© International Journal of Combinatorial Optimization Problems and Informatics, Vol. 3, No. 3, Sep-Dec 2012, pp. 104-123. ISSN: 2007-1558.

Meta-Heuristics Algorithms based on the Grouping of Animals by Social Behavior for the Traveling Salesman Problem

Jorge A. Ruiz-Vanoye, Ocotlán Díaz-Parra, Felipe Cocón, Andrés Soto,
Ma. De los Ángeles Buenabad Arias, Gustavo Verduzco-Reyes, Roberto Alberto-Lira
Universidad Autónoma del Carmen, México.
jorge@ruizvanoye.com

Abstract: In this paper, we show a survey of meta-heuristics algorithms based on grouping of animals by social behavior for the Traveling Salesman Problem, and propose a new classification of meta-heuristics algorithms (not based on swarm intelligence theory) based on grouping of animals: swarm algorithms, schools algorithms, flocks algorithms and herds algorithms: a) The swarm algorithms (inspired by the insect swarms and zooplankton swarms): Ant Colony Optimization algorithm – ACO (inspired by the research on the behavior of ant colonies), Firefly Algorithm (based on fireflies), Marriage in Honey Bees Optimization Algorithm - MBO algorithm (inspired by the Honey Bee), Wasp Swarm Algorithm (inspired on the Parasitic wasps), Termite Algorithm (inspired by the termites), Mosquito swarms Algorithm – MSA (inspired by mosquito swarms), zooplankton swarms Algorithm - ZSA (inspired by the Zooplankton) and Bumblebees Swarms Algorithm – BSA (inspired by Bumblebees). b) The school algorithms (inspired by the fish schools): The Particle Swarm Optimization algorithm – PSO (inspired by social behavior and movement dynamics of fish or schooling). c) The flock algorithms (inspired by the bird flocks): the flocking algorithm, and the Particle Swarm Optimization algorithm (inspired on the dynamics of the birds), d) The herd and pack Algorithms (inspired by the mammal herds and packs): bat algorithm (inspired by bat), wolf pack search algorithm - WPS (inspired by wolfs), Rats herds algorithm - RATHA (inspired by Rats), Dolphins Herds Algorithm - DHA (inspired by Dolphins) and the feral-dogs herd algorithm - FDHA (inspired by feral-dogs herd).

Keywords: Traveling Salesman Problem swarms Algorithms, schools algorithms, flocks algorithms, herds algorithms, pack algorithms, insect swarms, zooplankton swarms, fish school, bird flocks, mammal herds, mammal packs.

Received Oct 10, 2011 / Accepted Dec 31, 2011

1. Introduction

Grouping of animals is a natural phenomenon in which a number of animal individuals are involved in movement as forming a group; there are insect swarms, zooplankton swarms, fish schools, bird flocks, and mammal herds [1]:

1. Swarms. The swarm is a social grouping (of the same species) of insects and marine zooplankton. There are several types of swarms, two of the best known are insects swarms and marine zooplankton swarms. Insects swarms consist of the following insects: honey bees, Africanized Honey Bees, ants, termites, desert locusts, gnats, midges, mosquito, houseflies, African Fly of the Nile river, pine beetles, ladybug, aphids, Monarch butterflies, Bumblebees, Fire Ants, Army Ants, Yellow Jackets, and others). Zooplankton swarms contains animal organism called zooplankters (copepods, mysids, segetids, Scyphomedusae, and others) [2].

2. Schools. The school is a social grouping (of the same species) of fishes and marine animals. Schools are groups of individuals engaging in cohesive movements with parallel orientation, this presence or absence of parallel orientation distinguishes schools from swarms [1]. The schooling fish is a synchronous swimming of fish at the same speed and in the same direction, usually of the same species and the same age/size [3]. The schools consist of the following fishes and marine animals: sardines, salmon, barracuda, sticklebacks, mummichog, European minnows, spottail shiner, krill, Basslets, Anchovy fish, jellyfish, and others.

3. Flocks. The flock is a social grouping (of the same species) of birds. The Bird flocking is the coordinated behavior of large groups of birds (of the same species) when flying at the same speed and in the same direction [4]. There may be a fundamental difference between fish schooling and bird flocking, in fish schools individuals are reacting more or less to their immediate neighbors owing to the limitation in vision, while, in bird flocks, individuals are able to view a wider part of flock motions [1]. Birds consist of the following animals: dunlin, starling, Ducks, Geese, Pelicans, Ravens, Sandpipers, shorebirds, flamingo, parrots, gulls, pigeons, macaws and others).

4. Herds. The herd is a social grouping (of the same species) of mammal animals. Large groups of social grouping of carnivores are called packs [5]. Herds consists of the following animals: African wild dogs, Gray wolves, Black-backed jackals, ethiopian wolf, new guinea singing dog, feral dogs, bats, buffalo, zebra, bison, sheep, desert bighorn, Elephants, wolves, feral-dogs, pigs, wild horses, Rhinos, Wildebeest, llamas, Giraffes, Antelope species (steenbok, Kirk's dikdik, bushbuck,

Bohor reedbuck, mountain reedbuck, Thompson's gazelle, impala, waterbuck), Whales, Dolphins, rats, and others.

2. A new Classification of Meta-heuristics Algorithms based on grouping of animals by social behavior

We propose a new classification of meta-heuristics algorithms based on grouping of animals by social behavior: swarm algorithms, schools algorithms, flocks algorithms and herd algorithms. The new classification of algorithms is not based on swarm intelligence theory.

1. Swarm Algorithms. The term swarm algorithm refers to any algorithm that models the grouping of insects and zooplankton swarms by social behavior. The swarm algorithms are inspired by the insect swarms and zooplankton swarms. Some of the most popular swarms algorithms are: The Ant Colony Optimization algorithm (ACO) was inspired by the research on the behavior of ant colonies [6]; the Firefly Algorithm is based on insects called fireflies [7]; the Marriage in Honey Bees Optimization Algorithm (MBO algorithm) is inspired by the process of reproduction of Honey Bee [8], the Artificial Bee Colony Algorithm (ABC) is based on the recollection of the Honey Bees [9], the Wasp Swarm Algorithm was inspired on the Parasitic wasps [10], Bee Collecting Pollen Algorithm (BCPA) [11], Termite Algorithm [12], Mosquito swarms Algorithm (MSA)[23], zooplankton swarms Algorithm (ZSA) [50] and Bumblebees Swarms Algorithm (BSA)[69].

2. School Algorithms. The term school algorithm refers to any algorithm that models the grouping of fish schools by social behavior. The school algorithms are inspired by the fish schools. Some of the most popular school algorithms are: The Particle Swarm Optimization algorithm (PSO) was inspired by social behavior and movement dynamics of fish (schooling) [13].

3. Flock Algorithms. The term flock algorithm refers to any algorithm that models the grouping of bird flock by social behavior. The flock algorithms are inspired by the bird flocks. Some of the most popular flock algorithms are: the flocking algorithm and the three flocking rules of Reynolds (flock centering or cohesion, collision avoidance or separation, and velocity matching or alignment) [4], The Particle Swarm Optimization algorithm (PSO) was inspired by social behavior and movement dynamics of birds (flocking) [13].

