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Swarm Intelligent in Bio-Inspired Perspective: A Summary

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ABSTRACT

This paper summarizes the research performed in the field of swarm intelligent in recent years. The classification of swarm intelligence based on behavior is introduced. The principles of each behaviors, i.e. foraging, aggregating, gathering, preying, echolocation, growth, mating, clustering, climbing, brooding, herding, and jumping are described. 3 algorithms commonly used in swarm intelligent are discussed. At the end of summary, the applications of the SI algorithms are presented.

Keywords: Animal Behavior, Ant Colony Optimization, Firefly Algorithm, Particle Swarm Optimization, Swarm Intelligent

1. INTRODUCTION

Swarm intelligence (SI) was first introduced by Beni and Wang [1] in 1993. Since then, SI, as a part of Artificial Intelligences (AI) has attracted many researchers. SI imitated the natural colony social behavior, for instances: colonies of ant [2], flocks of birds [3], and fish schools [4]. In general, SI is formed by simple individual agents with limited abilities. They usually consist of low cost, lost computation, and small in size agents [5]. However, along with their simplicity and limitation of individual agents, a swarm should be robust and powerful. When the individual agents are combined together, they should show their group collective intelligence and make that intelligence as intelligent solution in overcoming complex problems.

Commonly, the individual agents of swarm do not know the condition of their global group [6]. They are not commanded by leader who can guide them to the target. Each of them has their own knowledge and has a chance to be leader or to be follower. The target can only be reached by the cooperation among the individual agents. The swarm will not be able to accomplish its task without the help or interaction among the individual agents in swarm. The cooperation gives benefits to the swarm that works based on the search space information. It preserves the information during the iteration. Therefore, it needs fewer operators and parameters to adjust so that it is easier to be implemented. Moreover, it utilizes less memory to save the best solution [7].

The summary presented in this paper has purpose to give a simple illustration of SI in bio-inspired perfective and the recent swarm intelligent research. The behavior-based classification of swarm intelligent and the algorithm principles of three swarm optimizations are described in section 2. The recent research is discussed in section 3. Section 4 gives the conclusion of this summary.

2. SWARM INTELLIGENCES

To achieve their goals, swarms used a decentralized control system. This system gives a freedom for the individual agents in deciding and doing the self-organization [8]. Moreover, it decreases the responsibility of the leader. The agents do not need to wait the central instruction. They have the same rights and obligations based on their cooperation. This cooperation will give some other advantages, such as: 1. Increasing the passion of the swarm in conducting the task, 2. Shortening the working time due to each of the agents can make their own decision 3. Be efficient in all aspect. In this sub section, it will be discussed the classification of SI and three classes of the swarm-intelligence algorithms, namely: Ant Colony Optimization (ACO), firefly algorithm, and Particle Swarm Optimization.

2.1 CLASSIFICATION

In this paper, the swarming behavior is categorized as in Figure 1. The foraging, aggregating, gathering, preying, echolocation, growth, mating, clustering, climbing, brooding, herding, and jumping are behaviors that can be found in animals. They used those behaviors to find their target.

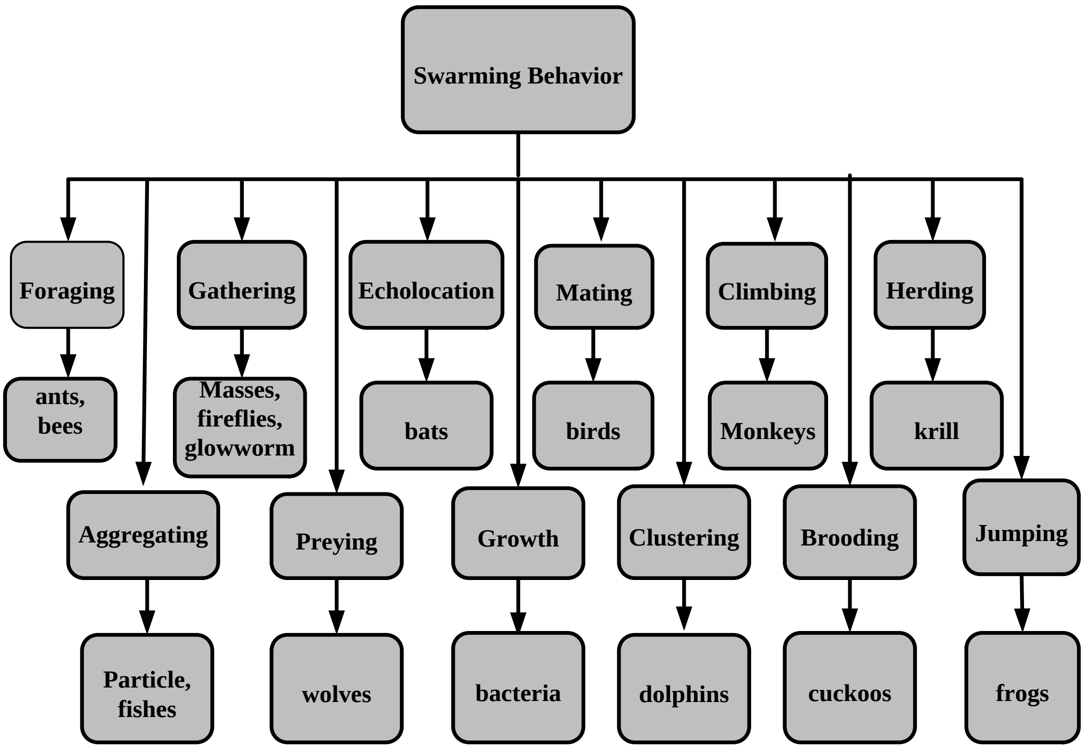

FIGURE 1. Classification of swarming intelligent based on swarming behavior [9].

Foraging means to go from place to place searching, especially for food (Cambridge dictionary online). The foraging behavior in SI imitated the animal

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social foraging that relies on the information of signs or cues which have been left behind by the animals [10]. When an animal moves to find the target, they coincidentally left the signs or cues that can be tracked by the other. In other words, the animal movements provide the information about their travel to the others.

