} \Delta\tau_{ij}^{k} \quad (2)$$

Equation (1) on the probabilistic decision-making equation $\left(P_{ij}^{k}\right)$, integrates the pheromone trace $\left(\tau_{ij}^{\alpha}\right)$ and the heuristic desirability $\left(\eta_{ij}^{\beta}\right)$ between nodes for the search and harvest process. The uniqueness of the ACO algorithm lies in the dynamic feedback mechanism $\left(\tau_{ij}\right)$ in Equation (2). Using the pheromone evaporation (ρ) and ant deposition $\left(\tau_{ij}^{k}\right)$ to update the pheromone trial can avoid local optimality and converge to the optimal solution. Through a complex interplay of exploration, exploitation, and adaptive feedback, ACO leverages biomimetic approaches to efficiently solve computational problems.

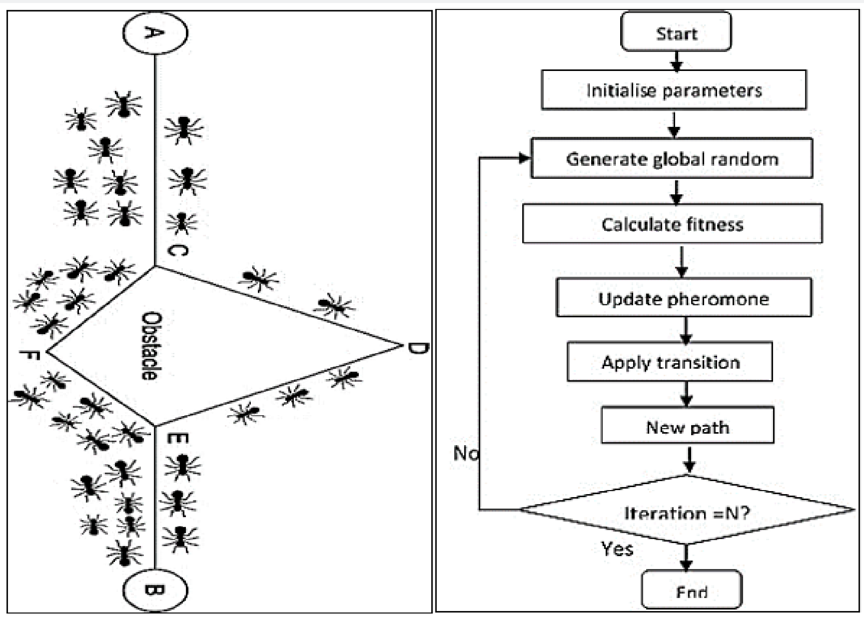

Figure 1: ACO schematic diagram [9] and finite state flowchart [10].

Particle Swarm Optimization (PSO) Algorithm

The particle swarm optimization (PSO) algorithm is a meta-heuristic algorithm inspired by the social behavior of birds and fish and was proposed by Eberhart and Kennedy in 1995 [11,12]. The PSO algorithm illustrates the interactions and collaborations of fish schools and birds to optimize problems through social learning. PSO schematic diagram [13] and finite state flow chart [14] involve initializing the agents in the swarm and iteratively updating their speed and position using the individual experience

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and consensus in the swarm, to update to the final optimal position through the global position, thereby effectively navigating to the optimal solution, as shown in (Figure 2).

$$V_i^{t+1} = \underbrace{WV_i^t}_{Inertia} + \underbrace{c_1U_1^t\left(P_b^t - P_i^t\right)}_{Personal} + \underbrace{c_2U_2^t\left(g_b^t - P_i^t\right)}_{Global} \quad (3)$$

$$P_i^{t+1} = P_i^t + V_i^{t+1} \quad (4)$$

Equation (3) on the updated speed mechanism $\left(V_i^{t+1}\right)$ integrates the inertia of particles with cognitive and social components through personal memory and global consensus. The acceleration coefficients (c1 & c2) and random variables $\left(U_1^t\right)$ and $\left(U_2^t\right)$ are used to balance global and local searches. $\left(P_i^{t+1}\right)$ in the position updates Equation (4) incorporates the updated speed, and the optimal position is refined through the fitness value. Through complex collective intelligence and social learning, PSO can adapt to involve complex optimization strategies and search for the global optimum.

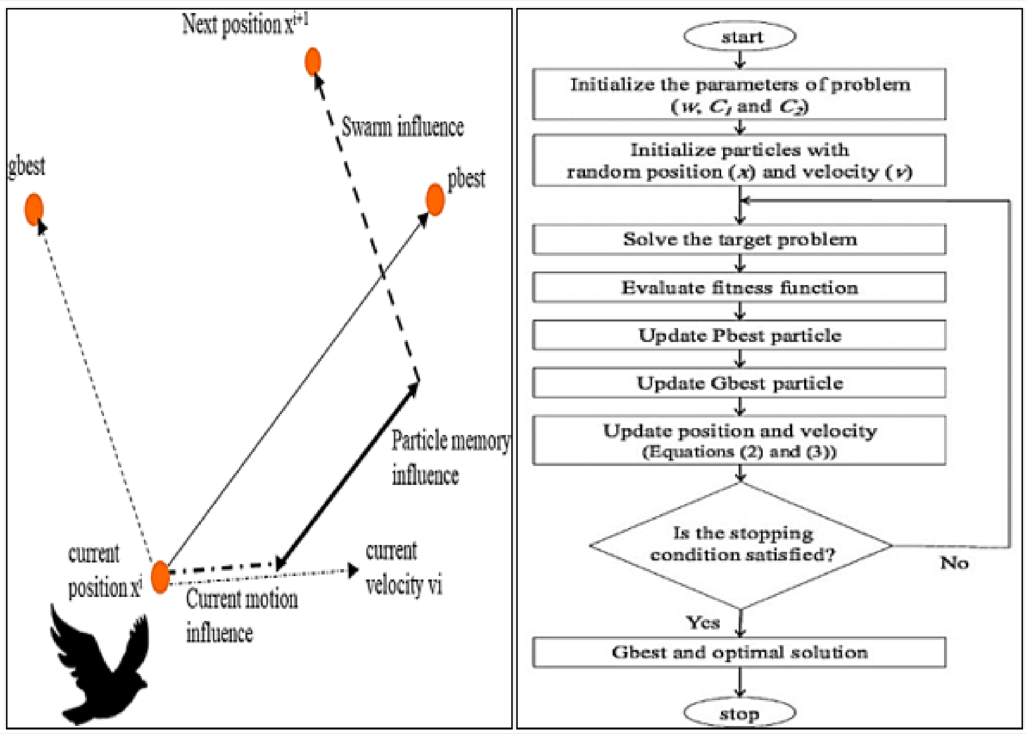

Figure 2: PSO schematic diagram [13] and finite state flowchart [14].