4. Herd and Packs Algorithms. The term herd and pack algorithm refers to any algorithm that models the grouping of mammal herds and packs by social behavior. The herd and pack Algorithms are inspired by the mammal herds and packs. Some

of the most popular herd algorithms are: bat algorithm [14], wolf pack search algorithm [15], Rats herds algorithm (RATHA) [17], Dolphins Herds Algorithm (DHA) [31], and feral-dogs herd algorithm (FDHA) [38].

2.1. Swarm Algorithms

The swarm algorithms were developed by analogy with aspects of the insect swarms and zooplankton swarms. In this section we only show the algorithms: Mosquito swarms Algorithm (MSA)[23], zooplankton swarms Algorithm (ZSA) [50] and Bumblebees Swarms Algorithm (BSA)[69].

2.1.1. Mosquito Swarms Algorithm (MSA)

Ruiz-Vanoye and Díaz-Parra (2012) [23] propose the Mosquito Swarm Algorithm (MSA). The MSA is considered as a meta-heuristics algorithm, a bio-inspired algorithm, parallel or distributed algorithm based on the research on the social behavior of mosquito swarm [23].

Mosquitoes (gnats) have sensors designed to track their prey: A) Chemical sensors, mosquitoes can sense carbon dioxide and lactic acid up to 36 meters away. Mammals and birds gives off these gases as part of their normal breathing. Certain chemicals in sweat also seem to attract mosquitoes. B) Heat sensors, Mosquitoes can detect heat, so they can find warm-blooded mammals and birds very easily once they get close enough. A mosquito swarm exists close to areas with standing water.

Based on the above description of mosquito swarm process, Ruiz-Vanoye and Díaz-Parra propose the Mosquito Swarm Algorithm. The structure of the MSA is as follows [23]:

```
Input: number of mosquitoes (n)
1. Initialize a Mosquito Population with Chemical Sensors (CS) and Heat Sensors (HS).
2. Generating the initial locations (x) of the mosquitoes (n).
3. Initialize the temperature (t) and Maximum Temperature (T).
4. Repeat (total of mosquitoes) //by parallel  and/or distributed processing
5. Repeat (maximum temperature)
6. Generate new solutions by adjusting the Heats (HS) and Updating the locations (x).
7. Verify and assign the feasibility of the solution by the Chemical Sensor (CS).
8. Select the best solution (S).
9. While t < T   // (Maximum Temperature)
10. While (n total of mosquitoes)
11. Report the best solutions.
```

2.1.2. Zooplankton Swarm Algorithm (ZSA)

Ruiz-Vanoye and Díaz-Parra (2012) [50] propose the Zooplankton Swarm Algorithm (ZSA). The ZSA is considered as a meta-heuristics algorithm, a bio-inspired algorithm, parallel or distributed algorithm based on the research on the social behavior of zooplankton swarm [50].

The term zooplankton swarm refers to densities of zooplankton of the order of 100-1000 animals*m^{-3} and swarms are abundant and large about 60 m^3 [73]. Swarming is just one example of complex behavioral adaptations evolved by resident plankton species to survive within the reef ecosystem [75]. The distribution of swarms implicates vision-mediated behavior and occurs over white sand near coral boulders [75]. In calm water each swarm actively maintains position, moving back toward orienting to the dark bulk of the coral boulder [75]. The dispersion of swarms at night further supports the role of vision in maintaining swarm integrity [75]. The zooplankton swarm (Acartia swarms) color the water grayish-blue [74], this reduce the visibility of predators.

Based on the above description of zooplankton swarm process, Ruiz-Vanoye and Díaz-Parra propose the Zooplankton Swarm Algorithm. The structure of the ZSA is as follows [50]:

Input: Number of zooplankton animals (*n*)
1. Initialize a zooplankton Population with uniformed distributed Position (*x*) and Orientation (*y*) of the zooplankton and the dark bulk of the coral boulder (*CB*).
2. Repeat (total of zooplankton). //by parallel and/or distributed processing
3. Generate new solutions by adjusting the coral boulder location (*CB*) and Updating the positions (*x*) and the Orientation (*y*).
4. Verify and assign the feasibility of the solution by the Color of the Water (*CW*).
5. Select the best solution (*S*).
6. While (*n* total of zooplankton)
7. Report the best solutions.

2.1.3. Bumblebees Swarms Algorithm (BSA)

Ruiz-Vanoye and Díaz-Parra (2012) [69] propose the Bumblebees Swarms Algorithm (BSA). The BSA is considered as a meta-heuristics algorithm, or a bio-inspired algorithm based on the research on the social behavior of Bumblebees Swarm [69].

The bumblebees use a combination of colour and spatial relationships in learning which flowers to forage from. Bumblebees are also capable of buzz pollination. Once a bumblebee has visited a flower, it leaves a scent mark on the flower (deters visitation of the flower by other bumblebees until the scent degrades). The scent mark is a general chemical bouquet that bumblebees leave behind in different locations (e.g. nest, neutral, and food sites) [76] and they learn to use this bouquet to identify both rewarding and unrewarding flowers [77]. The mature bumblebee nests will hold fewer than 50 individuals.

Based on the above description of Bumblebees Swarm process, Ruiz-Vanoye and Díaz-Parra propose the Bumblebees Swarm Algorithm. The structure of the BSA is as follows [69]:

Input: Number of Bumblebees animals (n)
1. Initialize a bumblebees Population with x_{ij} random solutions (food source positions).
2. Repeat (total of bumblebees). //by parallel and/or distributed processing
a) Apply the scent mark on the selection of x_{ij} flowers.
b) Produce randomly new initial food source positions x_{ij} in the neighborhood of the bumblebees from x_{ij}.
c) Verify and assign the feasibility of the solution by the Color of the flowers (*CF*).
d) Select the best solution (*S*).
e) Memorize the best food source position achieved so far.
3. While (n total of bumblebees)
4. Report the best solutions.

2.2. School Algorithms

The school algorithms were developed by analogy with aspects of the fish schools. In this section we show the algorithms: Particle Swarm Optimization algorithm (PSO) [13].

2.2.1. Particle Swarm Optimization algorithm (PSO)

Kennedy and Eberhart (1995) [13] propose the Particle Swarm Optimization algorithm (PSO). The PSO is inspired by the research on the social behavior of fish schools [13].

Fish adjust their physical movement to avoid predators, seek food and mates, optimize environmental parameters such as temperature. The schooling fish is a synchronous swimming of fish at the same speed and in the same direction, usually of the same species and the same age/size [3].