Some examples of animals foraging behaviors can be got from ants [11], bees [12], [13], and rats [10], etc. When colony of rats travels to find food or water, they create trails through the undergrowth [10]. Those trails will influence the movements of the other rats that come after them. The rats came first to the target will leave the substrate as the result of their passage. This substrate will be the reference of the other in detecting, following and exploiting them. It is quite the same to the foraging in ants, bees, or birds. In ant, when one of them finds the food, it will lay the sign in the ground so that the other can track the path of that animal.

Cues and signs in foraging behavior of animals are not only useful as their reference, but also as their social learning. By having them, they would be able to decide when, where, what, which, and how to eat. Naturally, finding food for the continuing of life is not simple process [10]. It is a complex process that needs a precise decision. However, the foraging animals have been given a basic knowledge by God, such as: when they have to begin the foraging task, what they have to eat, where the place that they should take in order to find the food, how they can ingest the food, how they can coordinate the foraging task among them, etc. It is really clear that the knowledge supports the intelligences of animals in searching the foods for their life sustainability. The behavioral foraging of animals has inspired many researchers in developing an artificial system, mainly in the field of swarm intelligences. Two of them were developed by Dorigo [14] who analyzed the ant colony and Karaboga who studied the bee colony comprehensively [6].

Aggregating means to combine into a single group or total (Cambridge dictionary online). Aggregation in the world life can be classified into two categories, i.e. passive and active collection. In passive collection of organisms, abiotic factor become the cause of their occurrence. One of the examples is zooplankton that aggregates as the result of physical constraints from marine current (Hamner & Schneider 1986) in [15]. In active collection, the collection is divided into two classifications, namely: i) resulted from individual responses; and ii) resulted from social interaction. For the first class, the aggregation usually occurs due to the individual agent of collection wants to find more comfort area, such as in the fly Stomoxys calcitrans. The single agents would move to a area of certain temperature that can let them to live comfortly (Fraenkel & Gunn 1961) in [15]. The movements of every single agent to the zone would form an aggregation of those animals. For the second class, the gathering has been resulted from the social interaction [15] that involves the attraction among the members in that group. Each single agents of that group would maintain the distances of them. Basically, the distance of each single agents to the other is constant [16] and does not depends on the number of single agents in that group. No matter how many the number of the single agents in that group is, their distance will be the same. This constant distance indicates that the density in that group is uniform. In this aggregation behavior, when there are disturbances, such as: the occurrence of the environmental changes or obstacles in front of them, the individual agents would adjust and adapt to the changes and so would the structure of that group [16]. The scientist imitated this animals aggregation behavior and implement it to the Particle swarm optimization

(PSO) that was introduced by kennedy [17] and fish schools optimization by Li [18]. PSO imitated the aggregation of birds, while the fish school imitated the fish aggregation.

Gathering means a party or a meeting when many people come together as a group (Cambridge dictionary online). In this case a meeting of some particles based on Newton gravitational law. Scientists, such as Rashedi [19][20] focused the research on this gathering behavior. Rashedi stated that the attraction of each particle in the world to the other particles depended on the force, the mass, and also the distance among them. The force needed by particle to generate that attraction is proportional to the masses, but inversely proportional to the square of the distance among them [19]. Glowworm and firefly are the example of animals that move based on the attraction among them. Some optimization of gathering behaviors that have been developed by researchers include gravitational search algorithm [19] and binary gravitational search algorithm [20] analyzed by Rashedi, firefly algorithm introduced by Yang [21]–[23], and glowworm swarm optimization investigated by Krishnanand [24].

Preying means to kill and eat an animal (Cambridge dictionary online). Some researchers made researches based on this preying behavior. Seyedali [7] and Emary [25] made an observation on grey wolves and made an optimization based on that. The preying in wolves was done by cooperation of wolves in a group (5-12 wolves in each group). A group of grey wolves consists of 4 sub groups, namely Alphas, Betas, Deltas, and Omegas. Alphas, as leader of the group, have an authority to handle the command in that group. The leader does not focus on the gender. A male or female grey wolf can be the leader. Alphas is supported and assisted by Betas. They help Alphas to decide what they have to do. The Betas are Alphas' subordinate, while the Deltas is the subaltern of Betas, and the Omega is the lowest sub group of their hierarchical arrangement. Deltas should obey the Alphas and Betas rules and have to defer to them. Deltas have some essensial tasks, such as: i) watch their territorial boundaries, ii) warn their group if there is danger, iii) protect and ensure the safety of the members of the group, iv) help Alphas and Betas in hunting the prey, v) provide the food for the group, and vi) take care of weak, ill, and wounded members in that group [7].

Echolocation means the ability of animals in locating the objects by using reflected sound, in particular that used by dolphins and bats (Oxford Dictionary). Dolphins and bats use their bio sonar to locate and determine the position of objects around them. The sonar is produced by themselves biologically. The echolocation behavior of bat was investigated by Elisabeth [26] and Siemers [27]. The bats can determine the location of objects, habitats, and food in wide range due to the help of flight and echolocation. Echolocation not only allows the bats an access to the objects, but also to orientation at night and to a varying degree detection, classification, and localization of food. Signal structure produced by various bats in running the echolocation varies widely [26]. The optimization of bats was observed by Yang [28]–[30].

Growth means the process of developing physically, mentally, or spiritually (Oxford Dictionary). One of the examples of growth behavior can be found in bacteria. They search nutrients in order to maximize energy obtained per unit time. Individual bacterium also communicates with others by sending signals. After getting the energy, they can conduct the foraging behavior. They cannot proceed to do the foraging if they have not got the energy to grow yet. The manner to

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maximize energy (growth behavior) impressed some researchers to make an optimization [31].

The phase growth in *Escherichia coli* is started in the glucose. When cells are transferred to a medium, the culture will be in a lag phase and a re-initiation of exponential growth happens. Adapting themselves in producing the lactose can enhance the suitability of the cells to their new environment. The cell replication of the bacteria can be generated if they have sufficient energy. When the original cell divides, the new division cells will continue to generate energy and also synthesize new cellular material [32]. The bacteria population growth needs only a short time to make the population size becomes double [31].