Artificial Bee Colony (ABC) Algorithm

The artificial bee colony (ABC) algorithm is a swarm-based metaheuristic algorithm inspired by the foraging behavior of bees and was proposed by Karaboga in 2005 [15,16]. The ABC algorithm illustrates the social role allocation of bees, such as onlooker bees, employed bees, and scout bees. The mission of the scout bees is to explore the quality and location of nectar and inform the onlooker bees, who will decide on the nectar collection location through decision-making, and the recruits or employed bees will do the harvesting [17]. The ABC schematic diagram [18,19] and finite state flow chart [20] involve initializing the agent, searching for suitable nectar sources, and refining the solution through greedy selection, as shown in (Figure 3).

$$P_i = fit_i / \sum_{q=1}^{SN} fit_q \quad (5)$$

$$X_{ij}^* = X_{ij} + \varnothing_{ij}(X_{ij} - X_{1j}) \quad (6)$$

$$\left(X_k^{t+1},\ Y_k^{t+1}\right)\begin{cases} X_k^{t+1} = X_k^t + \varnothing\left(X_k^t - X_z\right) \\ Y_k^{t+1} = Y_k^t + \varnothing\left(Y_k^t - Y_z\right) \end{cases} \quad (7)$$

Equation (5) on the selection probability (P_i), combines the selection of observation bees with the adaptability of food sources, and selects sources with higher quality. The new exploration position $\left(X_{ij}^*\right)$ in the Equation (6), implements the perturbation vector $\left(\varnothing_{ij}\right)$ to modify the position of the bee to find the nearby food sources. The updated positions $\left(X_k^{t+1},\ Y_k^{t+1}\right)$ in Equation (7), illustrates that the hired bees use new information and old locations to refine the optimal location. Through sophisticated position updating and forging strategies, ABC can contribute to complex optimization tasks and optimization problems.

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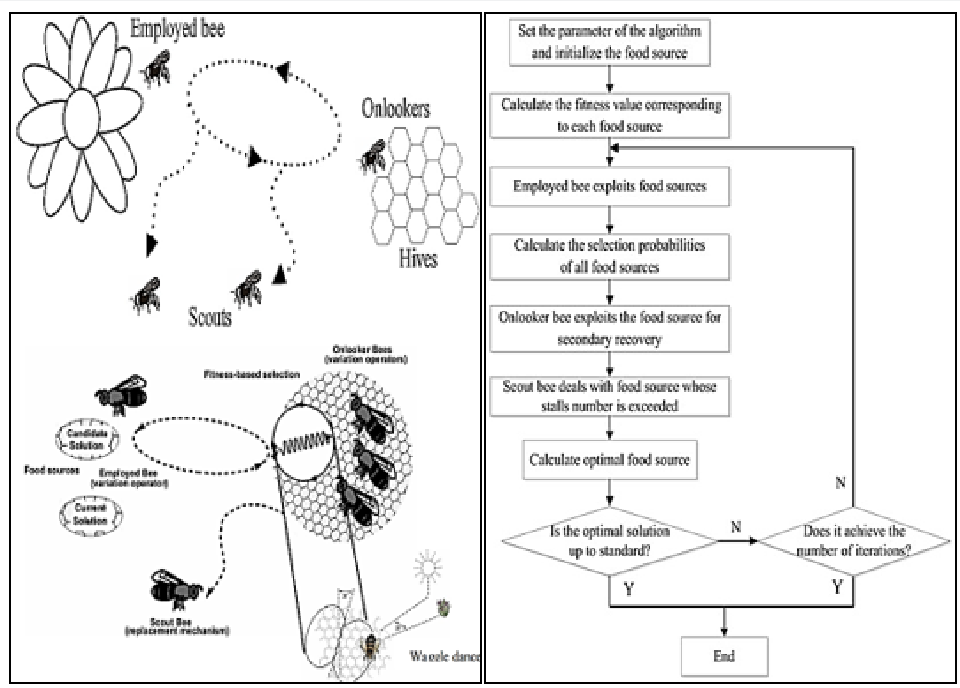

Figure 3: ABC schematic diagram [18,19] and finite state flowchart [20].

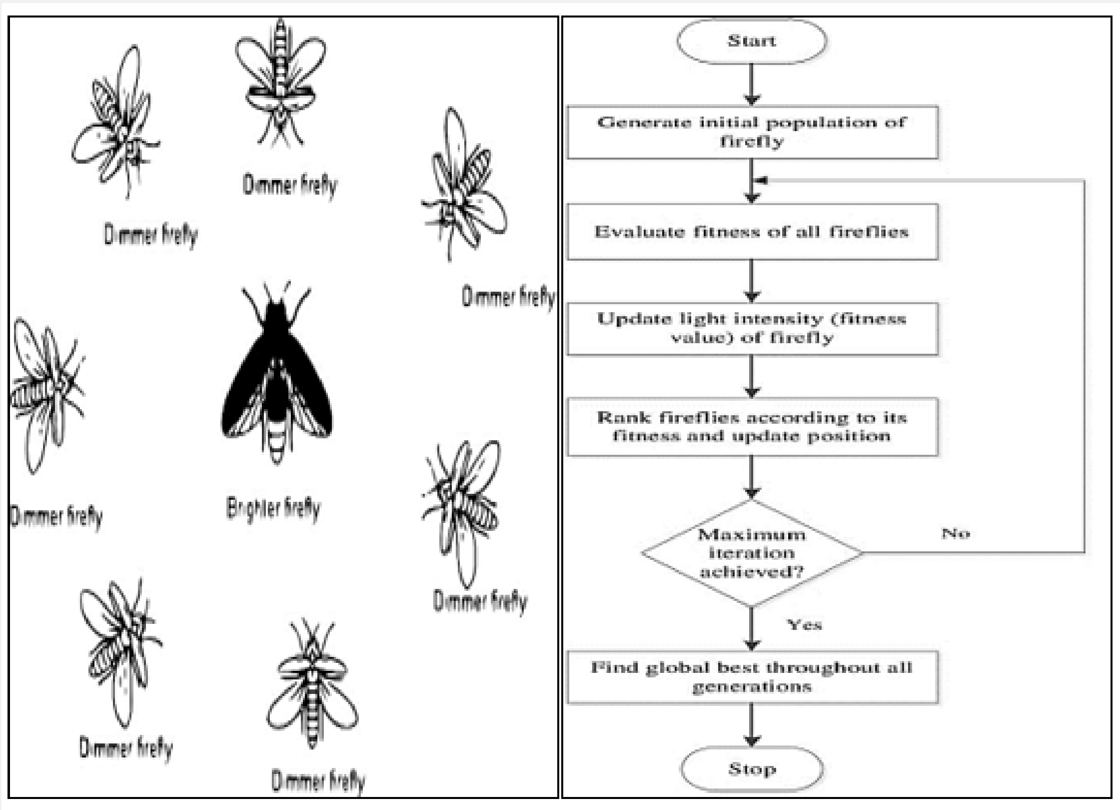

Figure 4: FA schematic diagram [23] and finite state flowchart [24].

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Firefly Algorithm (FA)

The Firefly Algorithm (FA) is a meta-heuristic algorithm inspired by the attraction of fireflies' bioluminescence and was proposed by Yang in 2007 [21, 22]. The FA algorithm illustrates the attraction of fireflies to different bioluminescence intensities (solution qualities) to find the best solution in the search space. FA schematics diagram [23] and finite state flow chart [24] involve initializing a population of agents in a search space and then updating their positions by light intensity to evaluate fitness, as shown in (Figure 4).

$$\mathrm{I}(r) = \mathrm{I}_0 e^{-\gamma r^2} \quad (8)$$

$$\beta(r) = \beta_0 e^{-\gamma r^2} \quad (9)$$

$$X_j^{t+1} = X_j^t + \left[\beta(r)\right]\left(X_i^t - X_j^t\right) + \alpha \in_j \quad (10)$$

Equation (10), the updated position equation $\left(X_j^{t+1}\right)$, is integrating optimal position updates based on light intensity (I) and attraction (β). Light intensity and attraction decrease with distance [25]. With complex position updates through optical attraction, FA can help to solve optimization problems to search for local and global optimal solutions.

