A Survey On Bee Colony Algorithms

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Abstract— **This paper presents a survey of current research activities inspired by bee life. This work is intended to provide a broad and comprehensive view of the various principles and applications of these bio-inspired systems. We propose to classify them into two major models. The first one is based on the foraging behavior in the bee quotidian life and the second is inspired by the marriage principle. Different original studies are described and classified along with their applications, comparisons against other approaches and results. We then summarize a review of their derived algorithms and research efforts.**

Keywords- metaheurstic, optimization, bee inspiration, foraging behavior, marriage behavior.

I. INTRODUCTION

In the last two decades, the computational researchers have been increasingly interested to the natural sciences, and especially biology, as source of modeling paradigms. Many research areas are massively influenced by the behavior of various biological entities and phenomena. It gave birth to most of population-based Metaheuristics such as Ant Colony Optimization (ACO), Evolutionary Algorithms (EAs), Particle Swarm Optimization (PSO), Bee Colony (BC) etc.

They modeled the insect social behaviors such as ant, fish, bird, bee etc. They could be regarded as belonging to the category of intelligent optimization tools used to solve a computational and complex problem in different areas. Honey bees are one of the most well studied social insects [32]. In the early years many studies based on the different bee behaviors have been developed to solve complex combinatorial and numerical optimization problems.

In this paper, we present a survey on bee colony algorithms and we suggest to classify them into two basic models. This classification is according to the bee behaviors criteria. Thereby, the first model represents the algorithms which are based on the foraging behavior in the bee colony. We can enumerate two sub-models in this category. The former is based on the food source searching behavior while the latter is inspired by the nest site searching behavior. In the other hand, the marriage behavior represents the second model of the algorithms inspired by bee life. We can mention here that there are a few studies based on the queen bee evolution but we considered them as an improvement of the genetic algorithms. They rely on the same principle.

For both models, we present the original studies as principle, tests, comparisons against other methods and the obtained results in its application. After, we quote other studies which are based on these original studies to solve other problems with the same idea. Then, we emphasize on their novelty, characteristics and results.

The rest of this paper is organized as follows. In section 2, we present briefly bee life in nature in an attempt to well understand the artificial inspiration. In section 3, we expose the two models of bee colony-based studies. We illustrate their principle, application, the type of solved problem: combinatorial, functional optimization or for theory objective. Finally, conclusions are drawn.

II. BEE IN NATURE

A. *Bee colony componants*

The bee (Apis mellifera) is a social and domestic insect native to Europe and Africa. There are between 60,000 and 80,000 living elements in the hive. The bees feed on nectar as a source of energy in their lives and use pollen as a source of protein in the rearing larvae. Generally, the bee colony contains a single breeding female known as the Queen, a few thousands of males called Drones, a several thousands of sterile females called Workers, and many young bee larvae called Broods.

B. *Bee communication*

The bees share a communication language of extreme precision, based on the dances. These dances are performed by the explorer bee “Scout”. After finding food and returning to the hive, this type of worker “scout” informs others about the distance, direction, quantity and quality of food founded. With their visual, tactile and olfactory perception, the other bees perceive the transmitted information.

There are two types of dances; the round dance when food is very close. This dance indicates only the direction. The second type is the waggle dance. It is a dance which forms an eight scheme. It indicates distance and direction of the food source. The distance between the food source and the hive is transmitted depending on the speed of the dance. If dance is faster then, the food distance is smaller. The direction (angle between the food source and the sun relative to the hive) is shown by the inclination of the dance from the vertical with accuracy of ± 3°.

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The nature of the food is indicated by the odor of the bee when it is rubbed. The amount of food depends on the wriggling of the bee. The more is the wriggling, the more is the quantity.

C. *Bee behavior*

1) *Foraging behavior:*

a) Nest site searching: the most prosperous colonies reproduce by swarming. In early spring, some queen cells are produced to generate new queen. Before its birth, the old queen leaves the colony with the half of the colony componants to form a new colony. They search new nest site. The scouts seek about twelve nest sites. They indicate the various locations of new nests by waggle dances. The dance quality is related to the nest site quality. Thus, and over time, selected sites decrease until a single site will be found.

b) Food source searching: first, some bees "scouts" navigate and explore the region in aim to find a food source. In the positive case, they come at the hive in place called "dance floor" to transmit and share this discovery with the others through dance language (round or waggle dance relating to the discovery distance). Some bees are recruited and then, become foragers. Their number is proportional to the food quantity information communicated by the scouts. We call this step exploration phasis which is followed by the exploitation step. Bee collects food and calculates their quantity to make a new decision. Either it continues collecting by the memorization of this best location, or it leaves the source and returns to hive as simple bee.