Mating means sex between animals (Oxford Dictionary). The example of mating can be found in birds, the birds tend to produce high quality breeding by choosing correct mate. The mate with high quality genes will give more chance of producing superior birds. They always try to find the best featured brood by using some strategies, such as: i) monogamy, ii) polygyny, iii) polyandry, iv) parthenogenesis and v) promiscuity [33]. The terms of mating strategies in bird mating are the same with human, i.e. monogamous means that a male mates with only one female; polygyny refers to a male that tends to mate with several females; while polyandrous is the contradiction of the polygyny in which a female tends to mate with several males; parthenogenesis is a special case which denotes a mating system in which a female is able to raise brood by herself (no need male help); and promiscuity mating systems which has unstable relationships. This type of mating involves two birds in only one-time event. Basically, during mating season, birds in every category employ a variety of intelligent behaviors, such as: singing, tail drumming or dancing to attract potential mates. [33].

Clustering means a group of similar things or people positioned or occurring closely together (Oxford Advanced Learner's Dictionary). Yang Shiqin et al [34] used dolphin behavior as the basic of the optimization. Basically, the dolphin uses its sound in conducting its task, such as: finding way, searching food, and talking to each other. Besides those characteristics, dolphin also uses cooperation strategy in finding their prey. It uses its 5 intelligent principles in seeking prey, such as: i) clustering, ii) role recognizing, iii) communicating, iv) leadership conducting, and v) following. Each task of prey searching can be describes as follow: in clustering strategy, the dolphin will make its own team; in role recognizing strategy, the dolphin that has the best fitness will lead the team; communicating strategy will be useful in producing cooperation among the partners of one team or with the partner from other team. All the “team best position” coming from the whole partners is notified to the dolphin, he should remember the best one of them as a reference named “neighbor team best position”. So each dolphin can mark their “neighbor team best fitness” by exchanging information with his partner [34]. The communication can be executed many times, and the best fitness information of other dolphin far away can be spread around the groups.

Climbing means the sport or activity of climbing mountains or cliffs (Oxford Dictionary). Climbing behavior in animals’ word is identical with monkey. The monkeys have a habit to make sign in the better branches that it has found. When they find a better branch they will have guidance and can decide which branch that it should climb. This sign will make them focus only on the better branches of the trees that they have found before. It becomes the best solution of their searching [35].

Brooding means Engaged in or showing deep thought about something that makes one sad, angry, or worried (Oxford dictionary). Yang [36] investigated the cuckoo behavior. The parasitic cuckoos like to lay their eggs to the other birds nest that is called as host. When the junior cuckoos hatched, this junior will mimic the sound of the host chicks in order to get food from the host [36].

Herding means A large group of animals, especially hoofed mammals, that live together or are kept together as livestock (Oxford Dictionary). A. H. Gandomi [37] focused to make an optimization based on krill behavior. The formation of animals in the world is always non-random. The krill formation can be investigated by seeing the phenomena of their aggregation. They can combine together with other by making formation 100 m. When the predators, such as seals, penguins, or sea birds, come to prey them, they will remove individual krill. This will help the krill to decrease their density. The next formation of the krill, after being preyed by predators, will give advantages, i.e. give the opportunity of the krill to get closer to the food [37]. Thus, the fitness of each individual is supposed to be a combination of the distance from the food and from the highest density of the krill swarm [38].

Jumping means Push oneself off a surface and into the air by using the muscles in one's legs and feet (Oxford Dictionary). Jumping frog Optimization is the example of optimization that mimics the jumping behavior of frog. Garcia and Perez investigated and applied the jumping behavior to the jumping frog optimization [39].

2.2 ALGORITHM

There are a lot of algorithms that can be used in in Swarm Intelligent Implementation. In this chapter, there will be discussed only 3 algorithms, namely Ant Colony Optimization, firefly, and Particle Swarm Optimization.

Ant Colony Optimization

Ant colony optimization (ACO) was introduced by M. Dorigo and teams in the early of 1990 [40]. ACO imitated the colony of Ants behavior. When group of ants want to find the food, they will make a great cooperation by using their foraging behavior. At the beginning of their searching, they will move to their surrounding randomly. When one of them has found the source of the food, it will take back that food to its nest. Along of its way back, it will release a pheromone to the ground. This pheromone is very useful for the other ant due to it will guide the other to track the food source [40]. The steps of ants in finding the food can be described in ACO algorithm can be described as follow: At the beginning, the ants are put on the random node of a graph. To move to next path, the ant should choose the node that they never visit. The probabilities of the ants to move depend on: i) the distance of the current node and the next node that they will occupy, and ii) the pheromone on the edge of the occupied node [9]. This movement will continue until all of them have traversed all the nodes on the graph. This complete movement is called one cycle. The probability of the ant to move from one node to the other node can be expressed as in equation (1):

$$P_{i,j} = \frac{\left(\tau_{i,j}^{\alpha}\right)\left(\eta_{i,j}^{\beta}\right)}{\Sigma\left(\tau_{i,j}^{\alpha}\right)\left(\eta_{i,j}^{\beta}\right)} \qquad (1)$$

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where:
$\tau_{i,j}$ is the amount of pheromone on edge i, j;
α is a parameter to control the influence of $\tau_{i,j}$;
$\eta_{i,j}$ is the desirability of edge i, j;
β is a parameter to control the influence of $\eta_{i,j}$.

After completing a cycle, the update should be done to the pheromone deployments. Whenever an ant moves trough an edge, the pheromone on that edge is reinforced, otherwise it would evaporate and be exhausted. The path with highest pheromone density that is the representation of optimal solution will be found after some certain cycles [9]. The amount of the pheromone is updated according to the equation (2):

$$\tau_{i,j} = (1-\rho)\tau_{i,j} + \Delta\tau_{i,j} \tag{2}$$

where:
ρ is the rate of pheromone evaporation;
$\Delta\tau_{i,j}$ is the amount of pheromone deposited.

In general, $\Delta\tau_{i,j}$ is given by equation (3):

$$\Delta\tau_{i,j}^{k} = \begin{cases} \frac{1}{L_k} if ant k travel on edge i,j \\ 0 otherwise \end{cases} \tag{3}$$

where:
ρ is the cost of k^{th} ant 's tour (distance).