Bat Algorithm (BA)

The Bat Algorithm (BA) is a meta-heuristic algorithm inspired by the echolocation behavior of microbats and was proposed by Yang in 2010 [26]. The BA algorithm illustrates the foraging behavior of bats and uses sound pulses to detect food or prey. This can also be used to avoid obstacles caused by bats' poor vision and find the optimal solution in the search space [27]. BA schematics diagram [28] and finite state flow chart [29] involve initializing the agent and then evaluating position and velocity updates based on local search and pulse return feedback (e.g. pulse rate and loudness), as shown in (Figure 5).

$$V_i^t = V_i^{t-1} + \left(X_i^t - X_{gbest}^t\right) f_i \quad (11)$$

$$X_i^t = X_j^{t-1} + V_i^t \quad (12)$$

$$X_{new} = \mathrm{X}_{old} + \varepsilon A^t \quad (13)$$

Equation (11), the velocity update $\left(V_i^t\right)$, combines the frequency of bat echolocation with the global optimal position of the colony. The new velocity update is applied to the position update $\left(X_i^t\right)$ in Equation (12). By adjusting the frequency and intensity of the pulse and reflection, and the bat's sensory modulation of prey detection through amplitude modulation (A), the echolocation accuracy and the optimal solution can be improved. The new optimal position $\left(X_{new}\right)$ is obtained by Equation (13). By performing complex position updates via pulse frequency and intensity adjustments, BA can help to solve optimization problems on navigating and searching in multidimensional space problems.

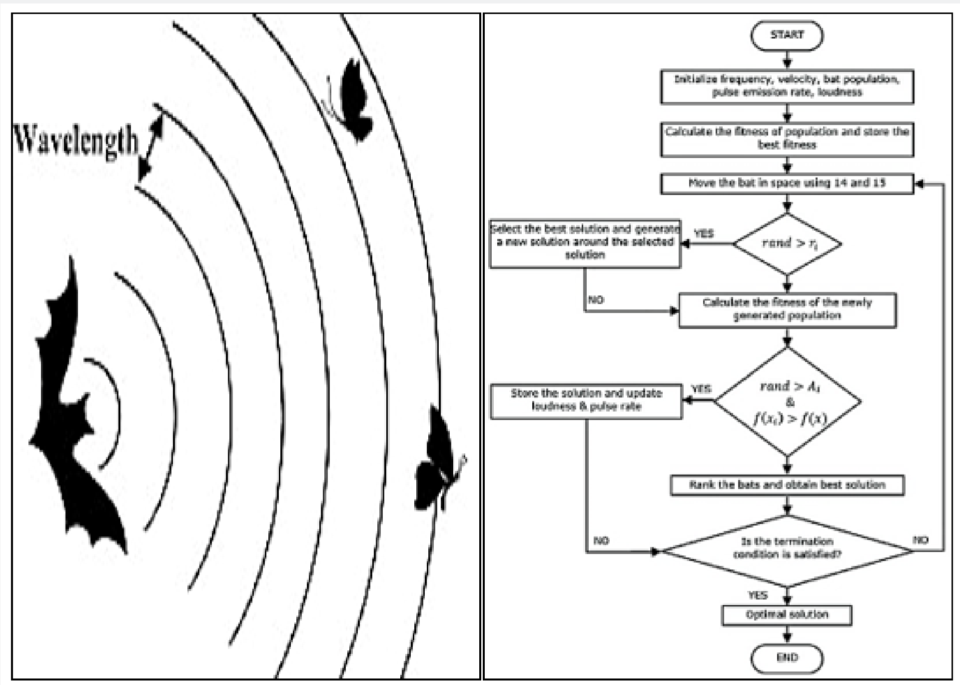

Figure 5: BA schematic diagram [28] and finite state flowchart [29].

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Krill Herd (KH) Algorithm

The krill herding (KH) algorithm is a swarm-based metaheuristic algorithm inspired by the krill swarm behavior and proposed by Gandomi and Alavi in 2012 [30]. The KA algorithm illustrates the induced motion, foraging movement, and physical diffusion for navigating and searching in multidimensional spaces [30, 31]. The KH schematic diagram [32] and finite state flow chart [33] involve initializing the agent and fitness, followed by three motion evaluations to search for optimal solutions and maintain cohesion within the group, as shown in (Figure 6).

$$d_{s,i} = \frac{1}{5N}\sum_{j=1}^{N}\left\| X_i - X_j \right\| \quad (14)$$

$$\frac{dX_i}{dt} = \underbrace{\left(\alpha_i^{local} + \alpha_i^{target}\right)N^{\max} + \omega_n N_i^{old}}_{Ni} + \underbrace{\left(\beta_i^{food} + \beta_i^{best}\right)V_f + \omega_f F_i^{old}}_{Fi} + \underbrace{D^{\max}\left(1 - t / t_{\max}\right)\delta}_{Di} \quad (15)$$

$$X_i\left(s + \Delta s\right) = X_i\left(s\right) + \Delta s \frac{dX_i}{dt} \quad (16)$$

Equation (14), the perceived distance between krill $\left(d_{s,i}\right)$ is calculated by combining the three movements with the global movement speed $\left(\frac{dX_i}{dt}\right)$ in Equation (15), and to calculate the best new position $X_i\left(s+\Delta s\right)$ Equation (16) is used. This movement mechanism demonstrates the social dynamics of krill movement of searching and navigating in multi-dimensional space to effectively converge, avoid falling into local optima, and maintain group cohesion [33].

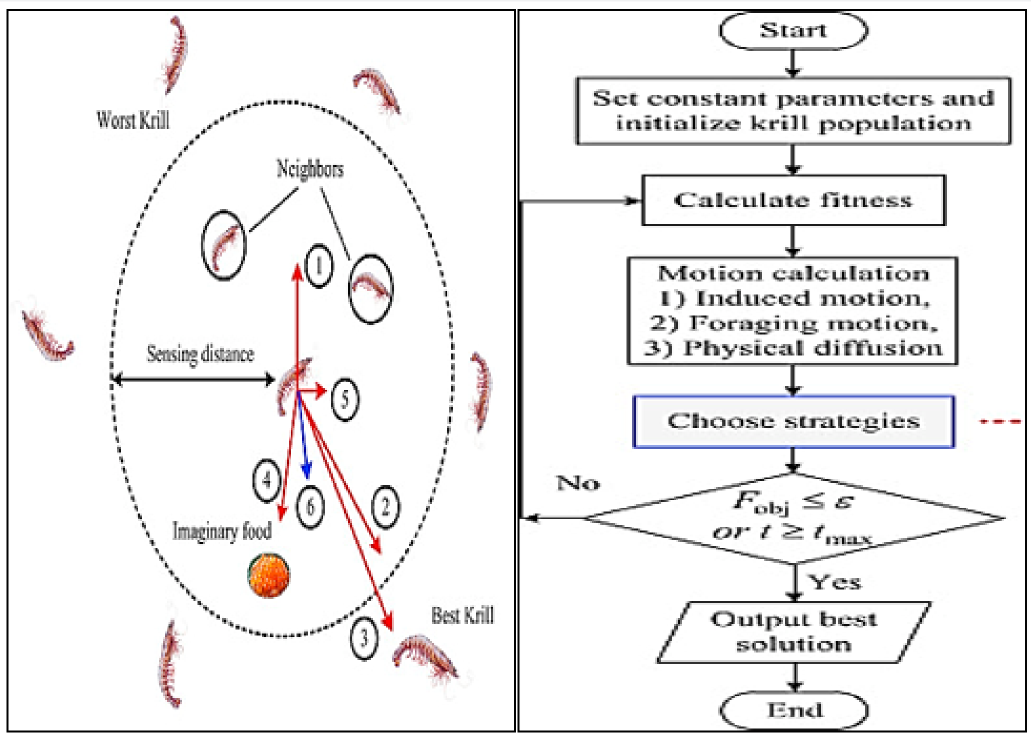

Figure 6: KH schematic diagram and finite state flowchart [32].