2) Marriage behavior: the reproduction phenomenon in the bee colony is guaranteed by the queen. After its birth, the young queen will engage in nuptial flights. It will join a gathering point with some drones. The queen will mate with several males in full flight, until her spermatheca is full. After three days, it lays eggs. The unfertilized egg will give rise to a drone, while, the fertilized egg gives rise to worker or queen depending on food quality given to larvae.

III. BEE COLONY ALGORITHMS MODELS

We propose in this section a classification of different algorithms based on bee life. It is the result of a synthesis study effectuated by the authors after a large bibliographic research on the various computational systems inspired by the different bee behaviors. We have observed that the various computational studies in the literature can be divided into two major models. The first model represents the algorithms that are inspired by the foraging behavior. In its turn, it can be divided into two sub-models; the first one is based on the food source searching and the second represents studies which turn round the new nest site searching. The second model groups different algorithms which are inspired by marriage behavior. There are other algorithms that are inspired by the evolution of the queen that can be considered as genetic algorithms improvement.

A. *Foraging behavior model*

The most research activities inspired by bee swarm belong to this model. There are more than 60% of them. We suggest two sub-models relevant to the foraging behavior types; either food source searching as first sub-model, in which there are more than 90% of studies in this category and less than 10% concerning the nest site searching sub-model; it is the second one. We explain below these two sub-models.

1) *Food source searching sub-model:*

In the literature, many research activities have been inspired by the bee food source searching. All of these algorithms seem to be similar but they have significant differentiations in terms of principles, projections, objectives and applications.

Generally, they solve optimization problems, whether combinatorial or numerical. In the following, we present for this sub-model the original algorithms. An explanation of their principle, classification, application and advantages is illustrated too. We clarify and explain these works in chronological order.

Lucic and Teodorovic in [22] developed a new system called Bees system (BS) based on food source searching as foraging behavior of bee colonies. It was tested through many instances of the traveling salesman problem (TSP). The main idea is to locate the hive in one of the nodes on the graph. When foraging, the bees are trying to collect as much nectar as possible. They consider that the shorter the link, the higher the nectar quantity collected along that link when flying. After that, the hive changes randomly its position. The bees will start to collect the nectar from the new location. Each iteration is composed of a certain number of stages. During one stage the bee will visit s nodes, create a partial traveling salesman tour and after that return to the hive. Now, the bee will decide whether to abandon the food source and become again uncommitted follower, to continue to forage at the food source without recruiting the nest mates, or to dance and thus recruit the others before returning to the food source. Bee system was tested on ten benchmark problems. In all the cases, one of the tour improving algorithms was employed; there are 2-opt, 3-opt and 3-opt short version. The results showed that bee system was able to obtain the objective function values that are very close to the optimal values of the objective function. Moreover, in all instances with less than one hundred nodes, the Bee system produced the optimal solution in low time.

In what follows, there are other researches based on bee system [22] applied for other applications. We mention [21] where Lucic projected the algorithm to the stochastic vehicle routing problem VRP. Author dealt with two steps. In the first one, bee system solves VRP as TSP and creates a "Giant route", while in the second step, it is possible to decide by walking along the created giant route, when to finish one vehicle's route and when to start with the next vehicle's route. These decisions could be made easily since knowledge about demand at every node which described by known probability density function and vehicle capacity is assumed. Similarly, Lucic and Teodorovic in [23] developed a model which is based on the combination of the new computational paradigm: the Bee System and Fuzzy Logic applied to the VRP. It makes "real-time" decisions regarding route shapes for situations in which locations of the depot, nodes to be served and vehicle capacity are known, and the demand at the nodes is only approximated. The results are found to be very close to the best solution assuming that the future node demand pattern is known. The system applications appear to be very promising. Teodorovic and Dell'Orco proposed Bee Colony Optimization (BCO) [36] which is an improvement and generalization of the Bee System. It was capable to solve combinatorial problems characterized by uncertainty. Authors applied Fuzzy Bee system that represents one of the possible BCO to the ride-sharing problem. They obtained very promising results. BCO gave birth to BCO-RWA [24] in which Markovic et al. tailored it for the Routing and Wavelength Assignment (RWA) problem in all-optical networks without wavelength conversion in intermediate nodes. The proposed algorithm has been applied for static case in which lightpath requests are known in advance. Authors proved that BCO–RWA is able to produce optimal or near-optimal solutions in a reasonable amount of computer time.