Firefly Algorithm

Fireflies have a characteristic of generating flashes in rhythmic pattern. This pattern is really useful for attracting partner to be mated and prey to be eaten [21]. Besides that, the flashing can also be as the protective warning pattern for the same species and as allure for other species. Female fireflies can mimic the mating flashing pattern of other species so as to lure and eat the male fireflies [21].

Yang et al in the research [21][22][23] assumed 3 things, namely: 1) all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex; 2) attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less brighter one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly; and 3) the brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem, the brightness can simply be proportional to the value of the objective function. Other forms of brightness can be defined in a similar way to the fitness function in genetic algorithms.

The attractiveness of fireflies β with distance r can be calculated using equation (4):

$$\beta = \beta_0 e^{-\gamma r^2} \tag{4}$$

where β_0 is the attractiveness at $r = 0$.
The movement of a firefly i is attracted to another more attractive firely j is determined as in equation (5).

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j^t - x_i^t\right) + \alpha_t \epsilon_i^t \tag{5}$$

Particle Swarm Optimization

Particle Swarm Optimization was introduced first by Kennedy in 1995 [41]. It is simple and effective to be used as optimizer in wide range of functions. It has a great relation with a social life and ties with the evolutionary computation. Conceptually, PSO lies between genetic algorithm and evolutionary algorithm [41]. The algorithm used in PSO is simpler and consists of very few lines of code. It needs only few parameters and does not need specification out of the problem to be solved. Therefore, it only necessitates a small memory for computation. Moreover, PSO generally performed well in a large number of hard combinatorial optimization problems, especially in continuous optimization (Sandeep Rana et al. 2011; Berro et al. 2010) in [42].

PSO consists of two cognitive aspects, individual learning and learning from a social group. Where an individual finds itself in a problem space it can use its own experience and that of its peers to move itself toward the solution [43]. In PSO algorithm, each particle will present potential solution. Its characteristic is almost the same with evolutionary algorithm. The "swarm" is similar to "population", and "particle" is the same with individual. Each particles position is adjusted base on its own experience and that of its neighbor.

The relation between updated velocity and its personal best and global best was represented using equation (6), as follows [44]:

$$v_i^{t+1} = w_i\left(v_i^t + c_1.Rand(\quad).(p_i^t - x_i^t) + c_2.rand(\quad)\left(p_g^t - x_i^t\right)\right) x_i^{t+1} = x_i^t + v_i^{t+1} \tag{6}$$

While each particle updated its position using the equation (7):

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{7}$$

3. SWARM INTELLIGENCES APPLICATIONS

SI is still the most favorite researches until now. Some of SI applications are showed in Table 1. The applications are not limited only in engineering field but also to the social and economic field. Many benefits can be got by implementing the SI to those fields, as represented in Table 1.

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TABLE 1.
Some examples of SI algorithm application in recent year

No.	Algorithm	Application
1	Ant Colony Optimization (ACO)	vehicle routing problem [45], [46], solving fixed destination multi-depot multiple traveling salesmen problems [47], design of wind farm layout [48], forecast energy demand [49]
2	Particle Swarm Optimization (PSO).	maximum power point tracker for photovoltaic system [50], optimal DG location and sizing in distribution systems [51], job-shop scheduling [52], for environmental/economic dispatch [53], optimization of daily electrical power consumption [54], Test Point Selection [55], and RNA Secondary Structure Prediction [56]
3.	Bee Algorithm	feature selection [57][58], dynamic clustering [59], optimal power flow solution [60], design optimization of real world steel space frames [61].
4.	Fruit fly Optimization algorithm	joint replenishment [62], optimizing a location allocation-inventory problem [63], gasification process operation [64], for the semiconductor final testing scheduling problem [65].
5.	Gravitational search algorithm	optimal power flow [66], for the optimization of modular neural networks in pattern recognition [67], for short term hydrothermal scheduling [68], for nearest neighbor classification [69].
6.	Firefly algorithm	solar and wind power estimation and economic load dispatch [70], for mechanical design optimization problems [71], for load frequency control of power system [72], protein complex identification [73].
7.	Glowworm	vehicle routing problem [74], cost and CO2 emission optimization [75], unit commitment in wind [76].
8.	Gray wolf optimizer	for parameter estimation in surface waves [77], for hyper spectral band selection [78], for solving optimal reactive power dispatch problem [79].
9.	Bat algorithm	load frequency controller design [80], planning the sports sessions [81], speed control of brushless DC motor [82].
10.	Bacteria Foraging Optimization	optimal power flow solution of wind-thermal generation system [83], optimal location and sizing of capacitor placement [84], global optimization [85].
11.	Artificial Fish School Algorithm	finding rough set reducts [86], solving large-scale reliability–redundancy application problem [87], for energy-efficient routing technique [88].
12.	Bird Mating Optimizer	for Diseases Classification [89], determination of photovoltaic modules parameters [90], phase adjustment of open-wye/open-delta transformers in a power grid [91].
13.	Dolphin Partner Optimization	[92].
14.	Monkey Search	Allocation of capacitor banks in distribution systems [93], for a 0-1 knapsack problem [94].
15.	Roach Infestation Optimization	[95].
16.	Cuckoo Search Algorithm	for nonlinear interconnected power system [96], forecast the annual foreign tourist arrivals to China [97], for power loss minimization and voltage profile improvement [98].
17.	Krill Herd Algorithm	for optimal location of distributed generator [99], for optimal location of capacitor [100], for Global Numerical Optimization [101]
18.	Jumping Frog Optimization	for solving transportation network design problem [102], for parameter identification [103].

4. CONCLUSION

The behaviors of some animals were analyzed, investigated, and implemented to some optimization by the previous researchers. Each animals has various characteristics and excellent intelligent that can be translated into many algorithms. The researchers are still attracted with PSO, Bee colony, Ant colony, etc. To the author's best knowledge, there are still little attention to the Dolphin Partner Optimization, Monkey Search, and Roach Infestation Optimization. For dolphin partner optimization (that imitate the clustering of dolphin behavior), author cannot find other researchers that focused on that algorithm recently. There is only a research in 2013 that uses dolphin behavior that based on dolphin's echolocation [80]. For jumping frog optimization, some authors used the term 'leaping' instead of jumping [90] and [91].