Based on the above description of fish schools process, Kennedy and Eberhart propose the Particle Swarm Optimization algorithm. PSO is based on five basic principles [13]: First is the proximity principle: the population should be able to carry out simple space and time computations, Second is the quality principle: the population should be able to respond to quality factors in the environment, Third is the principle of diverse response: the population should not commit its activities along excessively narrow channels, Fourth is the principle of stability: the population should not change its mode of behavior every time the environment changes, Fifth is the principle of adaptability: the population must be able to change behavior mode when it's worth the computational price. The structure of the PSO algorithm is as follow [13]:

Input: Number-of-particles, number-of-generations.

1. Initialize a particles (x_{id}) population with random position (pb_{id}) and speed (v_{id}).
2. Repeat (number-of-generations).
3. Repeat (number-of-particles).

a) To select the best position of the particle (pb_{id}) until the moment.// If $x_i > pb_i$ then $pb_{id} = x_{id}$.
b) To select the index (g) of the best individual in the neighborhood. // If $pb_j > pb_g$ then $g = j$.
c) To calculate the velocity (v_{id}) of the particle and the particle (x_{id}).
// $v_{id} = v_{id} + c_1 * \text{rand}_1 (pb_{id} – x_{id}) + c_2 * \text{rand}_2 * (p_{lbd} – x_{id})$; $x_{id} = x_{id} + v_{id}$
c_1, c_2: Positive constant. rand_1, rand_2: random numbers between [0,1]. *lb*: represent the index of the best particle of the neighborhood (*lbest*).

4. While number-of-particles not met.
5. While number-of-generations not met.
6. Report the best solution.

The PSO could be considered as a flock algorithm too.

2.3. Flock Algorithms

The flock algorithms were developed by analogy with aspects of the bird flocks. In this section we show the algorithm: Flock Algorithm [72].

2.3.1. Flock Algorithm

Craig Reynolds (1987) [72] proposes the Flock Algorithm. The Flock Algorithm is inspired by the research on the social behavior of bird flocks.

Birds adjust their physical movement to avoid predators, seek food and mates, and optimize environmental parameters such as temperature. The Bird flocking is the coordinated behavior of large groups of birds when flying at the same speed and in the same direction [72].

Based on the above description of bird school process, Reynolds proposes the flock algorithm [72]. The global behaviors of a flock of birds can be achieved in a virtual environment by having each bird agent or boid adhere to three rules as it flies [72]: A) Collision Avoidance: Boids steer from any nearby boid that is within some threshold distance, B) Velocity Matching: Boids modify their velocities to match the average velocity of their k-nearest flockmate, C) Flock Centering: Boids steer toward the centroid of their k-nearest flockmates. If repeatedly applying these flocking rules to each boid in the flock, a realistic flocking behavior of the swarm can be achieved. The structure of the generalized flocking algorithm is as follows [72]:

```
Create N boid agents and initialize with random position and velocity
For each boid:
    vAvoid = collision avoidance force
    vMatching = velocity matching force
    vCentering = flock centering force
    boid.velocity += (c1 * vAvoid) + (c2 * vMatching) + (c3 * vCentering)
    boid.position += boid.velocity
done            //c1,c2,c3 are constants  with relative influence of the velocity (to some maximum)
```

2.4. Herd and Pack Algorithms

The herd and pack Algorithms were developed by analogy with aspects of the mammal herds and packs. In this section we show the algorithms: bat algorithm [14], wolf pack search algorithm [15], Rats herds algorithm (RATHA) [17], Dolphins Herds Algorithm (DHA) [31], and feral-dogs herd algorithm (FDHA) [38].

2.4.1. Bat algorithm

Xin-She Yang (2010) [14] propose the Bat Algorithm (BA), BA is inspired by the research on the social behavior of bats. The BA is based on the echolocation behaviour of bats. Microbats use a type of sonar (echolocation) to detect prey, avoid obstacles, and locate their roosting crevices in the dark. These bats emit a very loud sound pulse and listen for the echo that bounces back from the surrounding objects. Their pulses vary in properties and can be correlated with their hunting strategies, depending on the species [14]. Based on the above description of bat process, Xin-She Yang proposes the Bat algorithm. The structure of the pseudo code of the Bat Algorithm is as follows [14]:

Objective function $f(x)$, $x = (x_1, \ldots, x_d)^T$
Initialize the bat population x_i ($i = 1, 2, \ldots, n$) and v_i
Define pulse frequency f_i at x_i
Initialize pulse rates r_i and the loudness A_i
While (t < Max Number of iterations)
Generate new solutions by adjusting frequency
And updating velocities and locations/solutions:

$$fi = f_{\min} + \left(f_{\max} - f_{\min} \right) \beta,$$

$$v_i^t = v_i^{t-1} + \left(x_i^t - x_* \right) f_i,$$

$$x_i^t = x_i^{t-1} + v_i^t$$

```
        If (rand > r_i)
        Select a solution among the best solutions
        Generate a local solution around the selected best solution
        End if
        Generate a new solution by flying randomly
        If (rand < A_i and f(x_i) < f(x_*))
        Accept the new solutions
        Increase r_i and reduce A_i
        End if
Rank the bats and find the current best x_*
End while
Postprocess results and visualization
```

Bats fly randomly with velocity v_i at position x_i with a fixed frequency f_{min}, varying wavelength λ and loudness A_0 to search the prey, they can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r \in [0,1]$, depending on the proximity of their target. Although the loudness can vary from a large positive A_0 to a minimum constant value A_{min}. For simplicity, $f \in [0, f_{max}]$, the new solutions x_i^t and velocities v_i^t at time step t; and $\beta \in [0,1]$ is a random vector drawn from a uniform distribution, x_* is the current global best location (solution) among all the n bats [14].

2.4.2. Wolf Pack Search algorithm (WPS)

Chenguang Yang et al. (2007) [15] propose the Wolf Pack Search Algorithm (WPS). The WPS Algorithm is inspired by the research on the social behavior of wolf pack. Wolf Pack Search algorithm simulates the hunting process of a pack of wolves. The arrest activity of a wolf pack can be described as the following process [15]: First, the wolves walk around. When the odor is left by the quarry, the wolves begin searching the smell in the direction of the thickest odor. Also the coat and egesta the quarry left along the road also help the wolves to track the quarry. The thicker the odor is becoming, the nearer the wolves from the quarry. The wolves will separate into several sub-groups. Each sub-group will approach the quarry in different routes, and towards the directions of the thickest smell. If there is an emergency, wolves will call together the other wolf group, and they will attack the quarry. Finally, one wolf will bite into the throat of the quarry till it falls down. And then the wolves will share in the food.

Based on the above description of wolf pack process, Chenguang Yang et al. propose the Wolf Pack Search algorithm. The structure of the WPS Algorithm is as follows [15]:

1) Initialize Step;
2) Initialize randomly a pack of wolves;
3) Compare and decide the best wolf *GBest* and its fitness *GBFit*;
4) Circulate and update the formula below, until the states of all the wolves are the same or the iteration time reaches the limit;

$$wolf_{new} = wolf + step * (GBest - wolf) / \left| Gbest - wolf \right|$$

5) If the fitness of $wolf_{new}$ is optimizer than *GBFit*, replace *GBest* and *GBFit* with $wolf_{new}$ and its fitness respectively.