Bianco presented mapping paradigm which takes advantage of bee searching and traveling as an original idea allowing precise large scale navigation [7]. This latter is performed through the use of two distinct sets of landmarks: global landmarks guide roughly the agent to a place, with local landmarks the agent performs very precise motion to the final destination. The paradigm is equivalent to a map composed of two distinct levels: the agent like bee, navigates from place to place following the global potential function. When the agent is close to the place of interest then it switches to a finer map about the specific place. Tests have demonstrated that such capabilities are sufficient to get rather good precision showing that biology offers simple but powerful models.

In [25], Nakrani and Tovey proposed a Honey Bee Algorithm founded on self-organization of honey bee colonies to allocate foragers among food source. It was applied to the dynamic allocation of internet services. Because of the many similarities between server and nectar collection, they modeled servers as foraging bees and HTTP request queues as flower patches. This algorithm was been compared against an omniscient algorithm that computes an optimal allocation policy, a greedy algorithm that uses past history to compute allocation policy and an optimal-static algorithm that computes omnisciently the best among all possible static allocation policy. The results supported the effectiveness of the algorithm, particularity in the highly dynamic and unpredictable Internet environment. The experimental results show too, that this algorithm performed better than static or greedy algorithms. In contrast, it was outperformed by greedy for some low variability access patterns. Based on this algorithm, Chong et al. in [12] had proposed an application to the job shop scheduling. Experimental results comparing this algorithm with ant colony and tabu search were found that the performance of the algorithm is comparable to ant colony algorithms, but gaps behind the efficient tabu search heuristics.

BeeHive Algorithm [38] is another bee inspired algorithm proposed by Wedde et al. and applied to the routing in the wired computer networks. It has been inspired by the communicative and evaluative methods and procedures of honey bees. It is fault tolerant, scalable and relies completely on local or regional information. The algorithm does not need any global information such as the structure of the topology and cost of links among routers, rather it works with the local information that a short distance bee agent collects in a foraging zone. It works without the need of global clock synchronization which not only simplifies its installation on real routers but also enhances fault tolerance. In this algorithm, bee agents travel through network regions called foraging zones. On their way their information on the network state is delivered for updating the local routing tables. The bee agents take less than 1% of the available bandwidth but provide significant enhancements in throughput and packet delay. It was tested on the Japanese Internet Backbone NTTNet and compared with AntNet (network routing algorithm based on Ant Colony Optimization -ACO-), DGA (Distributed Genetic Algorithm) and OSPF (Open Shortest Path First protocol for routing in Internet Protocol based on Dijkstra's algorithm). Authors had demonstrated that BeeHive achieves a better or similar performance as compared to AntNet and DGA. However, this enhancement in performance is achieved with a routing table whose size is of the order of OSPF.

For energy efficient routing in mobile ad hoc networks, Wedde et al. in [39] had proposed BeeAdhoc. It is inspired by the foraging principles of honey bees. The algorithm mainly utilizes two types of agents, scouts and foragers for doing routing in mobile ad hoc networks. BeeAdHoc is a reactive source routing algorithm and it consumes less energy as compared to DSR (Dynamic Source Routing), AODV (Ad-hoc On-demand Distance Vector), and DSDV (Destination-Sequenced Distance Vector) existing routing algorithms because it utilizes less control packets to do routing, without making any compromise on traditional performance metrics: packet delivery ratio, delay and throughput.