Grey Wolf Optimization (GWO) Algorithm

The Grey Wolf Optimization (GWO) algorithm is a meta-heuristic algorithm inspired by the social hunting behavior and hierarchical structure of grey wolves and was proposed by Mirjalili and Lewis in 2014 [34]. The GWO algorithm illustrates the social structural roles of Alpha, Beta, Delta, and Omega used in solving optimisation problems in wolf siege and hunting strategies [35]. GWO schematic diagram [34] and finite state flow chart [36] involve initializing each agent in the search space, then updating the position according to the movement of Alpha, Beta and Delta, and further recalculating the distance according to the hierarchical role to adjust the strategy, as shown in (Figure 7).

$$\vec{D} = \left|\vec{C} \times \vec{X_p}\left(t\right) - \vec{X}\left(t\right)\right|,\ \vec{X}\left(t+1\right) = \vec{X_p}\left(t\right) - \vec{A} \times \vec{D} \quad (17)$$

$$\vec{D_\alpha} = \left|\vec{C_1} \times \vec{X_\alpha} - \vec{X}\right|,\ \vec{X_1} = \vec{X_\alpha} - \vec{A_1} \times \vec{D_\alpha}$$

$$\vec{D_\beta} = \left|\vec{C_2} \times \vec{X_\beta} - \vec{X}\right|,\ \vec{X_1} = \vec{X_\beta} - \vec{A_3} \times \vec{D_\beta}$$

$$\vec{D_\delta} = \left|\vec{C_3} \times \vec{X_\delta} - \vec{X}\right|,\ \vec{X_3} = \vec{X_\delta} - \vec{A_3} \times \vec{D_\delta}$$

$$\vec{X}\left(t+1\right) = \left(\vec{X_1} + \vec{X_2} + \vec{X_3}\right) / 3 \quad (18)$$

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Equation (17), the position of the leader wolf $(\vec{D})$ uses the coefficient vectors $(\vec{A})$ and $(\vec{C})$ to integrate hunting movements and to update the positions of other pack members $\vec{X}(t+1)$ in Equation (18). These hunting mechanisms illustrate the social dynamics of grey wolves and can be used in complex multidimensional optimization problems with efficient convergence capabilities.

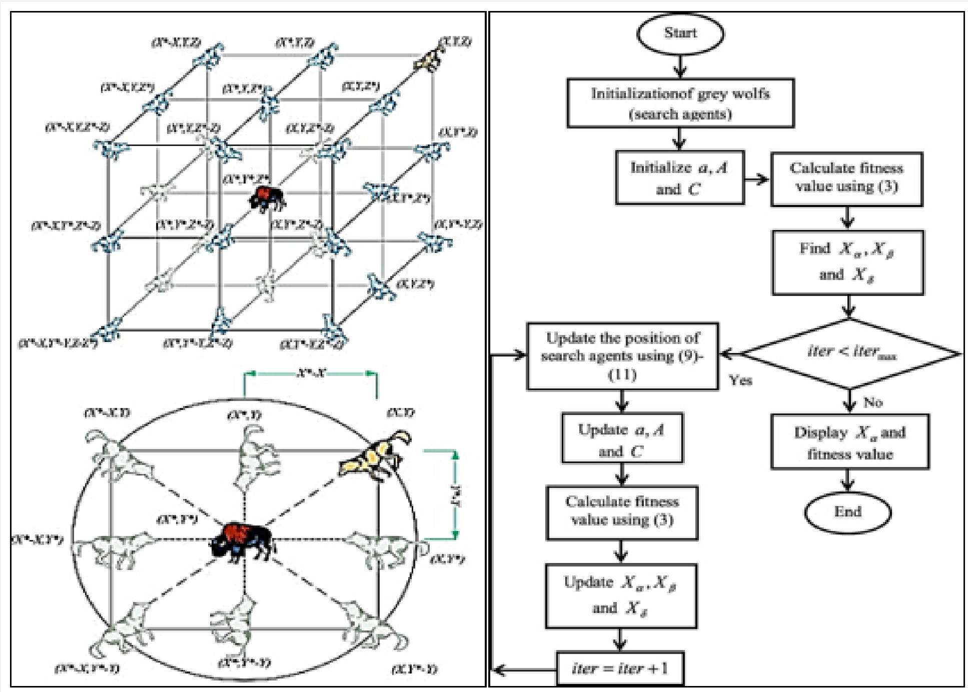

Figure 7: GWO schematic diagram [34] and finite state flowchart [36].

Salp Swarm Algorithm (SSA)

The salp swarm algorithm (SSA) is a meta-heuristic algorithm inspired by the leader-follower formation of salp chains and was proposed by Mirjalili in 2017 [37]. The SSA algorithm illustrates the formation of a leader-follower, in which the salp leader guides the group to search for plankton, and the followers update their positions based on the salps ahead to search in multidimensional space. The SSA schematic diagram [37] and finite state flow diagram [38] involve initializing the agent and fitness, followed by position updates based on the leading salp to maintain the formation, as shown in (Figure 8).

Equations (19) and (20), show the updated positions of the leader and follower, and the salp motion is determined by integrating the Newtonian motion principle. The leader salps update food location, search range and randomness (yi), (ubi) and (lbi) respectively, to search in multi-dimensional space. These chain-forming mechanisms allow SSA algorithm counters to optimize tasks and avoid local maxima.

Grasshopper Optimization (GOA) Algorithm

The grasshopper optimization (GOA) algorithm is a meta-heuristic algorithm inspired by grasshopper swarming and foraging behavior and was proposed by Saremi, Mirjalili, and Lewis in 2017 [39,40]. The GOA algorithm illustrates the three-motion account for social interaction, gravity, and advection in navigating and moving in large groups [41]. The GOA schematic diagram [42] and the finite state flow chart [28] involve initialising the agent and fitness, and then conducting three motion evaluations to search for the optimal solution and maintain cohesion within the group, as shown in (Figure 9).

The movement of the grasshopper (X_i) in Equation (22) is determined by integrating the social interaction, gravity, and wind direction, 〖(S〗_i),〖(G〗_i) and (A_i) respectively, and Euclidean distance between the grasshoppers. These grasshopper swarm dynamics mechanism allows the GOA algorithm to search in multidimensional space.