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This section is optional. Any acknowledgement which the author(s) may wish to make may appear here.

REFERENCES

[1] G. B. and J. Wang, "Swarm intelligence in cellular robotic systems." Robots and Biological Systems: Towards a New Bionics?," *Springer, Berlin, Heidelb.*, pp. 703–712, 1993.
[2] B. Tutuko, "Fuzzy Logic-Ant Colony Optimization for Explorer-Follower Robot with Global Optimal Path Planning," *Comput. Eng. Appl. J. 7*, vol. 7, 2018.
[3] N. L. Husni, "Swarm Robot Implementation in Gas Searching Using Particle Swarm Optimization Algorithm," *Comput. Eng. Appl. J.*, vol. 6, no. 3, 2017.
[4] M. Neshat, G. Sepidnam, M. Sargolzaei, and A. N. Toosi, "Artificial fish swarm algorithm: a survey of the state-of-the-art, hybridization, combinatorial and indicative applications," *Artif. Intell. Rev.*, vol. 42, no. 4, pp. 965–997, 2014.
[5] S. Nurmaini and S. Z. M. Hashim, "Swarm Robots Control System based," no. August, pp. 20–21, 2014.
[6] I. Navarro and F. Matía, "An Introduction to Swarm Robotics," *ISRN Robot.*, vol. 2013, pp. 1–10, 2013.
[7] S. Mirjalili, S. M. Mirjalili, A. Lewis, G. W. Optimizer, S. Mirjalili, S. M. Mirjalili, A. Lewis, C. Technology, and S. Beheshti, "Grey Wolf Optimizer 1 1," vol. 69, pp. 46–61, 2014.
[8] D. Karaboga, B. Gorkemli, C. Ozturk, and N. Karaboga, "A comprehensive survey: Artificial bee colony (ABC) algorithm and applications," *Artif. Intell. Rev.*, vol. 42, no. 1, pp. 21–57, 2014.
[9] S. Zhang, C. K. M. Lee, H. K. Chan, K. L. Choy, and Z. Wu, "Swarm intelligence applied in green logistics: A literature review," *Eng. Appl. Artif. Intell.*, vol. 37, pp. 154–169, 2015.
[10] B. G. Galef and L. A. Giraldeau, "Social influences on foraging in vertebrates: Causal mechanisms and adaptive functions," *Anim. Behav.*, vol. 61, no. 1, pp. 3–15, 2001.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

[11] A. Deshpande, M. Kumar, and S. Ramakrishnan, "Robot Swarm for Efficient Area Coverage Inspired By Ant Foraging - The Case of Adaptive Switching Between Brownian motion and Le´vy Flight ," *Proc. ASME 2017 Dyn. Syst. Control Conf.*, pp. 1–8, 2017.
[12] H. Verlekar and K. Joshi, "Ant & bee inspired foraging swarm robots using computer vision," *Int. Conf. Electr. Electron. Commun. Comput. Technol. Optim. Tech. ICEEECCOT 2017*, vol. 2018–January, pp. 191–195, 2018.
[13] A. Sáez, C. L. Morales, L. A. Garibaldi, and M. A. Aizen, "Invasive bumble bees reduce nectar availability for honey bees by robbing raspberry flower buds," *Basic Appl. Ecol.*, vol. 19, pp. 26–35, 2017.
[14] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization Artificial Ants as a Computational Intelligence Technique," *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28–39, 2006.
[15] R. Jeanson, C. Rivault, J. L. Deneubourg, S. Blanco, R. Fournier, C. Jost, and G. Theraulaz, "Self-organized aggregation in cockroaches," *Anim. Behav.*, vol. 69, no. 1, pp. 169–180, 2005.
[16] A. Mogilner, L. Edelstein-Keshet, L. Bent, and A. Spiros, *Mutual interactions, potentials, and individual distance in a social aggregation*, vol. 47, no. 4. 2003.
[17] J. Kennedy and R. Eberhart, "Particle swarm optimization," *Neural Networks, 1995. Proceedings., IEEE Int. Conf.*, vol. 4, pp. 1942–1948 vol.4, 1995.
[18] L. Xiao-lei, L. Fei, T. Guo-hui, and Q. Ji-xin, "Applications of artificial fish school algorithm in combinatorial optimization problems.pdf," *J. Shandong Univ. (Engineering Sci.*, vol. 05, 2005.
[19] E. Rashedi and H. N. Saeid, "BGSA : binary gravitational search algorithm," no. December 2009, pp. 727–745, 2010.
[20] E. Rashedi, H. Nezamabadi-pour, and S. Saryazdi, "GSA : A Gravitational Search Algorithm," *Inf. Sci. (Ny).*, vol. 179, no. 13, pp. 2232–2248, 2009.
[21] X. Yang, "Stochastic Algorithms: Foundations and Applications," vol. 5792, no. May, 2009.
[22] X. Yang, "Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)," vol. 284, no. March 2014, 2010.
[23] X. Yang, *Firefly Algorithm*. 2010.
[24] K. N. Krishnanand and D. Ghose, "Detection of multiple source locations using a glowworm metaphor with applications to collective robotics," *Proc. - 2005 IEEE Swarm Intell. Symp. SIS 2005*, vol. 2005, pp. 87–94, 2005.
[25] E. Emary, H. M. Zawbaa, and A. E. Hassanien, "Binary grey wolf optimization approaches for feature selection," *Neurocomputing*, vol. 172, pp. 371–381, 2016.
[26] E. K. V. Kalko, H. U. Schnitzler, I. Kaipf, and A. D. Grinnell, "Echolocation and foraging behavior of the lesser bulldog bat, Noctilio albiventris: Preadaptations for piscivory?," *Behav. Ecol. Sociobiol.*, vol. 42, no. 5, pp. 305–319, 1998.
[27] B. M. Siemers, E. K. V. Kalko, and H.-U. Schnitzler., "Echolocation and foraging behavior of the lesser bulldog bat, Noctilio albiventris: Preadaptations for piscivory?," *Behav. Ecol. Sociobiol.*, p. 50: 317-328, 2001.
[28] X. Yang and A. Hossein Gandomi, "Bat algorithm: a novel approach for global engineering optimization," *Eng. Comput.*, vol. 29, no. 5, pp. 464–483,