2.4.3. Rats herds Algorithm (RATHA)

Ruiz-Vanoye and Díaz-Parra (2012) [17] propose the Rats Herd Algorithm (RATHA). The RATHA is considered as a meta-heuristics algorithm, or a bio-inspired algorithm based on the research on the social behavior of Rats Herds [17].

Rats have the ability to learn and may exhibit general intelligence by simple avoidance conditioning. Avoidance conditioning is the behavioral pattern of a subject, when it becomes aware of an impending aversive situation that is to take place. The subject reacts by adopting an avoidance technique, using which it totally avoids the said aversive situation and prevents it from affecting its own functioning. In simple words, when someone becomes aware of a possible unfavorable event that will take place in the near or not so near future, that person takes steps which facilitate the overall avoidance of that particular unfavorable event. By doing this, the person also ensures that he or she does not have to put up with the situation, and neither will the occurrence of the event affect his or her activities in any way [78].

Based on the above description of rats herd process, Ruiz-Vanoye and Díaz-Parra propose the Rats Herd Algorithm. The structure of the RATHA is as follows [17]:

Input: Number of Rats (*n*)
1. Initialize a Rats Population with x_{ij} random solutions (food source positions).
2. Repeat (total of rats). //by parallel and/or distributed processing
3. Generating the initial locations (*x*) of the rats (*n*).
4. Generate new solutions by using the avoidance conditioning (as tabu search) and Updating the locations (*x*).
5. Rank the rats and find the current best Solution.
6. Select the best solution (*S*).
7. Memorize the best food source position achieved so far.
8. While (*n* total of rats)
9. Report the best solutions.

2.4.4. Dolphins Herds Algorithm (DHA)

Ruiz-Vanoye and Díaz-Parra (2012) [31] propose the Dolphins Herds Algorithm (DHA). The DHA is considered as a meta-heuristics algorithm, or a bio-inspired algorithm based on the research on the social behavior of Dolphins herds [31].

Dolphins live in pods of a dozen to more than 1000 dolphins in places with a high abundance of food. Dolphins communicate using a variety of clicks, whistles-like sounds and other vocalizations and the interchange between pods is common [79]. Dolphin hunt for food by use of echolocation (they direct clicks into the water and listen to the strength of the rebounded echo from which they know the distance from the feed). Echolocation is a process where a dolphin emits a steady series of split-second clicks (pulses repeated 800 times/second of ultrasonic sound. The dolphins are able to determine the distance of a target on a continuing basis by measuring the time between emitting the clicks and their return. The dolphins can create an acoustic picture of its surroundings and can determine the size, shape, direction of movement and distance of objects in the water. This permits dolphins to hunt prey over a greater range than the limits of visibility allow.

Based on the above description of dolphins herd process, Ruiz-Vanoye and Díaz-Parra propose the Dolphins Herds Algorithm. The structure of the DHA is as follows [31]:

Input: number of dolphins (*n*)
1. Initialize a dolphins pods Population with direction of movement (*dm*) and Echolocation (*E*).
2. Repeat (*n*) //by parallel and/or distributed processing
3. Generating the initial locations (*x*) of the dolphins (*n*).
4. Generate new solutions by adjusting the direction of movement (*dm*), Echolocation (*E*) and Updating the locations (*x*).
5. Rank the dolphins and find the current best Solution.
6. While (*n* total of dolphins)
7. Report the best solutions.

2.4.5. Feral-Dogs Herd Algorithm (FDHA).

Ruiz-Vanoye and Díaz-Parra (2012) [38] propose the Feral-Dogs Herd Algorithm (FDHA). The FDHA is considered as a meta-heuristics algorithm, or a bio-inspired algorithm based on the research on the social behavior of Feral-Dogs herds [38].

Feral-dogs are wild-living domestic dogs. The feral-dogs have two kinds of movement: a searching movement (apparently associated with hunting), and an exploratory movement (probably for contact and communication with other dogs). Feral-Dogs packs have hierarchies for males and females, and the ranking order is mostly established through ritualized aggression, especially among males. Dogs of higher rank show this behavior from time to time, to confirm their status, while those of lower rank are more prone to show conflict-preventive behavior. Bigger packs (feral-dogs herds) are often splintered into sub-groups of flexible size. Territory size and individual areas change over time depending on the availability of prey, but are not connected to pack size. Feral-dogs only rarely move outside of their territories. The areas of individuals can overlap. When territories of neighboring packs overlap, the packs tend to avoid contact. How big the territory and home range of dogs are depends for the most part on the availability of prey. Home ranges are generally stable, but can change over time due to outside circumstances or changes in social organization. Individuals who start to detach themselves from the pack have bigger home ranges at first before they finally disperse. The feral-dogs do not travel more than 20 km per day (young males), but they can travel to 300 km^2 (range increases with the age) [5].

Based on the above description of Feral-Dogs herds process, Ruiz-Vanoye and Díaz-Parra propose the Feral-Dogs Herds Algorithm. The structure of the FDHA is as follows [38]:

Input: number of dogs (*n*)
1. Initialize a feral dogs Population with Searching Movement (*SM*) and Exploratory Movement (*EM*).
2. Repeat (*n*) //by parallel and/or distributed processing
3. Generating the initial locations (*x*) of the dogs (*n*).
4. Generate new solutions by adjusting the Searching Movement (*SM*), Exploratory Movement (*EM*) and Updating the locations (*x*).
5. Rank the feral dogs and find the current best Solution.
6. While (*n* total of dogs)
7. Report the best solutions.

3 Algorithms based on grouping of animals by social behavior for the Traveling Salesman Problem

The Traveling Salesman Problem (TSP) is a problem in discrete or combinatorial optimization and it is a prominent exemplification of a class of problems in computational complexity theory which are classified as NP-complete [16]. In the computer science, there are various algorithms to solve the Traveling Salesman Problem (Table 1), we mention only some of the most popular algorithms to solve the TSP.

Table 1. Related Works

Research	Algorithm	New Methods used to solve TSP
Dorigo [6]	ACO	The first ACO algorithm.
Ruiz-Vanoye and Díaz-Parra[17]	RATHA	Rats Herds Algorithm (RATHA) is inspired on the social grouping of Rats Herd to solution the Traveling Salesman Problem.