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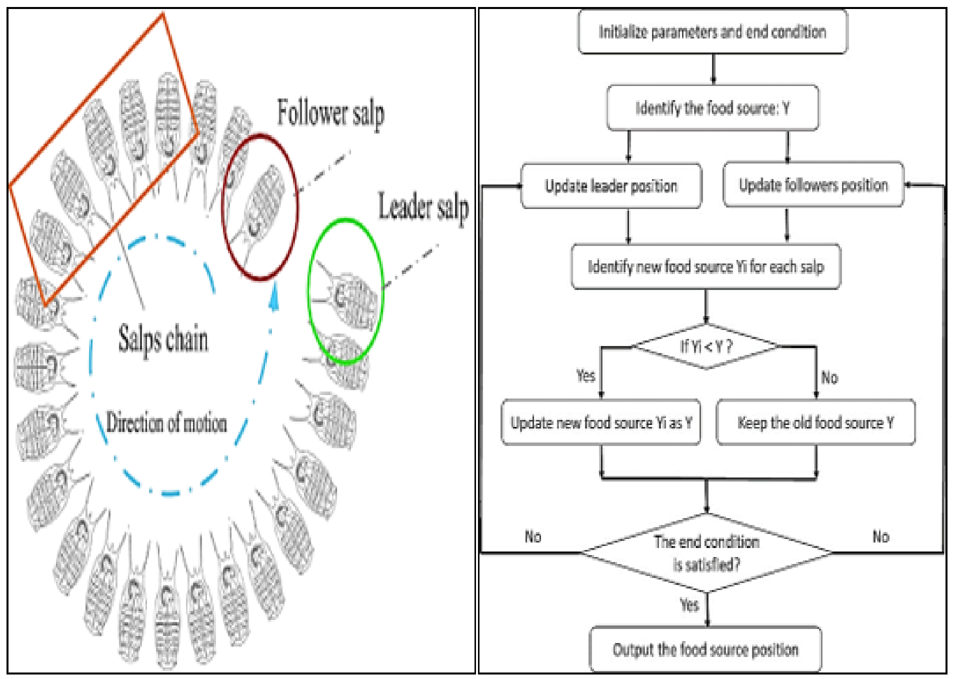

Figure 8: SSA schematic diagram [37] and finite state flowchart [38].

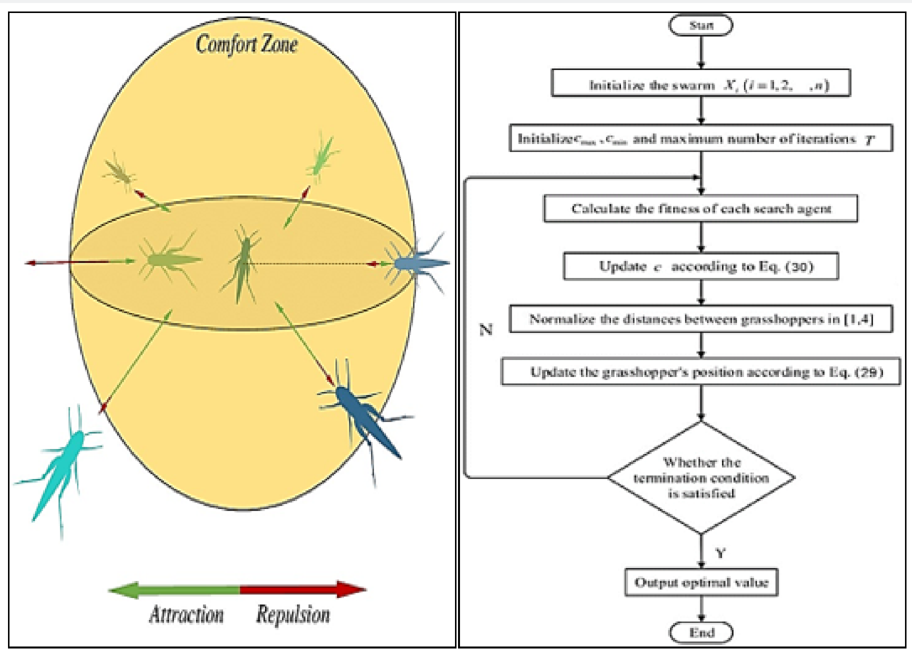

Figure 9: GOA schematic diagram [41] and finite state flowchart [42].

Swarm Algorithms in Robotics

Currently, Swarm robotics is being successfully applied to solve problems in various fields, such as in agriculture, where SAGA uses bee foraging models for field mapping and weeding [43], or in construction, where TERMES uses the termite colony concept to build autonomous building structures [44]. The applications

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of swarm robots are impressive, but the knowledge behind how swarm robots collaborate, reach consensus, communicate, and share information, and take inspiration from nature is an important subject to understand.

According to Brambilla's 2013 study on the classification of swarm robots, the behavior of swarm robots can be divided into four categories: spatial organization, navigation, decision-making, and miscellaneous [46,47], as shown in (Figure 10). This classification facilitates designing swarm robots to meet specific operational needs. In this study, a comprehensive framework will be established to further analyse the research on nine swarm-based algorithms considered in this paper, that can be applied to swarm robot behavior classification.

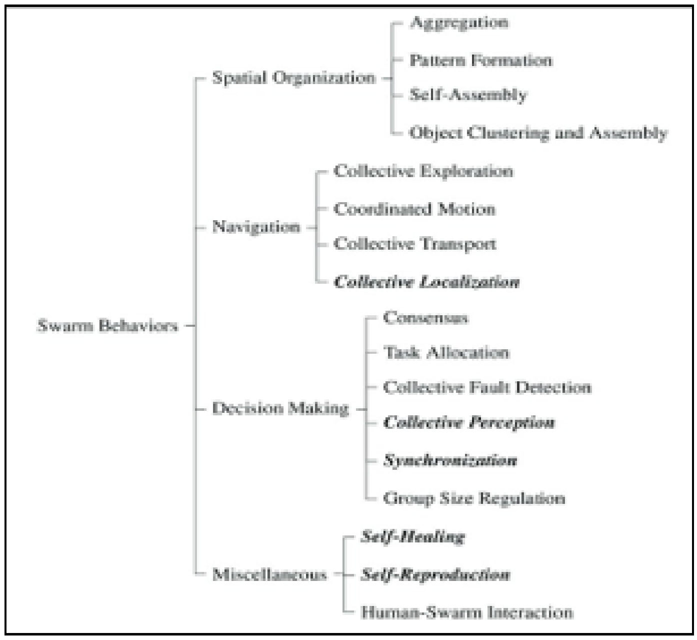

Figure 10: Taxanomy of swarm behaviours [47].

Spatial organization

Spatial organization refers to the collective intelligence of swarm robots that can interact and organize within allocated areas to aggregate, execute patterns, assemble, or collect objects [46,47]. The PSO algorithm illustrates the aggregation and pattern formation of fish schools that swim to avoid predators [48], similar to the KH algorithm where large groups of krill gather and form large swarms to avoid predators and stay cohesive [49]. The GOA algorithm illustrates the aggregation of group dynamics of grasshopper movements in large groups [40]. The ABC algorithm illustrates object clustering based on how bees cluster themselves and the nectar in their hives [50]. The FA algorithm illustrates the clustering toward high light intensity [51]. The SSA algorithm illustrates the pattern formation of how salps form chains [52].