Another research activity called Bee Swarm Optimization (BSO) has been introduced by Drias et al. in [13]. It was inspired by the bee behavior, whose principle is to harvest the nectar of the easiest and richest sources using the bee dances. They were interested to the Maximum Weighted SATisfiability (Max-W-SAT) problem and then, compared against Generic seaRch Algorithm for the Satisfiability Problem (GRASP), Scaller Search for the

SATisfiability problem (SS-SAT) and ACO. Authors concluded that BSO results are very satisfactory.

Karaboga in [15] suggested a new algorithm called Artificial Bee Colony algorithm (ABC) in the aim to solve multi-dimensional and multi-modal optimization problems. Author was simulated this algorithm for three continuous functions; Sphere function, Rosenbrock function and Rastrigin function. The results reached had given a successful optimization for this kind of problems. ABC algorithm is very simple, very flexible and very robust and can be applied to the combinatorial optimization. In the ABC a food source represents a possible solution to the problem. The nectar amount of a food source corresponds to the quality of the solution which is determiner first. After, ABC placed the employed foragers on the food sources and then, it will send the onlookers onto the food sources. Next, the scouts are sent for searching new foods. This process is repeated until the optimal solution is reached.

Basturk and Karaboga [5] made deeper the ABC algorithm which is tested on five multi-dimensional benchmark functions: sphere function, Rosenbrock Valley, Griewank function, Rastrigin function and Step function. It gave more performed results after comparison with the genetic algorithm. These simulation results show that the ABC algorithm is quite robust for multimodal problems, since it has multiagents that work independently and in parallel. In the same context, Karaboga et al. in [16] has been used ABC to train feed-forward artificial neural networks for classification purpose. The performance of the algorithm has been compared with the traditional back propagation algorithm and the genetic algorithm which is a well-known evolutionary algorithm. Results of the experiments show that the ABC algorithm can be successfully applied to train feed-forward neural networks. To proof more efficiency of [15], Karaboga and Basturk in [17] compared the ABC performance with that of differential evolution (DE), particle swarm optimization (PSO) and evolutionary algorithm (EA) and tested for five multi-dimensional numerical benchmark functions. They reached to the conclusion that ABC gets out of a local minimum, more efficient for multivariable and multimodal function optimization and outperformed DE, PSO and EA.

Yang in [41] proposed a new Virtual Bee Algorithm (VBA) which addresses the numerical optimization problems for engineering applications. It was tested on two continuous functions with two parameters; the first is De Jong's test function (single-peaked) and the second is Keane's multi-peaked bumpy function. VBA was been compared to genetic algorithm. Comparison suggests that virtual bee algorithms work more efficiently due to the parallelism of the multi-bees.

Pham et al. in [26] proposed Bee Algorithm (BA) for combinatorial and numerical optimization inspired by the natural foraging behavior of honey bees and applicable to both combinatorial and numerical optimization problems. The algorithm starts with the n scout bees being placed randomly in the search space. After that, the fitnesses of the sites visited by the scout bees are evaluated. Bees that have the highest fitnesses are chosen as "selected bees" and sites visited by them are chosen for neighborhood search. Then, the algorithm conducts searches in the neighborhood of the selected sites, assigning more bees to search near to the best sites. The bees can be chosen directly according to the fitnesses associated with the sites they are visiting. Alternatively, the fitness values are used to determine the probability of the bees being selected. Searches in the neighborhood of the best sites which represent more promising solutions are made more detailed by recruiting more bees to follow them than the other selected bees. However, for each patch only the bee with the highest fitness will be selected to form the next bee population. Next, the remaining bees in the population are assigned randomly around the search space scouting for new potential solutions. These steps are repeated until a stopping criterion is met. The first application has been applied for two standard functional optimization problems with two and six dimensions respectively. The results have proved the ability of the algorithm to find a solution very close to the optimum. The second application concerned eight benchmark functions. After comparison with a deterministic simplex method, stochastic annealing optimization procedure, genetic algorithm and ant colony system, authors had concluded that Bee algorithm outperformed the other techniques in terms of optimization speed and accuracy of results. We have found three studies based on this algorithm for optimizing neural networks.

Pham et al. in [27] presented the use of Learning Vector Quantization (LVQ) networks for recognizing patterns in control charts. The LVQ networks were trained by employing Bee Algorithm. Despite the high dimensionality of the problem in which each bee represented 2160 parameters that had to be determined, Bee algorithm still succeeded to train more accurate classifiers than that produced by the standard LVQ training algorithm.

