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Cheetah (Cutting hot edge evolving technology- algorithms hive)

Evolution of Mimics of Algorithms of Nature (E-man)

Part 7#: Prospects of Honey-bee-foraging-algorithm (Hb_Fa) and Honey-bee-Mating-algorithm (Hb_Ma) in Omnimetrics#

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CONSPECTUS

Background

The implicit knowledge of bio-processes of honey bees in hive site selection, foraging, communication of status of nectar resources through waggle dance, defense against invaders, mating, fertilization and brood care in nature is mimicked in nature inspired optimization algorithms. This tutorial, Eman.Hb_Fa and brood care, Eman.Hb_Ma is focused around pedagogy of state-of-honeybee_inspired_algorithms in Omnimetriccs and futuristic research in chemical sciences by 2020.

Honey bees in nature:The honey bees in nature fulfills the diverse traits viz. site selection for hive, honey bee hive building /maintenance/defense, foraging food, conversion of nectar from the flower patches into honey in its gut through a series of biochemical changes, preserving honey for long shelf life etc. The honey making process begins with the secretion of an enzyme on the nectar in the work bee stomach. The bee unloads the nectar to empty honeycomb cells and some extra substances are added in order to avoid the fermentation and the bacterial attacks. The filled cells with the honey and enzymes are covered by wax.

*Honey bee dances:*The waggle dance, round dance, jostling dance, tremble dance, grooming dance, and jerking dance are expressions of the honeybees after grasping the angle between sun-hive-food source and the effort needed or distance of the flower patch from the hive. They also communicate new hive selection through dance patterns. The queen bee performs a pre-mating flight dance to inform the drones of the colony.

Honey bee foraging algorithm (HB_Fa): An off shoot sprinkle from knowledge pool of Mother Nature is the inspiration for artificial bee algorithm (ABC). Koraboga group proposed it in the year 2005.The location of flower patches corresponds to the converged solution and amount of nectar to fitness function value. The search of foraging/scout bees (for better sources of food) is similar to global and neighborhood search of optimum solutions on response surface. The onlooker bees' decision to continue or reject the food source is akin to continue the local search or to start afresh from another location. The basic version of ABC underwent several modifications over a decade and is now one of the trustworthy procedures in

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the nature inspired algorithm warehouse. The modifications include Levy flight in initiation of artificial foraging bees. The functioning of foraging algorithm for different simulated and real life data sets are compared with GA, PSO, DE and PS_EA. The binary hybridization of Hb_Fa with Levy flightdistribution,Grenade Explosion, chaotic probes, heuristic search methods and neighbourhood structure increased the potential/scope of algorithm. A part of honey bee dance is translated in bee dance algorithm and improvements for wide spread use are awaited

HB_Fa applications: The applications spread into diverse tasks viz. nuclear power reactors, protein sequence prediction, electrical power generation/distribution, image analysis, clustering, and communications. Hb_Fa has success in continuous/discrete optimization of several simulated bench mark functions.

Queen bee mating in nature:The function of a queen bee is to participate in mating flights with a series of drones until the spermatheca is full, generation of broods almost all through its life span (i.e. over a period of three to four years). Drones are male species of honeybee family and what all they do is participating in mating flight with queen bee. Any of the individual members of honey bee family, right from long lived queen, drones dying immediately after mating with queen/driven off from the hive in winter, work-bees/foraging bees do not have intelligence leave alone super-/hyper-intelligence. But, not only the life cycle but also a stable species all over the globe in widely varying environment is a just consequence of common genetic expressed knowledge, sharing information, communication amongst them, following hierarchy, performing its duty in Toto, service/sacrifices. The special biochemical skills inherited through genes in synthesis of royal jelly (a food material for queen), stickysubstance for hive, pheromones to keep female work bees sterile normally and so on. Any of tasks cited, leave alone all in such a tiny size in an artificial honeybee is no doubt beyond realm with today's artificial intelligence tools.

Honey bee mating algorithm (HB_Ma): The honey bee mating algorithm translated from part of queen bee mating with drones can be understood in a nut shell as a combination of simulated annealing, genetic algorithm and local search procedures.Thequeen has best genes and they continue both in female and male off spring in unfertilized and fertilized eggs. It is similar to elite preservation. The different versions mathematical procedures used a variety of cross-over/ mutation operators, altruism, multiple-populations, Pareto front etc. Care taking of broods by work bees is equivalent to applying heuristics in refinement of solution. One of the popular paradigms, chaotic local search is used to generate initial population of broods and improved local refinement. Hb_Ma found a niche in industrial synthesis of phthalic anhydride, simulation of cancer, optimization of solar cell model parameters, electrical thermal power systems/ distribution, dispatch of power and time series tasks. It hybridized with SAA, neighborhood structure, chaotic search, Linde–Buzo–Gray (LBG), vector quantization, fuzzy sets, greedy search, cooperative PSO and so on. The efficiency and cost to benefit ratios are compared with performance of PSO, Binary_PSO, Hybrid cooperative- comprehensive- learning based PSO algorithm (HCOCLPSO), Fast Otsu's method, fuzzy logic, Nelder–Mead simplex search + PSO [PSO-NM], ACO, exhaustive search, GA and Taboo search.