Navigation

Navigation refers to the collective intelligence of a swarm of robots that can determine a known location and guide themselves or other robots to a specific location. Namely, it includes swarm exploration, movement under set coordinates, swarm transportation and localization [46,47]. The foraging behavior of the ACO, ABC, KHA, SSA, BA, GOA and GWO algorithms reflects collective exploration and localization, and they tend to explore and locate food in large groups to achieve continuous harvesting. The FA algorithm's bioluminescent light attraction illustrates collective localization, where all fireflies follow basic rules to attract towards higher light intensities [53]. The synchronized movement of the PSO [54], KHA [55] and GOA [40] algorithms illustrate coordinated movement, with the entire colony having local and global positions to adjust to with the aim to avoid predators, similar to SSA, where salps always adjust their position as the position of the leading salp is updated [37]. ACO's unique harvesting behavior exemplifies collective transportation, with ants tending to pick up heavier or larger objects and place them into the hive.

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Decision making

Decision-making refers to the collective intelligence of a swarm of robots that is capable of reaching consensus, allocating tasks amongst the swarm, detecting failures, sensing and adapting to the surrounding environment, performing synchronized tasks, and controlling swarm size [46,47]. The collective swarm behavior of the ACO, PSO, ABC, FA, BA, KHA, GWO, SSA and GOA algorithms illustrates the tendency of consensus mechanisms and collective perception to perceive and make consistent decisions within large groups to reach consensus, such as ants based on pheromone trails or bees based on waggle dance to harvest food; birds, fish, and krill use global motion to update their positions; fireflies and bats receive brightness and echoes to determine direction, and wolves update their positions based on social structure.

The specific role assignments for ACO, ABC and GWO illustrate the distribution of specific tasks within the group. Leafcutter ants separate tasks such as cutting and transporting leaves and cultivating fungi [56]; bees separate tasks such as exploring nectar sites, selecting high-quality nectar, and collecting nectar [15]; wolves separate tasks such as exploring, surrounding prey, attacking, and hunting. The self-diagnostic capabilities of SSA and KHA illustrate collective fault detection, with old or damaged salps in the chain detaching from the chain or changing positions with more fit salps [57], similar to krill who sense and moving toward healthy krill position [30], and both mechanisms are able to sense neighbouring agents to maintain formation. The FA algorithm illustrates synchronisation by the blink technique, whereby male fireflies tend to respond to female fireflies with synchronized flashes [58].

Miscellaneous

Under miscellaneous category is referred to the collective intelligence of a swarm of robots that can heal themselves, replicate their members, and interact with humans. The ACO's rerouting strategy illustrates self-healing, and when pheromone trial is hindered, the ants execute a self-healing rerouting strategy [59, 60].

Swarm formation control

Swarm robot formation control refers to a swarm of robots collaborating while maintaining a predetermined formation [61]. There are two types of formation control for swarm robots: centralized control and decentralized control. Centralized control relies on a single command or master switch to control all robots, which is more efficient, but has limitations in scalability and adaptability [62]; on the other hand, decentralized control allows a group of robots to use behaviours inspired by nature, according to interactive and local information from nearby neighbouring agents or environments automatically make decisions, making them more scalable, resilient, and adaptable in unknown environments [63].

Virtual structure formation control was proposed by Lewis and Tan in 1997 [64]. This is a type of centralized control that connects all robots with virtual structures to maintain geometry and provide coordinated motion. However, it has limitations due to its susceptibility to single points of failure and the difficulty of formation adjustment. The SSA algorithm illustrates virtual structure formation control, in which a chain of salps guides the entire formation through a virtual structure connecting the leading and following salps in the chain formation [65].

Behaviour-based formation control was proposed by Balch and Arkin in 1998 [66]. This is a type of decentralized control inspired by nature's forming behavior. This structured network of interactive behaviours receives information from other robots and derives decisions from a behavioural coordinator, requiring less group communication load than that for the centralized control. However, its limitation lies in formation convergence. Swarm algorithms such as ACO, PSO, ABC, FA, BA, GWO, KHA, SSA and GOA illustrate behaviour-based formation control [63]. Each algorithm has its own unique way of communicating and exchanging information with neighbouring agents, such as pheromone trial in ants, position adjustments of neighbouring agents in fish, fireflies, bats, wolves, krill, salps and grasshopper, and waggle dances in honeybees.

Leader-follower formation control was proposed by Desai, Ostrowski, and Kumar in 2001 [67]. This is a type of centralized control where all robots rely on or are controlled by a leader, with followers adjusting and obeying commands accordingly to provide superior, simplified, and complete control. However, its limitation is that the leader's failure can lead to the failure of the entire formation or system. The GWO [68] and SSA [69] algorithms illustrate leader-follower relationships, where the leader wolf and the leader salp will be the main controllers and all followers will obey and follow the leader's decision.

Graph-based formation control was proposed by Desai, Ostrowski, and Kumar in 1998 [70]. This is a type of decentralized control where all robots are modelled in a mathematical graph and each robot is treated as a vertex with edge connections representing the flow of information from one agent to another. The ACO algorithm illustrates graph-based formation control, where ants use graph-based functions to detect pheromone intensity to find the shortest path [71-73].

Artificial potential formation control was proposed by Khatib in 1986 [74]. This is a type of decentralized control where all robots interactively control the distance and spacing between adjacent agents using attractive and repulsive forces. The KHA

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algorithm illustrates an artificial potential formation control, where each krill has a sensed distance to adjust its position relative to the adjacent krill and uses attraction to move toward the krill with a higher fitness, and uses repulsion to maintain the distance between krill to maintain in a large group [75]. Similar to the GOA algorithm, each grasshopper is attracted and repelled by the group movement when it is too close to another grasshopper to maintain its comfort zone [39, 40].

Swarm behaviour and control

Although swarm robotics has been successfully applied to various fields and industries, such as construction, agriculture, entertainment, medical care, etc., , there is a very limited research on the application of swarm robotics for the machinery in mining operations. While some mines are already applying remote operating systems to control autonomous haul trucks, and other processes at a mine site, the decentralized control where robots can collaborate and communicate with each other to perform mining tasks , thus achieving a fully automated mining systems is still in development. This research examines further integration of swarm algorithms into specific mining operations with the aim to improve overall mining productivity, safety, and environmental sustainability. Table 1 summarises the comprehensive study of the nine nature-inspired swarm algorithms considered in this paper, each grouped into specific classifications of swarm behavior and swarm robot formation control.

Table 1: Taxonomy of swarm behaviour and formation control in swarm robotics.

Swarm Algorithm	Behaviour Taxonomy	Formation Control
Ant colony optimisation	Decision-making, navigation, miscellaneous	Decentralised control, behaviour-based method, graph-based method
Particle swarm optimisation	Spatial organisation, decision making, navigation	Decentralised control, behavior-based method
Artificial bee colony	Spatial organisation, decision-making, navigation	Decentralised control, behavior-based method
Firefly algorithm	Spatial organisation, decision-making, navigation	Decentralised control, behavior-based method
Bat algorithm	Spatial organisation, decision-making, navigation	Decentralised control, behavior-based method
Krill herding algorithm	Spatial organisation, decision-making, navigation	Decentralised control, behavior-based method, artificial potential method
Grey wolf optimisation	Decision-making, navigation	Decentralised control, behavior-based method, leader-follower method
Salp swarm algorithm	Spatial organisation, decision-making, navigation	Centralised control, virtual structure method, behavior-based method, leader-follower method
Grasshopper optimisation algorithm	Spatial organisation, decision making, navigation	Decentralised control, behavior-based method, artificial potential method

Applications of Swarm Algorithms in Mining

Mining is the process of extracting natural resources or minerals from the earth. The mining life cycle [76] begins with the exploration phase, where mineral deposits are explored, mining sites are identified based on core log data from drill samples, and the presence of valuable minerals is assessed. The next stage is the planning stage, where pre-feasibility studies and feasibility studies are conducted to determine the economic feasibility of the project, considering market demand, mining methods, market prices, ore quality, environmental impacts, and regulatory requirements. If the project is feasible, the construction phase follows that includes the construction of mining facilities, roads, mine trucks, tailings dams and more. Mining operations involve extraction and secondary processing of minerals for sale. The final phase is the mine closure that involves reclamation and restoration, as well as continuing to address environmental impacts, as shown in (Figure 11).