Same authors in [28] used Bee Algorithm to train the multi-layered perceptrons (MLP) neural network for control chart pattern recognition. Results showed that BA succeeded to train more accurate classifiers than that produced by the Backpropagation algorithm which is a reference algorithm used to training MLP despite the high dimensionality of the problem (each bee represented 2310 parameters).

In [29] they used bee algorithm to the optimization of neural networks for wood defect detection. The results showed that BA achieved more accuracy than the backpropagation method and a notable difference in the number of iterations required to optimize the neural network in which the former required a total of 1300 iterations whereas the latter required 65305 iterations.

We can find other studies using the food source searching of the bees which were not applied to the optimization problems. In [42] Yonezawa and Kikuchi had examined an algorithm based on bee collective intelligence for honey collection. They demonstrated the intelligent collective cooperation solution of the colony which is started from a simple and non intelligent individual behavior of the honey bees. Two simulations based on one and three forager bees are applied. The reached results have provided the understanding of the selection and transmission mechanism at honey collection. They cleared up that three bees are most fast than one at decision makes process and their behavior is adaptive to complex environment related on quantity and distance honey. Finally, scientists proved the intelligence of the insect population behavior which emerged from an individual insect behavior non intelligent.

The research activity [31] proposed by Sato and Hagiwara used bee foraging behavior to improve genetic algorithm. The proposed Bee System must carry out a global search to obtain superior chromosomes with pretty high fitness using the simple genetic algorithm. After that, it is the local search. All population chromosomes will be crossover with superior chromosomes in concentrated crossover manner. Next, the populations will migrate between them to transfer generation individual to the neighboring population. The authors enhanced the local search ability of their proposed algorithm using a pseudo-simplex method. This work was been commented on by noticing that the concentrated crossover and the pseudo-simplex method ensured the high ability for local search as lack of the genetic algorithm without degrading global search ability. Bee system possessed better performance against conventional GA especially, for high complex multivariate functions.

Tereshko developed in [37] a model of foraging behavior of honey bee colony based on reaction-diffusion equations. He sought to know how mapping information about the explored environment determines the honey bee behavior and compared this model with those of ant colonies. The results confirm that when there is more useful information, there is more profitable food source. This study proved the complex behavior emerging from simple individual interactions. After comparison, bee model provided the ability of finding the optimal solution, however, ant model failed in the case of the less profitable source.

Lemmens in [20] demonstrated how pheromone-based navigational algorithms inspired by ant colony behavior are outperformed by non pheromone-based navigational algorithms which are inspired by bee colony behavior in the task of foraging. He created a simulation environment termed BeeHave in which the objective is to compare bee and ant algorithms (non pheromone based algorithm against pheromone based algorithm). The strategy used two important axes: the recruitment and navigation behaviors and three different functions: manage bee activity, calculate vectors (to find food source) and moving policy using Markov Decision Process. This study has confirmed that non pheromone based algorithm (NPBA) -bee algorithm- outperforms eventually pheromone based algorithm (PBA) -ant algorithm- on a time per time measure in growing world sizes. However, PBA used less time per iteration in small-sized worlds. In the point of view speed, NPBA is faster when finding and collecting food. It is more scalable but less adaptive than PBAs.

Another inspiration by bee food searching has been studied by Bitam and Batouche [8]. Here, authors were proposed a new bee system for the topology discovery as the first step in the routing process for the mobile ad hoc networks. The main idea is to allow each node to discover the whole network topology as global vision (macroscopic behavior) from its particular knowledge as a local vision (microscopic behavior). The process is assumed without any central control and allows an adaptive aspect to the mobility of nodes in such network type and then to the frequently changes in the topology. Each node collects information about distance and/or direction of the other nodes in the network using two types of bee dances; round and waggle relating to the distance between the discovery and the current node (the beehive). There are two types of discovered node; direct and indirect. This study had been simulated using NetLogo simulator and the results confirmed the ability of node to reach all information about the network in distributed and adaptive manner.