Guntsch [18]	ANT	Strategies for pheromone modification of ant algorithms in reaction to the insertion/deletion. One strategy acts globally without consideration of the position of the inserted/deleted city. The other strategies perform pheromone modification only in the neighborhood of the inserted/deleted city, where neighborhood is defined differently for the two strategies.
Pilat [19]	ACS-TSP	The addition of Genetic Algorithms to Ant Colony System (ACS-TSP) to improve the performance.
Yong [20]	DACO	Simulate real ants with more aspects: Updating of pheromones is more likely to be the real situation in the natural world. The Dynamic Ant Colony Optimization (DACO) Algorithm.
Kang [21]	PSO	An application of particle swarm optimization with the concept of swap operator and swap sequence, and redefined some operators on the basis of them.
White [22]	ACO	Ant Colony Optimization and local best tour with pheromone during an iteration to mimic the search focusing of the elitist ants.
Ruiz-Vanoye and Díaz-Parra [23]	MSA	Mosquito Swarms Algorithm (MSA) is inspired on the social grouping of Mosquito swarms to solution the Traveling Salesman Problem.
Panta [24]	BS	The Bee system (BS) is an artificial bee swarm.
Zhi [25]	PSO	A novel discrete particle swarm optimization (PSO) method with an uncertain searching strategy and local searching techniques to accelerate the convergent speed.
Wei [26]	PSO	A modified Particle Swarm Optimization to search in the Cartesian continuous space, and constructed a mapping from continuous space to discrete permutation space. Local search technique was introduced to enhance the ability to search, and chaotic operations were employed to prevent the particles from falling into local optima prematurely.
Zne-Jung [27]	ACO	Combines ant colony optimization (ACO) with genetic algorithm (GA).
Lope [28]	PSO	A hybrid model based on Particle Swarm Optimization and Fast Local Search, with concepts of Genetic Algorithms.
Wanhui [29]	SDTS	A Swarm Double-Tabu Search (SDTS) algorithm adopted the particle swarm and the double-tabu strategies.
Gao [30]	GPSO	General particle swarm optimization (GPSO) model is based on PSO mechanism, but the updating operator could integrate with other solutions such as GA, simulated annealing and taboo search easily.
Ruiz-Vanoye and Díaz-Parra [31]	DHA	Dolphins Herds Algorithm (DHA) is inspired on the social grouping of Dolphings to solution the Traveling Salesman Problem.
Gouvêa [32]	PSO	A competitive Particle Swarm Optimization algorithm with the velocity operator is based upon local search and path-relinking procedures.
Xiaoxian [33]	REA	The Route-Exchange Algorithm (REA) is inspired by the information interaction of individuals in swarm intelligence in which the individuals of the swarm search the state space independently and simultaneously. When one encounters another in the process, they would interact with each other, exchange the information of routes toured, and utilize the more

		valuable experiences to improve their own search efficiency. An elite strategy is designed to avoid vibrations.
Bo [34]	PSOMA	An effective Particle Swarm Optimization (PSO) based Memetic Algorithm (MA) called PSO-based MA (PSOMA), a novel encoding scheme is developed and a local search based on Simulated Annealing (SA) with adaptive meta-Lamarckian learning strategy is proposed and incorporated into PSO.
Bin [35]	IFD-PSO	An improved fuzzy discrete Particle Swarm Optimization method (IFD-PSO).
Hara [36]	AS	A new method using multiple colonies search for the solution while doing colony fission and extinction, and the improved ASelite (one of the extensions of the original ant system AS).
Shigeyoshi [37]	cAS	A variant of an ACO algorithm called the cunning Ant System (cAS).
Ruiz-Vanoye and Díaz-Parra [38]	FDHA	The feral-dogs algorithm (FDHA) is inspired by the hunting activity of feral-dogs herds to solution the Traveling Salesman Problem.
Mohammadi [39]	ACS	A simple and efficient approach based on distribution of ant parameters for optimizing ACS algorithm
Xiaojun [40]	ACO	An improved ant colony optimization algorithm based on the inver-over operator.
Wen-liang [41]	C3DPSO	A novel discrete PSO (C3DPSO) with modified update formulas and a new parameter c3 (called mutation factor, to help to keep the balance between exploitation and exploration).
Yang [15]	WPS-MBO	A new algorithm named Wolf Pack Search (WPS), which is abstracted from the behavior feature of the wolf pack. Utilize the WPS algorithm into the Marriage in Honey Bees Optimization algorithm, with this gives a new algorithm called Wolf Pack Search-Marriage in Honey Bees Optimization (WPS-MBO).
Rais [42]	IDACS	An improve dynamic to the fundamental of ant colony system (ACS) algorithm by pheromone updates which manipulating and empowering the searching experiences of individual ants.
Changsheng [43]	IDPSO	An Improved discrete particle swarm optimization (DPSO)-based algorithm with a novel depressor is proposed and a diversity measure to control the swarm is also introduced which can be used to switch between the attractor and depressor.
Yong-Qin [44]	GRPSAC	The use of particle swarm optimization and ant colony optimization (GRPSAC)
Gomez-Cabrero [45]	ACPS2	A combination of particle swarm optimization (PSO) and ant colony system (ACS) called ACPS2.
Yan [46]	QSE	A novel quantum swarm evolutionary algorithm (QSE) based on the quantum-inspired evolutionary algorithm (QEA), and an improved particle swarm optimization (PSO) is employed to update the quantum angles automatically.
Zhenglei [47]	CPSO	An algorithm based on particle optimization algorithm (PSO) and chaos optimization algorithm (COA).
Issmail [48]	ACS	An improvement by combining the Multiple Ant Colony System with a local search procedure.
Yiheng [49]	CPSO	A new approach based on the cooperative particle swarm optimization (CPSO) with introducing dynamic splitting schemes.

Ruiz-Vanoye and Díaz-Parra [50]	ZSA	Zooplankton swarms Algorithm (ZSA) is inspired on the social grouping of zooplankton to solution the Traveling Salesman Problem.
Zhaoquan [51]	MSACO	An improved ant colony optimization (MSACO), the improvement is mainly on a new transition rule which can lead artificial ants search in local, global and comprehensive directions.
Xueyan [52]	BCPA	Bee Collecting Pollen Algorithm (BCPA) is inspired by the behaviour of the honeybees' collecting pollen.
Vivek [53]	MAF-ACO	The MAF-ACO algorithm emulates the foraging behavior of ants and introduce an incremental learning component.
Liaoliao [54]	RSEDPSO	A reinforced self-escape discrete particle swarm optimization algorithm (RSEDPSO) with 5-relative nearest neighbor method.
Aybars [55]	ACO	A web-based simulation and analysis software (TSPAntSim) using ACO algorithms with local search heuristics.
Li [56]	BCO	A Bee Colony Optimization (BCO) algorithm with 2-opt local search.
Weitang [57]	APSO	A new variation on the traditional PSO algorithm called adaptive particle swarm optimization (APSO), APSO employing adaptive behavior to significantly improve the performance of the PSO: Every particle chooses its inertial factor according to the fitness of itself and the optimal particle in the presented algorithm.
Jiang [58]	IPSO	The improved particle swarm optimization (IPSO) algorithm with the tentative behavior of individuals and the mutation of velocity have been introduced according to the law of evolutionary process.
Zhilu [59]	PDACO	Population declining ant colony optimization (PDACO) algorithm can enlarge searching range through increasing the initial population of the ant colony, and the population declines in successive iterations.
Yuhong [60]	PSO-AS	A hybrid discrete PSO algorithm with ant search. Particle swarm search firstly, and worse chromosomes of the particle swarm is replaced by solutions obtained from ant colony search. By setting the initial pheromone trail based on the best chromosome of all particles, the accumulation process of pheromone trail is greatly shortened, and the searching speed of ants is quickened.
Bing [61]	PS-ACO	A hybrid PS-ACO algorithm: ACO algorithm modified by particle swarm optimization (PSO) algorithm. The pheromone updating rules of ACO are combined with the local and global search mechanisms of PSO.
Ai [62]	PSO-ACO	An improved particle swarm optimization-ant colony algorithm (PSO-ACO) with delete-crossover strategy.
Zhen [63]	CAS-TSP	The Chaotic Ant Swarm for TSP (CAS-TSP) introducing a mapping from continuous space to discrete space, reverse operator and crossover operator into the CAS.
Banharnsakun [64]	ABC-GSX	They extend the Artificial Bee Colony algorithm (ABC) with the hibridation with the Greedy Subtour Crossover to improve the precision, the new method is called Artificial Bee Colony algorithm with Greedy Subtour Crossover (ABC-GSX).
Zhong [65]	MDPSO	A special mixed discrete particle swarm optimization (MDPSO)