2012.
[29] X. Yang, "A New Metaheuristic Bat-Inspired Algorithm," vol. 284, no. April 2010, 2010.
[30] X. Yang, "Bat Algorithm : Literature Review and Applications," pp. 1–10, 2013.
[31] K. M. Passino, "Biomimicry of Bacterial Foraging for Distributed Optimization and Control," *Control Syst. IEEE*, vol. 22, no. 3, pp. 52–67, 2002.
[32] R. L. Buchanan, R. C. Whiting, and W. C. Damert, "When is simple good enough : a comparison of the Gompertz , Baranyi , and three-phase linear models for fitting bacterial growth curves 1," pp. 313–326, 1997.
[33] A. Askarzadeh, "Commun Nonlinear Sci Numer Simulat Bird mating optimizer : An optimization algorithm inspired by bird mating strategies," *Commun. Nonlinear Sci. Numer. Simul.*, vol. 19, no. 4, pp. 1213–1228, 2014.
[34] S. Yang, J. Jiang, and G. Yan, "A dolphin partner optimization," vol. 1, pp. 124–128, 2009.
[35] A. R. Kammerdiner, A. Mucherino, and P. M. Pardalos., "Application of Monkey Search Meta-heuristic to Solving Instances of the Multidimensional Assignment Problem," *Optim. Coop. Ctrl. Strateg. LNCIS 381*, pp. 385–397, 1988.
[36] X. Yang and S. Deb, "Engineering Optimisation by Cuckoo Search," pp. 1–17, 2009.
[37] A. H. Gandomi and A. H. Alavi, "Krill herd: A new bio-inspired optimization algorithm," *Commun. Nonlinear Sci. Numer. Simul.*, vol. 17, no. 12, pp. 4831–4845, 2012.
[38] A. H. Gandomi and A. H. Alavi, "Lagrangian model of the krill herding Commun Nonlinear Sci Numer Simulat," vol. 17, p. 4831–4845 4833, 2012.
[39] F. J. . Garcia and J. A. . Perez, "Jumping Frogs Optimization: A New Swarm Method for discrete optimization," *Doc. Trab. del DEIOC*, vol. 3, p. 10, 2008.
[40] M. Dorigo, V. Maniezzo, and A. Colorni, "Positive Feedback as a Search Strategy," *Citeceer*, 1991.
[41] J. Kennedy and R. Eberhart, "Particle swarm optimization," *Proc. ICNN'95 - Int. Conf. Neural Networks*, vol. 4, pp. 1942–1948, 1995.
[42] S. Larabi Marie-Sainte, "A survey of Particle Swarm Optimization techniques for solving university Examination Timetabling Problem," *Artif. Intell. Rev.*, vol. 44, no. 4, pp. 537–546, 2015.
[43] A. Banks, J. Vincent, and C. Anyakoha, "A review of particle swarm optimization. Part II: Hybridisation, combinatorial, multicriteria and constrained optimization, and indicative applications," *Nat. Comput.*, vol. 7, no. 1, pp. 109–124, 2008.
[44] W. Jatmiko, F. Jovan, R. Y. S. Dhiemas, a M. Sakti, F. M. Ivan, a Febrian, T. Fukuda, and K. Sekiyama, "Robots implementation for odor source localization using PSO algorithm," *WSEAS Trans. Circuits Syst.*, vol. 10, no. 4, pp. 115–125, 2011.
[45] M. Reed, A. Riannakou, and R. Evering, "An ant colony algorithm for the multi-compartment vehicle routing problem," *Appl. Soft Comput.*, vol. 15, no. February, pp. 169–176, 2014.
[46] S. R. Balseiro, I. Loiseau, and J. Ramonet, "An Ant Colony algorithm hybridized with insertion heuristics for the Time Dependent Vehicle Routing Problem with Time Windows," *Comput. Oper. Res.*, vol. 38, no. 6, June, pp.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

954–966, 2011.
[47] S. Ghafurian and N. Javadian, “An ant colony algorithm for solving fixed destination multi-depot multiple traveling salesmen problems,” vol. 11, pp. 1256–1262, 2011.
[48] Y. Eroĝlu and S. U. Seçkiner, “Design of wind farm layout using ant colony algorithm,” *Renew. Energy*, vol. 44, no. August, pp. 53–62, 2012.
[49] M. S. Kiran, E. Özceylan, M. Gündüz, and T. Paksoy, “A novel hybrid approach based on Particle Swarm Optimization and Ant Colony Algorithm to forecast energy demand of Turkey,” *Energy Convers. Manag.*, vol. 53, no. 1, January, pp. 75–83, 2012.
[50] K. Ishaque and Z. Salam, “Maximum Power Point Tracker for Photovoltaic System,” *Ind. Electron. IEEE Trans.*, vol. 60, no. 8, pp. 3195–3206, 2012.
[51] M. H. Moradi and M. Abedini, “A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems,” *Int. J. Electr. Power Energy Syst.*, vol. 34, no. 1, January, pp. 66–74, 2012.
[52] G. Moslehi and M. Mahnam, “A Pareto approach to multi-objective flexible job-shop scheduling problem using particle swarm optimization and local search,” *Int. J. Prod. Econ.*, vol. 129, no. 1, January, pp. 14–22, 2011.
[53] Y. Zhang, D. W. Gong, and Z. Ding, “A bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch,” *Inf. Sci. (Ny).*, vol. 192, no. 1 June, pp. 213–227, 2012.
[54] A. Askarzadeha and L. Dos Santos Coelhob, “Using two improved particle swarm optimization variants for optimization of daily electrical power consumption in multi-chiller systems,” *Appl. Therm. Eng.*, vol. 89, no. 5 October, pp. 640–646, 2015.
[55] W. P. Xiaifeng Lv, Ling Ma, Jing Sun, “Test Point Selection Method Research Based on Genetic Algorithm and Binary Particle Swarm Optimization Algorithm,” *Proc. Second Int. Conf. Mechatronics Autom. Control*, vol. 334, no. of the series Lecture Notes in Electrical Engineering, pp. 577–585, 2015.
[56] J. Agrawal and S. Agrawal, “Acceleration based Particle Swarm Optimization (APSO) for RNA Secondary Structure Prediction,” *Prog. Syst. Eng.*, vol. 330, no. of the series Advances in Intellegent System and Computing, pp. 741–746, 2014.
[57] E. Hancera, B. Xue, D. Karaboga, and M. Zhang, “A binary ABC algorithm based on advanced similarity scheme for feature selection,” *Appl. Soft Comput.*, vol. 36, no. November, pp. 334–348, 2015.
[58] A. Moayedikia, R. Jensen, U. K. Wiil, and R. Forsati, “Weighted bee colony algorithm for discrete optimization problems with application to feature selection,” *Eng. Appl. Artif. Intell.*, vol. 44, no. September, pp. 153–167, 2015.
[59] C. Ozturk, E. Hancer, and D. Karaboga, “Dynamic clustering with improved binary artificial bee colony algorithm,” *Appl. Soft Comput.*, vol. 28, no. March, pp. 69–80, 2015.
[60] R. Roy and H. T. Jadhav, “Optimal power flow solution of power system incorporating stochastic wind power using Gbest guided artificial bee colony algorithm,” *Int. J. Electr. Power Energy Syst.*, vol. 64, no. January, pp. 562–