Mine exploration and assessment

Mine exploration phase includes core drilling, geological analysis, and identification of mineral sites and deposits. A variety of swarm algorithms have been integrated into the mine exploration stage to improve exploration accuracy and efficiency. Nhleko and Musingwini's 2019 PSO study demonstrated how PSO algorithms can be used in conjunction with surveying techniques to delineate underground stopes, further improve resource extraction efficiency and operational safety [77]. Optimisation of mine mapping processes demonstrated PSO's ability to improve the efficiency and safety of underground mining exploration. The study by Jafrasteh and Fathianpour in 2017 details the fuzzy artificial bee colony (FABC) algorithm for evaluating three-

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dimensional ore characteristics to optimise ore body size, such as spatial positioning, azimuth, and inclination of exploration boreholes [78]. Compared with traditional optimisation techniques, the FABC algorithm reduces the kriging variance by adjusting parameters, greatly improving the accuracy of mineral resource estimation, and further improving the quality of mineral resource assessment and exploration. The precise positioning of the borehole improves the accuracy of discovering ore bodies and reflects ABC's ability to improve mine exploration efficiency through effective core drilling. A 2023 study demonstrated the implementation of the Bat Algorithm (BA) in a hybrid support vector machine (SVM) for improving the accuracy of copper-gold mineralisation mapping, showing a 10% improvement in accuracy compared to traditional methods, with an average lower square value error of 6.6% and the accuracy being 94.3% [79], thus further improving the accuracy of mineral exploration. The improved accuracy of mineralisation maps demonstrates BA's ability to leverage accurate geological data to improve mine exploration and analysis efficiency. Research by Saremi, Mirjalili, and Lewis in 2017 details the implementation of the GOA algorithm in mine exploration [39], using grasshopper swarming behavior to identify and pinpoint valuable mining areas by balancing global and local search mechanisms, and iterating over time to make improvements. Effective mine mapping demonstrates GOA's ability to enhance mineral exploration. The comprehensive analysis on swarm algorithm into mine exploration and assessment stages has been reviewed and classified in Table 2.

Table 2: Mine exploration and assessment overview.

NIA	Mining stages	Problem addressed	Solution provided
PSO	Mine exploration and site assessment	Inefficient resource identification and boundary delineation.	Optimises mapping and survey routes for improved efficiency and safety.
ABC	Exploration, drilling	Inaccurate drill hole positioning and mineral estimation.	Integrating bee inspired fuzzy logic for precise positioning and enhance accuracy.
BA	Exploration, site assessment and mapping	Traditional prospectivity mapping inefficiencies.	Integrating hybrid SVM model to enhance mapping accuracy and efficiency.
GOA	Exploration, site assessment, mineral deposit identification	Ineffective identification of valuable mineral deposits.	Balances global and local search capabilities for efficient mineral exploration.

Mine planning and design

Mine planning and design phase includes mine layout, mining method selection, costs, operational assessment, mine safety and environmental sustainability. Studies show that the implementation of the PSO algorithm can be successfully used to determine efficient mine operations by improving open pit mine layout [80]. The PSO algorithm integrates variants that transform traditional block-level scheduling problems by iteratively improving these solutions using greedy heuristics to account for constraints and uncertainties. The refinement of the open pit mine layout demonstrates PSO's ability to enhance mine planning and scheduling problems. Korzeń and Kruszyna elaborated on the implementation of the ACO algorithm in the Wrocław underground railway project in their 2023 study [81], using the foraging behavior of ants to search for the best route, by considering the dense population, heavy traffic nearby, and calculations of public transport routes. The selection of the optimal route demonstrated the ACO's ability to enhance decision-making and optimise mine route planning. Khan's 2018 study demonstrated the application of the BA algorithm in mine planning to address long-term scheduling challenges under grade uncertainty [82]. The Bat algorithm incorporates uncertainty and shows higher efficiency than traditional commercial software. The generation of effective solutions illustrates BA's ability to enhance mine design and scheduling. Research by Tolouei and Moosavi in 2021 demonstrated the implementation of the GWO algorithm using the augmented Lagrangian relaxation (ALR) method to carry out long-term production scheduling (LTPS) in open pit mine design [83]. The hybrid ALR-GWO model showed more advancement than the traditional method, achieving a net present value increment of 13.39%. The improvement in net present value demonstrates GWO's ability to enhance mine planning through improved economic outcomes. Research in 2023 details the application of the SSA algorithm in an extreme learning machine (ELM) model to improve predictions of ground vibration intensities caused by explosions in the Coc Sau coal mine [84]. The hybrid SalSO-ELM model recorded 216 blasting performances and surpassed the traditional model with an accuracy of 90.5%. Enhanced peak particle velocity predictions demonstrate SSA's ability to enhance mine blast planning and improve mine safety. The comprehensive analyses on swarm algorithm applications in mine planning and design stages have been reviewed and classified in Table 3.

Mine operation and construction

Mine operation and construction phases include mine extraction for primary production and mine processing for secondary production. Research conducted at the Shenbao open

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pit mine in 2020 demonstrated the use of the PSO algorithm to optimize the mine equipment mismatch problem [85]. The PSO algorithm combined statistical analysis and uses triangular fuzzy numbers to achieve scheduling randomness, reducing the number of mining trucks, truck scheduling, transportation costs and queuing time. The optimization of mining equipment reflects PSO's ability to enhance mine operations and construction in terms of efficient mine operation scheduling. The study by Yan and Feng in 2013 detailed the implementation of the ACO algorithm in the Unified Tunnel Weight Calculation Model to analyse the search for escape routes during mine construction [86]. The Max-Min Ant System (MMAS) method was applied to establish a tunnel network partitioning strategy to search for the best route, and further testing was conducted in large domestic coal mines. The optimal escape route obtained was highly reliable and suitable for real-life situations. Enhancements to search escape route planning demonstrate ACO's ability to enhance the utility of mine construction with greater reliability. The 2021 study demonstrated the implementation of FA algorithm at Sungun Copper Mine to optimise mining fleet management [87]. The FA algorithm transformed fixed scheduling into flexible scheduling dispatch method, thereby improving mine performance, increasing productivity by 20%, and reducing idle time by 20%. Research in 2020 demonstrated the implementation of the GWO algorithm in a support vector machine (SVM) to optimise parameters to solve the problem of fault diagnosis of belt conveyor transportation systems in underground mines [88]. The integrated model was tested using the hybrid wolf optimizer, and the fault detection accuracy was as high as 97.22%, which is suitable for practical applications and avoids impact on safety and mine production. The improvements in belt conveyor reliability and safety reflect GWO's ability to enhance the construction of conveyor belt mining operations. The comprehensive analysis on the applications of the swarm algorithm to mine operation and construction stages has been reviewed and classified in Table 4.