		with a new formula of the velocity, via presenting the crossover and mutation of the genetic algorithm (GA).
Serban [66]	CGS-TSP	Consultant-Guided Search (CGS) based on the direct exchange of information between individuals in a population. CGS is a swarm intelligence technique inspired by the way real people make decisions based on advice received from consultants.
I-Hong [67]	HRKPG	A hybrid model named HRKPG that combines the random-key search method and an individual enhancement scheme to thoroughly exploit the global search ability of particle swarm optimization. With a genetic algorithm expand the area of exploration of individuals in the solution space.
Hendtlass [68]	PSO	Adding a memory capacity to each particle in a PSO algorithm.
Ruiz-Vanoye and Díaz-Parra [69]	BSA	Bumblebees Swarms Algorithm (BSA) is inspired on the social grouping of Bumblebees to solution the Traveling Salesman Problem.
Mehmet [70]	DPSO	A discrete particle swarm optimization hybridized with a local search, variable neighbourhood descend algorithm, to further improve the solution quality.
Tan [71]	AC-PSO	The AC-PSO algorithm combines the traditional ant colony system (ACS) with particle swarm optimization (PSO) and uses one by one tour building strategy like ACS to determine that the target point can be chosen like PSO.

4 Conclusions

We show a survey of meta-heuristics algorithms based on grouping of animals by social behavior for the Traveling Salesman Problem, and propose a new classification of meta-heuristics algorithms (not based on swarm intelligence theory) based on grouping of animals: swarm algorithms, schools algorithms, flocks algorithms and herds algorithms.

For future works we propose to development the algorithms based on social grouping of mammal animals as: African wild dogs, Gray wolves, Black-backed jackals, ethiopian wolf, new guinea singing dog, buffalo, zebra, bison, sheep, desert bighorn, Elephants, pigs, wild horses, Rhinos, Wildebeest, llamas, Giraffes, Antelope species, Whales and others.

References

1 Okubo, A.: Dynamical aspects of animal grouping: Swarms, schools, flocks, and herds. Advances in Biophysics, Vol. 22 (1986) 1-94.

2 Omori, M.: Zooplankton fisheries of the world: A review, Marine Biology, Vol. 48, No. 3 (1978) 199-205.

3 Helfman, G., Collette, B. and Facey, D.: The Diversity of Fishes, Blackwell Publishing (1997).

4 Reynolds, C.W.: Flocks, herds, and schools: a distributed behavioral model, Computer Graphics (ACM SIGGRAPH '87 Conference Proceedings), Vol. 21, No. 4 (1987) 25-34.

5 Earls, M.: Herd: How to Change Mass Behaviour by Harnessing Our True Nature. John Wiley & Sons (2007).

6 Dorigo, M.: Optimization, Learning and Natural Algorithms, Ph.D. Thesis, Politecnico di Milano, Italy (1992).

7 Yang, X.S.: Firefly Algorithm (chapter 8), Nature-inspired Metaheuristic Algorithms, Luniver Press (2008).

8 Abbass, H.A.: MBO: Marriage in Honey Bees Optimization-a Haplometrosis polygynous Swarming Approach. Proceedings of the 2001 Congress on Evolutionary Computation, Vol.1 (2001) 207-214.

9 Karaboga, D.: An idea based on Honey Bee Swarm for Numerical Optimization, Technical Report-TR06, Erciyes University, Engineering Faculty, Computer Engineering Department (2005).

10 Pinto, P.C. and Runkler, T.A. and Sousa, J. M.: Wasp Swarm Algorithm for Dynamic MAX-SAT Problems, in Proceedings of the 8th international conference on Adaptive and Natural Computing Algorithms, Part I (2007).

11 Xueyan, L. and Yongquan, Z.: A Novel Global Convergence Algorithm: Bee Collecting Pollen Algorithm. Advanced Intelligent Computing Theories and Applications. With Aspects of Artificial Intelligence, Lecture Notes in Computer Science , Vol. 5227 (2008) 518-525.

12 Roth, M.: Termite: A Swarm Intelligent Routing Algorithm For Mobile Wireless Ad-Hoc Networks. Theses and Dissertations, Cornell University Graduate School (2005).

13 Kennedy, J. and Eberhart, R.C.: Particle Swarm Optimization, Proceedings of IEEE International Conference on Neural Networks, Piscataway, NJ. (1995) 1942-1948.

14 Xin-She Yang.: A New Metaheuristic Bat-Inspired Algorithm. Nature Inspired Cooperative Strategies for Optimization (NICSO 2010). Studies in Computational Intelligence Vol. 284 (2010) 65-74.

15 Chenguang Yang , Xuyan Tu and Jie Chen.: Algorithm of Marriage in Honey Bees Optimization Based on the Wolf Pack Search. International Conference on Intelligent Pervasive Computing – IPC2007 (2007) 462-467.

16 Cirasella, J., Johnson, D.S., McGeoch, L.A., and Zhang, W.: The Asymmetric Traveling Salesman Problem: Algorithms, Instance Generators, and Tests. Third International Workshop. ALENEX 2001, Lecture Notes in Computer Science. Vol. 2153 (2001) 32-59. Springer-Verlag.

17 Ruiz-Vanoye, J.A. and Díaz-Parra, O.: A Rats Herds Algorithm for the Traveling Salesman Problem. Unpublished manuscript.

18 Guntsch, M. and Middendorf, M.: Pheromone Modification Strategies for Ant Algorithms Applied to Dynamic TSP. Applications of Evolutionary Computing. Lecture Notes in Computer Science, Vol. 2037 (2001) 213-222.

19 Pilat, M.L. and White, T.: Using Genetic Algorithms to Optimize ACS-TSP. Ant Algorithms. Lecture Notes in Computer Science, Vol. 2463 (2002) 101-172.

20 Yong Li and Shihua Gong, Dynamic ant colony optimisation for TSP. The International Journal of Advanced Manufacturing Technology, Vol. 22, No. 7-8 (2003) 528-533.