578, 2015.

[61] I. Aydoƚdu, A. Akin, and M. P. Saka, "Design optimization of real world steel space frames using artificial bee colony algorithm with Levy flight distribution," *Adv. Eng. Softw.*, vol. 92, no. February, pp. 1–14, 2016.

[62] L. Wang, Y. Shi, and S. Liu, "An improved fruit fly optimization algorithm and its application to joint replenishment problems," *Expert Syst. Appl.*, vol. 42, no. 9, 1 June, pp. 4310–4323, 2015.

[63] S. M. Mousavi, N. Alikar, S. T. A. Niaki, and A. Bahreininejad, "Optimizing a location allocation-inventory problem in a two-echelon supply chain network: A modified fruit fly optimization algorithm," *Comput. Ind. Eng.*, vol. 87, no. September, pp. 543–560, 2015.

[64] J. Niu, W. Zhong, Y. Liang, N. Luo, and F. Qian, "Fruit fly optimization algorithm based on differential evolution and its application on gasification process operation optimization," *Knowledge-Based Syst.*, vol. 88, no. November, pp. 253–263, 2015.

[65] X. L. Zheng, L. Wang, and S. Y. Wang, "A novel fruit fly optimization algorithm for the semiconductor final testing scheduling problem," *Knowledge-Based Syst.*, vol. 57, no. February, pp. 95–103, 2014.

[66] S. Duman, U. Güvenç, Y. Sönmez, and N. Yörükeren, "Optimal power flow using gravitational search algorithm," *Energy Convers. Manag.*, vol. 59, no. July, pp. 86–95, 2012.

[67] B. González, F. Valdez, P. Melin, and G. Prado-Arechiga, "Fuzzy logic in the gravitational search algorithm for the optimization of modular neural networks in pattern recognition," *Expert Syst. Appl.*, vol. 42, no. 14, 15 August, pp. 5839–5847, 2015.

[68] N. Gouthamkumar, V. Sharma, and R. Naresh, "Disruption based gravitational search algorithm for short term hydrothermal scheduling," *Expert Syst. Appl.*, vol. 42, no. 20, November, pp. 7000–7011, 2015.

[69] M. Rezaei and H. Nezamabadi-pour, "Using gravitational search algorithm in prototype generation for nearest neighbor classification Neurocomputing," *Neurocomputing*, vol. 157, no. 1 June, pp. 256–263, 2015.

[70] N. Saxena and S. Ganguli, "Solar and Wind Power Estimation and Economic Load Dispatch Using Firefly Algorithm," *Procedia Comput. Sci.*, vol. 70, pp. 688–700, 2015.

[71] A. Baykasoglu and F. B. Ozsoydan, "Adaptive firefly algorithm with chaos for mechanical design optimization problems," *Appl. Soft Comput.*, vol. 36, no. November, pp. 152–164, 2015.

[72] G. T. Chandra Sekhar, R. K. Sahu, A. K. Baliarsingh, and S. Panda, "Load frequency control of power system under deregulated environment using optimal firefly algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 74, no. January, pp. 195–211, 2016.

[73] X. Lei, F. Wang, F. X. Wu, A. Zhang, and W. Pedrycz, "Protein complex identification through Markov clustering with firefly algorithm on dynamic protein-protein interaction networks," *Inf. Sci. (Ny).*, vol. 329, no. 1 February, pp. 303–316, 2016.

[74] M. Marinaki and Y. Marinakis, "A Glowworm Swarm Optimization algorithm for the Vehicle Routing Problem with Stochastic Demands," *Expert Syst. Appl.*, vol. 46, no. 15 March, pp. 145–163, 2016.

[75] V. Yepes, J. V. Martí, and T. García-Segura, "Cost and CO2 emission optimization of precast-prestressed concrete U-beam road bridges by a hybrid

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

glowworm swarm algorithm," *Autom. Constr.*, vol. 49, no. Part A, January, pp. 123–134, 2015.

[76] J. Yan, J. Zhang, Y. Liu, S. Han, L. Li, and C. Gu, "Unit commitment in wind farms based on a glowworm metaphor algorithm," *Electr. Power Syst. Res.*, vol. 129, no. December, pp. 94–104, 2015.

[77] X. Song, L. Tang, S. Zhao, X. Zhang, L. Li, J. Huang, and W. Cai, "Grey Wolf Optimizer for parameter estimation in surface waves," *Soil Dyn. Earthq. Eng.*, vol. 75, pp. 147–157, 2015.