Table 3: Mine planning and design overview.

NIA	Mining stages	Problem addressed	Solution provided
PSO	Feasibility and operational planning	Optimisation of open pit mines, including layout and scheduling.	Refines layouts and schedules, effectively managing constraints.
ACO	Operational planning	Infrastructure layout, method selection, and operational strategies.	Simulates efficient routes, emphasizing enhanced decision-making.
BA	Feasibility planning and mine scheduling	Long-term scheduling challenges under grade uncertainty.	Generates effective solutions quickly, managing uncertainties.
GOA	Feasibility and operational planning	Long-term production scheduling in open-pit mining with grade uncertainty.	Enhances economic outcomes, improving net present value.
SSA	Operational planning	Accuracy of peak particle velocity predictions for blasting operations.	Improves PPV prediction accuracy for safer and more efficient blasting.

Table 4: Mine operation and construction overview.

NIA	Mining stages	Problem addressed	Solution provided
PSO	Operational efficiency and safety	Mismatch in capacity among equipment.	Optimised equipment matching, reducing costs.
ACO	Mine safety and construction	Inadequate planning for escape route	Improved escape route planning, enhancing safety.
FA	Mine operation optimisation	Inefficiencies in production rate due to fixed dispatch methods.	Optimised fleet composition, improving productivity.
GWO	Mine safety and construction	Fault diagnosis in conveyor systems.	Enhanced fault diagnosis, improving system reliability.

Mine closure and rehabilitation

Mine closure and restoration phase includes restoring the landscape, waste management, soil detoxification, planting vegetation, creating wildlife habitat, mitigating environmental impacts, and ensuring public safety. The 2023 study illustrated the implementation of PSO in the support vector regression algorithm (PSO-SVR) to monitor the environment of the Hongshaquan mining area [89]. The integrated hybrid model has been applied to UAV measurements of vegetation index, surface temperature, salinity index and soil respiration (R^2=0.959, RMSE=0.497, AIC=-0.561). Advanced remote sensing models demonstrated the PSO's ability to continue mitigating and monitoring environmental sustainability during mine closures. The comprehensive analysis on swarm algorithm application in the mine closure and rehabilitation stages has been reviewed and classified in Table 5.

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Table 5: Mine closure and rehabilitation overview.

NIA	Mining Stages	Problem Addressed	Solution Provided
PSO	Environmental Monitoring	Inefficient of traditional method meets high quality data and computational resources.	Use cloud computing combine with hybrid model for advance remote sensing for environmental monitoring.

Overview of mine integration

The implementation of nine swarm algorithms in various mining stages has been comprehensively analysed and summarised in pervious sections of this paper. The contributions of swarm algorithms are comprehensively reviewed and classified in (Figure 12) to demonstrate that the application of swarm algorithms in the mining field can improve mine efficiency, mine safety, and environmental sustainability.

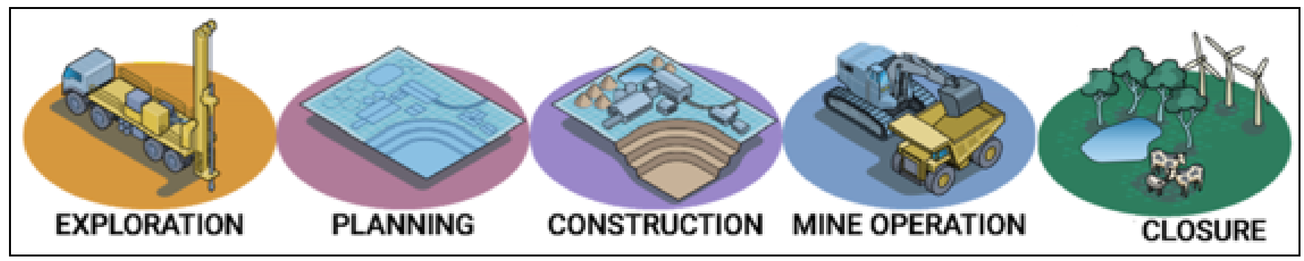

Figure 11: Mining Lifecycle [76].

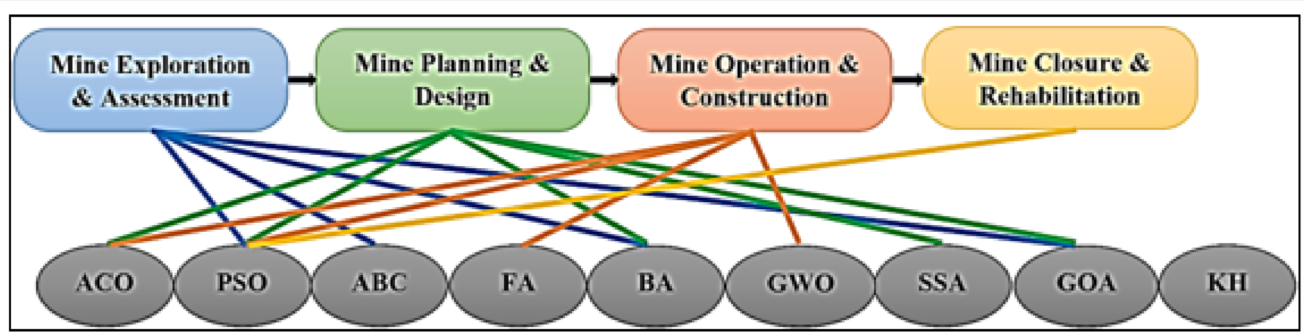

Figure 12: Swarm Algorithm Integration to Mining Lifecycle.

Conclusion

This paper provides a comprehensive study of nine swarm algorithms, their nature, mathematical and theoretical models of swarm behavior, and presents their implementation and classification in swarm robotics and mining operations. Swarm algorithms show good results in the applications to all stages of the mining life cycle (mine exploration and evaluation, mine planning and design, mine operation and construction, mine closure and rehabilitation). They can successfully be applied to improve aspects such as mapping accuracy and efficiency, drilling hole accuracy, mine layout and scheduling, production scheduling, blasting efficiency and safety, mining equipment scheduling and matching, escape route planning, conveyor belt fault diagnosis and environmental monitoring. Besides, integration of NIA also can increase the net present value of profits by reducing costs, enhancing benefits and safety, and improving environment impact, achieve increased productivity by having more reliable systems, more accurate feasibility studies and more environmental considerations. Current findings on the applications of swarm algorithms to mining are promising and further research and exploration will allow for more widespread applications of bio-inspired swarm algorithms in the mining industry. The classification of swarm behavior (spatial organization, navigation, decision-making and miscellaneous) and mining optimisation show that the applications of swarm algorithms and swarm robotics can contribute to creating more autonomous and robust smart mines without human intervention. Such innovation and development

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in global mining operations will help towards achieving more environmentally sustainable mining operations. This study explored the application of swarm intelligence algorithms to the mining industry, highlighting how nature-inspired algorithms can skillfully cope with the complexities of the mining life cycle. It has provided an in-depth review and evaluation on the integration of these algorithms with existing mining practices, demonstrating their superior performance compared to traditional methods, and has highlighted the potential of swarm algorithms to revolutionise the mining process and industry by providing more efficient, accurate and sustainable solutions.

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