21 Kang-Ping Wang; Lan Huang; Chun-Guang Zhou; Wei Pang;: Particle swarm optimization for traveling salesman problem. International Conference on Machine Learning and Cybernetics, Vol. 3 (2003) 1583-1585.

22 White, T., Kaegi, S. and Oda, T.: Revisiting Elitism in Ant Colony Optimization. Genetic and Evolutionary Computation - GECCO 2003. Lecture Notes in Computer Science, Vol. 2723 (2003) 122-133.

23 Ruiz-Vanoye, J.A. and Díaz-Parra, O.: A Mosquito Swarms Algorithm for the Traveling Salesman Problem. Unpublished manuscript.

24 Panta Lucic, Dusan Teodorovic: Computing with bees: attacking complex transportation engineering problems. International Journal on Artificial Intelligence Tools, Vol. 12, No. 3 (2003) 375-394.

25 Zhi, X.H., Xing, X.L., Wang, Q.X., Zhang, L.H., Yang, X.W., Zhou, C.G., Liang, Y.C.: A discrete PSO method for generalized TSP problem. International Conference on Machine Learning and Cybernetics, Vol. 4 (2004) 2378-2383.

26 Wei Pang, Kang-Ping Wang, Chun-Guang Zhou, Long-Jiang Dong, Ming Liu, Hong-Yan Zhang, Jian-Yu Wang.: Modified particle swarm optimization based on space transformation for solving

traveling salesman problem. International Conference on Machine Learning and Cybernetics, Vol. 4 (2004) 2342-2346.

27 Zne-Jung, L.: A hybrid algorithm applied to travelling salesman problem. International Conference on Networking, Sensing and Control, Vol. 1 (2004) 237-242.

28 Lope, H.S., Coelho, L.S.: Particle Swarn Optimization with Fast Local Search for the Blind Traveling Salesman Problem. Fifth International Conference on Hybrid Intelligent Systems - HIS'05. (2005) 245-250.

29 Wanhui Wen and Guangyuan Liu.: Swarm Double-Tabu Search. Advances in Natural Computation. Lecture Notes in Computer Science, Vol. 3612 (2005) 1231-1235.

30 Gao Hai-Bing, Zhou Chi, Gao Liang.: General particle swarm optimization model. Chinese Journal of Computers, Vol. 28, No. 12 (2005) 1980-1987.

31 Ruiz-Vanoye, J.A. and Díaz-Parra, O.: A Dolphins Herds Algorithm for the Traveling Salesman Problem. Unpublished manuscript.

32 Gouvêa Goldbarg, E.F., de Souza, G.R. and Goldbarg, M.C.: Particle Swarm for the Traveling Salesman Problem. Evolutionary Computation in Combinatorial Optimization, Lecture Notes in Computer Science, Vol. 3906 (2006) 99-110.

33 Xiaoxian He, Yunlong Zhu, Kunyuan Hu and Ben Niu.: Route-Exchange Algorithm for Combinatorial Optimization Based on Swarm Intelligence. Computational Intelligence and Bioinformatics. Lecture Notes in Computer Science, Vol. 4115 (2006).

34 Bo Liu, Ling Wang, Yi-hui Jin and De-xian Huang.: An Effective PSO-Based Memetic Algorithm for TSP. Intelligent Computing in Signal Processing and Pattern Recognition. Lecture Notes in Control and Information Sciences, Vol. 345 (2006) 1151-1156.

35 Bin Shen, Min Yao and Wensheng Yi.: Heuristic Information Based Improved Fuzzy Discrete PSO Method for Solving TSP. PRICAI 2006: Trends in Artificial Intelligence. Lecture Notes in Computer Science, Vol. 4099 (2006) 859-863.

36 Hara, A., Ichimura, T., Fujita, N. and Takahama, T.: Effective Diversification of Ant-Based Search Using Colony Fission and Extinction. IEEE Congress on Evolutionary Computation-CEC 2006 (2006) 1028-1035.

37 Shigeyoshi Tsutsui.: cAS: Ant Colony Optimization with Cunning Ants. Parallel Problem Solving from Nature - PPSN IX. Lecture Notes in Computer Science, Vol. 4193 (2006) 162-171.

38 Ruiz-Vanoye, J.A. and Díaz-Parra, O.: A Feral-dogs Herd Algorithm for the Traveling Salesman Problem. Unpublished manuscript.

39 Mohammadi Fardin Abdali; Fathi, Abdol Hossein, Manzurit, Mohammad Taghi.: Multi-Direction Searching Ant Colony Optimization for Traveling Salesman Problems. International Symposium on Communications and Information Technologies - ISCIT '06 (2006) 839-842.

40 Xiaojun Bi, Guangxin Luo: The Improvement of Ant Colony Algorithm Based on the Inver-over Operator. International Conference on Mechatronics and Automation - ICMA2007 (2007) 2383-2387.

41 Wen-liang Zhong, Jun Zhang, Wei-neng Chen: A novel discrete particle swarm optimization to solve traveling salesman problem. IEEE Congress on Evolutionary Computation - CEC 2007 (2007) 3283-3287.

42 Rais, H.M., Othman, Z.A. and Hamdan, A.R.: Improved Dynamic Ant Colony System (DACS) on symmetric Traveling Salesman Problem (TSP). International Conference on Intelligent and Advanced Systems - ICIAS2007 (2007) 43-48.

43 Changsheng Zhang, Jigui Sun, Yan Wang, Qingyun Yang: An Improved Discrete Particle Swarm Optimization Algorithm for TSP. International Conferences on Web Intelligence and Intelligent Agent Technology Workshops. (2007) 35-38.

44 Yong-Qin Tao, Du-Wu Cui, Xiang-Lin Miao and Hao Chen: An Improved Swarm Intelligence Algorithm for Solving TSP Problem. Advanced Intelligent Computing Theories and Applications. With Aspects of Artificial Intelligence. Lecture Notes in Computer Science, Vol. 4682 (2007) 813-822.

45 Gomez-Cabrero, D., Armero, C. and Nalin Ranasinghe, D.: The Travelling Salesman's Problem: A self-adapting PSO-ACS algorithm. International Conference on Industrial and Information Systems -

ICIIS2007 (2007) 479-484.

46 Yan Wang, Xiao-Yue Feng, Yan-Xin Huang, Dong-Bing Pu, Wen-Gang Zhou, Yan-Chun Liang and Chun-Guang Zhou.: A novel quantum swarm evolutionary algorithm and its applications. Neurocomputing, Vol. 70, No. 4-6 (2007) 633-640.

47 Zhenglei Yuan, Liliang Yang, Yaohua Wu, Li Liao, Guoqiang Li: Chaotic Particle Swarm Optimization Algorithm for Traveling Salesman Problem. International Conference on Automation and Logistics (2007) 1121-1124.

48 Issmail Ellabib, Paul Calamai and Otman Basir: Exchange strategies for multiple Ant Colony System. Information Sciences, Vol. 177, No. 5 (2007) 1248-1264.