2) Nest site searching sub-model:

The bee nest site searching is in a manner not very far than the food source searching. Of course, this behavior starts with the area exploration next, it is the discovery communication via dances and then the exploitation. The difference occurs in the quality of the searching nest site which is according to their properties such as cavity volume, entrance hole, perched several meters off the ground, facing south and located at the cavity floor. However, for the food source searching, bees consider the quality of the found food.

In this sub-model, we find one basic study which established the principle of the nest site searching. It is proposed by Seeley and Buhraman [33], when they deal with making decision strategy of the bees over the new nest site selection. The authors had studied three different bee colonies using observation of Lindauer in [19] as biological research activity. At the bee group level, authors found that the scout bees find potential nest sites in all directions and at distances of up to several kilometers. Scouts advertise a dozen or more sites with their dances. Within about an hour of the appearance of unanimity among the dancers, the swarm lifts off to fly to the chosen site. At the individual level, they found that the dances of individual scout bees tend to taper off and eventually cease, so that many dancers drop out each day. Some scout bees switch their allegiance from one site to another and the principal means of consensus building among the dancing bees is for bees that dance initially for a non-chosen site to cease their dancing altogether, not to switch their dancing to the chosen site. They concluded that the bee strategy of making decision here is a weighted additive strategy. It is an alternative evaluation relevant to the attributes (cavity volume, entrance height, entrance area, entrance direction and distance, presences of combs from previous colony). This strategy is the most accurate but the most information demanding one too.

Quijano and Passino [30] used [33] to introduce a model of honey bee social foraging to solve the resource allocation problems as a numerical optimization. They reached to an ideal free distribution and globally optimal allocation strategy.

B. Marriage behavior model:

There are many potential applications based on the marriage phenomenon among bees which represent the second class of bee colony algorithms. We can speak about one basic study; it is the scientific activity of Abbass [1]. He proposed the first novel search algorithm inspired by the marriage process in honey bees (MBO) algorithm. It is considered as combinatorial optimization algorithm applied to the 3-SAT problem. Abbass considered the mating operation in the honey bees assured by one queen and assisted by one worker. It is based on the mating–flight which can be visualized as a set of transitions in a state–space (the environment) where the queen moves between the different states in the space in some speed and mates with the drone encountered at each state probabilistically. At the start of the flight, the queen is initialized with some energy–content and returns to her nest when the energy is within some threshold from zero or when her spermatheca is full. A drone mates with a queen according to probabilistic factor (the probability of adding the sperm of drone to the spermatheca of queen; that is the probability of a successful mating). Author supposed that the probability of mating is high when either, the queen is still in the start of her mating–flight and therefore her speed is high, or when the fitness of the drone is as good as the queen's. After each transition in the space, the queen's speed and energy decay. MBO starts with initializing the queen's genotype at random. After that, the heuristic is used to improve the queen's genotype, therefore preserving the assumption that a queen is usually a good bee. Afterwards, a set of mating–flights is undertaken. In each mating–flight, the queen's energy and speed are initialized with some value at random. The queen then moves between different states (i.e. solutions) in the space according to her speed and mates with the drone. If a drone is successfully mated with the queen, his sperm is added to the queen's spermatheca (i.e. a list of partial solutions). After the queen finishes her mating–flight, it returns to the nest and starts breeding by selecting a sperm from her spermatheca at random followed by crossover with the queen's genome that complements the chosen sperm. This crossover process results in a brood. This is the haploid–crossover. Mutation then acts on the brood therefore, if the same sperm is used once more to generate a brood, the resultant brood will be different because of mutation. This process is followed by applying the worker to improve the broods. Afterwards, the queen is replaced with the fittest brood if the latter is better than the former. The remaining broods are then killed and a new mating–flight starts. Two versions of the proposed algorithm, which incorporate each a well known heuristic for SAT, are developed (MBO-GSAT and MBO-random walk). Results showed that MBO was very successful on a group of one–hundred hard 3-SAT problems. Moreover, it was shown that MBO-GSAT performed better than GSAT alone. Also, MBO-Random Walk found more solutions than random walk.

We note that all of the remainder research activities are based on MBO. In [2] abbass improved its algorithm by using more than one worker, however, more than one queen was considered in [3] to enhance the algorithm results.