[78] S. A. Medjahed, T. Ait Saadi, A. Benyettou, and M. Ouali, "Gray Wolf Optimizer for hyperspectral band selection," *Appl. Soft Comput.*, vol. 40, no. 28 November, pp. 178–186, 2015.

[79] M. H. Sulaiman, Z. Mustaffa, M. R. Mohamed, and O. Aliman, "Using the gray wolf optimizer for solving optimal reactive power dispatch problem," *Appl. Soft Comput.*, vol. 32, no. July, pp. 286–292, 2015.

[80] S. M. Abd-Elazim and E. S. Ali, "Load frequency controller design via BAT algorithm for nonlinear interconnected power system," *Int. J. Electr. Power Energy Syst.*, vol. 77, no. May, pp. 166–177, 2016.

[81] I. Fister, S. Rauterb, X. S. Yang, K. Ljubičd, and I. Fister Jr, "Planning the sports training sessions with the bat algorithm," *Neurocomputing*, vol. 149, no. Part B, 3 February, pp. 993–1002, 2015.

[82] K. Premkumar and B. V. Manikandan, "Speed control of Brushless DC motor using bat algorithm optimized Adaptive Neuro-Fuzzy Inference System," *Appl. Soft Comput.*, vol. 32, no. July, pp. 403–419, 2015.

[83] A. Panda and M. Tripathy, "Security constrained optimal power flow solution of wind-thermal generation system using modified bacteria foraging algorithm," *Energy*, vol. 93, no. Part 1, 15 December, pp. 816–827, 2015.

[84] K. R. Devabalaji, K. Ravi, and D. P. Kothari, "Optimal location and sizing of capacitor placement in radial distribution system using Bacterial Foraging Optimization Algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 71, no. October, pp. 383–390, 2015.

[85] A. N. K. Nasir, M. O. Tokhi, and N. M. A. Ghani, "Novel adaptive bacterial foraging algorithms for global optimisation with application to modelling of a TRS," *Expert Syst. Appl.*, vol. 42, no. 3, 15 February, pp. 1513–1530, 2015.

[86] Y. Chen, Q. Zhu, and H. Xu, "Finding rough set reducts with fish swarm algorithm," *Knowledge-Based Syst.*, vol. 81, no. June, pp. 22–29, 2015.

[87] Q. He, X. Hu, H. Ren, and H. Zhang, "A novel artificial fish swarm algorithm for solving large-scale reliability-redundancy application problem," *ISA Trans.*, vol. 59, pp. 105–113, 2015.

[88] A. O. Helmy, S. Ahmed, and A. E. Hassenian, "Artificial Fish Swarm Algorithm for Energy-Efficient Routing Technique," *Intell. Syst.*, vol. 322, no. of the series advances in Intelligent System and Computing, pp. 509–519, 2015.

[89] N. K. S. Behera, A. R. Routray, J. Nayak, H. S. Behera, and Á. Á. Multilayer, "Bird Mating Optimization Based Multilayer Perceptron for Diseases Classification," *Comput. Intell. Data Min. - Vol. 3*, vol. 33, no. Of the series Smart Innovation, Systems and Technologies, pp. 305–315, 2014.

[90] A. Askarzadeh and S. Coelho, "Determination of photovoltaic modules parameters at different operating conditions using a novel bird mating

optimizer approach," *ENERGY Convers. Manag.*, vol. 89, pp. 608–614, 2015.

[91] S. J. Huang, T. Y. Tai, X. Z. Liu, W. F. Su, and P. H. Gu, "Application of Bird-Mating Optimization to Phase Adjustment of Open-Wye/Open-Delta Transformers in a Power Grid," *Ind. Technol. (ICIT), 2015 IEEE Int. Conf.*, no. 17–19 March, pp. 1275–1279, 2015.

[92] A. Kaveh and N. Farhoudi, "A new optimization method: Dolphin echolocation," *Adv. Eng. Softw.*, vol. 59, no. May, pp. 53–70, 2013.

[93] F. G. Duque, L. W. De Oliveira, E. J. De Oliveira, A. L. M. Marcato, and I. C. Silva, "Allocation of capacitor banks in distribution systems through a modified monkey search optimization technique," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 420–432, 2015.

[94] Y. Zhou, X. Chen, and G. Zhou, "An improved monkey algorithm for a 0-1 knapsack problem," *Appl. Soft Comput. J.*, vol. 38, pp. 817–830, 2016.

[95] H. C. Tsai, "Roach infestation optimization with friendship centers," *Eng. Appl. Artif. Intell.*, vol. 39, pp. 109–119, 2015.

[96] A. Y. Abdelaziz and E. S. Ali, "Cuckoo Search algorithm based load frequency controller design for nonlinear interconnected power system," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 632–643, 2015.

[97] X. Sun, W. Sun, J. Wang, Y. Zhang, and Y. Gao, "Using a Grey-Markov model optimized by Cuckoo search algorithm to forecast the annual foreign tourist arrivals to China," *Tour. Manag.*, vol. 52, pp. 369–379, 2016.

[98] T. T. Nguyen and A. V. Truong, "Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 68, pp. 233–242, 2015.

[99] "Oppositional krill herd algorithm for optimal location of capacitor with reconfiguration in radial distribution system."

[100] S. Sultana and P. K. Roy, "Oppositional krill herd algorithm for optimal location of capacitor with reconfiguration in radial distribution system," *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 78–90, 2016.

[101] L. Guo, G. Wang, A. H. Gandomi, A. H. Alavi, and H. Duan, "Neurocomputing A new improved krill herd algorithm for global numerical optimization," *Neurocomputing*, vol. 138, pp. 392–402, 2014.

[102] N. Afkar. and A. Babazadeh, "Hybridized Particle Swarm Optimization Algorithm: Frog Leaping Concept For Solving Transportation Network Design Problem," pp. 647–652.

[103] M. A. Ahandani and H. Alavi-Rad, "Opposition-based learning in shuffled frog leaping: An application for parameter identification," *Inf. Sci. (Ny).*, vol. 291, no. C, pp. 19–42, 2015.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)