49 Yiheng Xu, Jinglu Hu, Hirasawa K., Xiaohong Pang: A new cooperative approach to discrete particle swarm optimization. SICE-2007 (2007) 1311-1318.

50 Ruiz-Vanoye, J.A. and Díaz-Parra, O.: A zooplankton Swarms Algorithm for the Traveling Salesman Problem. Unpublished manuscript.

51 Zhaoquan Cai: Multi-direction Searching Ant Colony Optimization for Traveling Salesman Problems. International Conference on Computational Intelligence and Security (2008) 220-223.

52 Xueyan Lu and Yongquan Zhou: A Novel Global Convergence Algorithm: Bee Collecting Pollen Algorithm. Advanced Intelligent Computing Theories and Applications. With Aspects of Artificial Intelligence. Lecture Notes in Computer Science, Vol. 5227 (2008) 518-525.

53 Vivek S. Borkar and Dibyajyoti Das: A novel ACO algorithm for optimization via reinforcement and initial bias. Swarm Intelligence, Vol. 3, No. 1 (2008) 3-34.

54 Liaoliao Li, Zhongkui Zhu, Wenfeng Wang: A Reinforced Self-Escape Discrete Particle Swarm Optimization for TSP. Second International Conference on Genetic and Evolutionary Computing - WGEC '08 (2008) 467-470.

55 Aybars Uğur and Doğan Aydin: An interactive simulation and analysis software for solving TSP using Ant Colony Optimization algorithms. Advances in Engineering Software, Vol. 40, No. 5 (2009) 341-349.

56 Li-Pei Wong, Low, M.Y.H., Chin Soon Chong: An efficient Bee Colony Optimization algorithm for Traveling Salesman Problem using frequency-based pruning. 7th International Conference on Industrial Informatics - INDIN 2009 (2009) 775-782.

57 Weitang Song, Shumei Zhang: A novel adaptive particle swarm optimization to solve traveling salesman problem. International Colloquium on Computing, Communication, Control, and Management - CCCM 2009 (2009) 459-462.

58 Jiang-wei Zhang, Wei Xiong: An Improved Particle Swarm Optimization Algorithm and Its Application for Solving Traveling Salesman Problem. World Congress on Computer Science and Information Engineering (2009) 612-616.

59 Zhilu Wu, Nan Zhao, Guanghui Ren, and Taifan Quan: Population declining ant colony optimization algorithm and its applications. Expert Systems with Applications, Vol. 36, No. 3, Part 2 (2009) 6276-6281.

60 Yuhong Duan, Sun Ying: A Particle Swarm Optimization Algorithm with Ant Search for Solving Traveling Salesman Problem. International Conference on Computational Intelligence and Security - CIS '09. (2009) 137-141.

61 Bing Shuang, Jiapin Chen and Zhenbo Li: Study on hybrid PS-ACO algorithm. Applied Intelligence, Vol. 34, No. 1 (2011) 64-73.

62 Ai Jia Ouyang, Yong Quan Zhou: An Improved PSO-ACO Algorithm for Solving Large-Scale TSP. Journal Advanced Materials Research, Vol. 143-144 (2010) 1154-1158.

63 Zhen Wei, Fangzhen Ge, Yang Lu, Lixiang Li and Yixian Yang: Chaotic ant swarm for the traveling salesman problem. Nonlinear dynamics, Vol. 65, No. 3 (2011) 271-281.

64 Banharnsakun, A., Achalakul, T. and Sirinaovakul, B.: ABC-GSX: A hybrid method for solving the Traveling Salesman Problem. Second World Congress on Nature and Biologically Inspired Computing – NaBIC (2010) 7-12.

65 Zhong Liu, Lei Huang: A mixed discrete particle swarm optimization for TSP. 3rd International Conference on Advanced Computer Theory and Engineering – ICACTE (2010) V2-208-V2-211.

66 Serban Iordache: Consultant-guided search: a new metaheuristic for combinatorial optimization problems. 12th annual conference on Genetic and evolutionary computation - GECCO '10 (2010).

67 I-Hong Kuo, Shi-Jinn Horng, Tzong-Wann Kao,Tsung-Lieh Lin, Cheng-Ling Lee, Yuan-Hsin Chen, YI Pan, Takao Terano: A hybrid swarm intelligence algorithm for the travelling salesman problem. Expert systems, Vol. 27, No. 3 (2010) 166-179.

68 Hendtlass, T.: Preserving Diversity in Particle Swarm Optimisation. Developments in Applied Artificial Intelligence. Lecture Notes in Computer Science, Vol. 2718 (2003) 155-199.

69 Ruiz-Vanoye, J.A. and Díaz-Parra, O.: A Bumblebees Swarms Algorithm for the Traveling Salesman Problem. Unpublished manuscript.

70 Mehmet Fatih Tasgetiren, Suganthan P.N., Quan-Qe Pan: A discrete particle swarm optimization algorithm for the generalized traveling salesman problem. 9th annual conference on Genetic and evolutionary computation -GECCO '07 (2007).

71 Tan Hao, Li Yu-Feng, Wang Jin-Yang, He Yi-Zheng, Shen Chun-Lin: AC-PSO Algorithm For UAV Mission Planning. Transactions of Nanjing University of Aeronautics and Astronautics. Vol. 22, No. 3 (2005) 264-270.

72 Reynolds, C.W.: Flocks, herds, and schools: A distributed behavioral model. In Conference Proceedings on Computer Graphics - ACM SIGGRAPH ’87, Vol. 21, No. 4 (1987) 25-34.

73 Tranter, D.J. and George, J.: Zooplankton abundace at kavaratti and Kalpeni Atolls in the Laccadives. In 1969 proceedings symposium of Corals and coral reefs (1972) 239-256, Mar. Biol. Assoc. India.

74 Emery, A.R.: Preliminary observations on coral reef plankton. Limnology and Oceanography Vol. 13 (1968) 293-303.

75 Hamner, W.M. and Carleton, J.H.: Copepod swarms:Attributes and role in coral reef ecosystems. Limnology and Oceanography, Vol. 24, No. 1 (January 1979) 1-14.

76 Nehal Saleh and Lars Chittka.: The importance of experience in the interpretation of conspecific chemical signals. Behavioral Ecology and Sociobiology, Vol. 61, No. 2 (2006) 215-220. doi:10.1007/s00265-006-0252-7.

77 Zimma, B.O., Ayasse, M., Tengo, J., Ibarra, F., Schulz, C. and Francke, W.: Do social parasitic bumblebees use chemical weapons? (Hymenoptera, Apidae). Journal of Comparative Physiology A - Neuroethology Sensory Neural and Behavioral Physiology Vol. 189, No. 10 (2003) 769-775. doi:10.1007/s00359-003-0451-x.

78 Thompson, R., Crinella, F. and Yu, J., Brain Mechanisms in Problem Solving and Intelligence. A Lesion Survey of the Rat Brain, Plenum, New York, 1990.

79 Whitlow W. L. Au: The Sonar of Dolphins. Springer, 1993.