Yang C. et al. based on MBO and proposed in [40] FMBO a Faster algorithm which had as a main objective to make better the results. They introduced the generation in each time of drone as mating agent in randomly manner. Moreover, they mate with finite quantity of queens with the absent of the energy or speed factors using in MBO. Results presented more performance of FMBO against MBO and genetic algorithm. Particularly, it is the global convergence proved by the use of Markov chain theory, easy implementation, adjustment of a few parameters and jumping of the local optimum.

In [18] new application using MBO had been submitted by Koudil et al. It was developed to the integrated partitioning and scheduling problem in codesign and compared with the genetic algorithm which had reached good results in terms of solution quality and execution time.

Already with the combinatorial optimization, we found Teo and Abbass paper [34] based on [1] and [3] in which they used more conventional annealing approach during the trajectory acceptance decision in 3-SAT problem. Authors had used five heuristics to improve broods by workers: GSAT, random walk, probabilistic greedy, one-point crossover and WalkSAT. They carry out three manners of experimental studies; testing each of five heuristics without MBO, testing each of five heuristics with the original MBO and modified MBO and testing the proposed algorithm against the original MBO using the five heuristics. These tests had been executed for ten 3-SAT problems. The results had shown that the proposed annealing function improved one of the MBO implementations and MBO outperformed all the standalone SAT heuristics. This last work had given birth to [35] proposed by Teo and Abbass with the test of a purely conventional annealing approach as the basis for determining the pool of drones. It was regarded as an improvement of the original paper.

Benatchba et al. in [6] was applied [1], [2], [3] to the data mining subject expressed as Max-SAT problem. They used a benchmark from medical domain to analyze the most revealing symptoms of the presence or not of laparotomy of the principal bile duct. Authors had used four heuristics to improve broods by workers: Local search algorithm, GSAT, HSAT, GWSAT. They reached the best satisfaction by using GSAT as worker and one queen.

Chang demonstrated MBO capability to solve combinatorial optimization problems (theoretical problems) and for solving infinite horizon-discount cost stochastic sequential dynamic programming problems [11].

In [14] Fathian et al. developed an application of honeybee mating optimization in clustering (HBMK-means) based on [1] applied to data mining clustering. This study was tested on several datasets such as Iris dataset, wine dataset, and Wisconsin breast cancer database. It was compared against several typical stochastic algorithms: ant colony optimization, simulated annealing, genetic algorithm and tabu search algorithm. As result, authors concluded that is a viable and an efficient heuristic to find optimal or near optimal solutions and their results are very encouraging in terms of quality of solutions, average number of function evaluations and the processing time required.

Nevertheless, we have found three algorithms which occur in the numerical optimization column. The first is [9] of Bozorg Haddad and Afshar. This study based on the marriage behavior algorithm of [3] and was applied to the water resources management problems. It gave a very good and promising results as well as global optimal results. We find too for continuous optimization the [10] of Bozorg Haddad et al. in which they proposed Honey-Bees Mating Optimization (HBMO) algorithm based on [1] and [3] for solving a highly non-linear constrained and unconstrained real valued mathematical models in the case of developing an optimum operation policy for a single reservoir. This study was tested on several constraint and unconstrained mathematical optimization functions and compared against the results obtained by genetic algorithm. This contribution mentioned a minor improvement in the HBMO solutions especially for solving the single reservoir problem. The last work is for Afshar et al. [4]. It presented an HBMO improved version for continuous optimization problems and its application to non-linear constrained continuous single reservoir problem. Obtained results compare well with those obtained using genetic algorithms, making the HBMO algorithm's application, quite promising and converges very rapid to global optimum values in comparision with the results obtained from traditional linear programming solver LINGO 8.0. The model performance in real-world water management problems, such as reservoir operation, proved to be very promising.

IV. CONCLUSION

In this paper, a survey on bee colony research activities is presented. Similar bee researches proposed in the literature are unified in the aim to contribute in their organization and to facilitate their application for solving other problems. All recent studies related to this area are briefly described. Definitions, explanations, applications on different problems, comparisons and results of these algorithms are presented. We suggest to group these research activities into two major models according to natural life criteria of bees. The first model is inspired by the foraging behavior. In this category, studies are divided into two sub-models; those which are based on the food source searching behavior and the others which are based on the nest site searching behavior. The second model represents the studies inspired by marriage behavior in the bee colony.

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