A few key features of honey bee mating translated into mathematical frame in Hb_Ma are (a) queen honey bee choosing a drone of highest fitness through matching her flying speed with that of drone (b) decrease of speed after every mating (c) pooling up sperm of different drones until spermatheca is full, (d) worker bee care of broods by feeding with royal jelly and other foods. In mathematical frame they correspond respectively to probability, annealing schedule, pooling up all best basic tools (with a little difference) at one place and local heuristic procedures. The definition base and jpeg images are integrated with in-house matlab programs for display purpose. E-man_ToolBox is updated with honey bee specific m-functions.

Keywords:E-man, Honeybee, Foraging, Mating, algorithm, Multi-object-functions, Nature mimicking mathematical procedures, knowledge_bio_processes,heuristics_choice_program_flow.

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INTRODUCTION

1.1 Evolution of Mimics of Algorithms of Nature (E-man)

The wave of nature mimicking algorithms started with simulated annealing algorithm (SAA) in 1960's taking inspiration (chemical) annealing of glass. Another land mark is Holland's GA in 1975 based on Darwinism of species evolution. Particle swarm optimization (PSO) has its roots on swarm intelligence of birds-flocking/fishes- school/social-interactions and is a noteworthy stochastic search based heuristic algorithm. Dorino's (1992) ant colony optimization (ACO) in spired by foraging tactics revolutionized search heuristics. The first decade of 21 century itself is a golden period for Evolution of Mimics of Algorithms of Nature(E-man). Honey bee foraging and honeybee mating based algorithms in the preceding decade topped the list and find a niche in data reduction/optimization/prediction etc. The literature on improvement of these algorithms and application in diverse fields exploded beyond leaps and bounds and in fact astounding. It is hard to search even abstracting services to get complete peer reviewed publications even keeping aside proceedings and limited circulated reports. It is needless to put on the record that it is just beyond the scope of a (normal) researcher to probe into the original research results in primary journals. The gap between awareness and practice is an insurmountable hurdle. A way out is algorithmic approach using white box software in portable language (MATLAB) with simulated data at least to keep abreast of the state-of-the-art-technology of this long-shelf-life and prospective tool of future. In this research tutorial we cover honeybee foraging/ mating algorithms, their modifications and applications in optimizations in diverse disciplines[1-112].

With continued interest in pursuing Chemometrics for over three and half decades and neural networks since 1990, we started research tutorials a couple of years ago covering nascent nature inspired viz. gravity, charge system, firefly, big bang/big crunch bat, mosquito algorithms [113-121] and science of matured neural network evolution through a third eye. The applications were neither elaborated nor confined to a discipline but broad spectrum of science, technology and commerce under the umbrella of Omnimetrics is documented. The laser focus is to impart impetus for post graduates about the extensive nature of applicability of future toolkit. The same object oriented mapping of algorithm/formulae into white box Matlab code is a torch for researchers to pick up an adequate method based on principle choosing from cafeteria menu. For practitioners of complex data analysis using high end computations, it is the first step to go through the details with tiny examples. This leaves an express high way with instar and outstar network of cross roads and also prepares to be open minded/adaptable in analyzing the research project data where solutions, conclusions are neither preset nor foreseen. These toolboxes are high energy packets playing a key role in indirect perception to refute, endorse, confirm and propose a new proposition/ hypothesis/ postulate/ theory/ phenomenon, hitherto unknown yet existing (or existed and later extinct) but unobserved moiety/characteristic property etc.

2. Honey-bee-foraging in nature (Hb_fin)

2.1 Honey bees in nature: The taxonomical classification of honey bees is briefly documented in chart 2.1. The anatomy from the point of interest in foraging, reproduction and intelligence are shown in fig.2.1.

Chart 2.1: Honey bees in nature

		Placing Bees in the Animal Kingdom
Phylum	Arthropod	○ External Skeleton, Chitinous, Segmented ○ Invertebrates
Class	Insecta Hexapoda	○ Six legged ○ 3 major body parts, head, thorax, abdomen
Order	Hymenoptera	○ 2 sets of joined wings connected by hooks, ○ young develop through metamorphosis, ○ ovipositor modified to stinger
SubOrder	Apocrita	○ Ants, Bees, and Wasps
SuperFamily	Apoidea	○ Bees
Family	Apidae	○ Food exchange, pollen baskets, ○ storage of honey & pollen ○ Over 20,000 species
SubFamily Tribe	Apini	○ Perennial, social colonies, highly eusocial

Fig. 2.1: Honey bee hive

Categories of honey bees in hive

- Queen
- Drones
- Broods
- Working bees

Genus	Apis	Honeybees 4 Species (and counting)
Species		

Life cycle

- Food foraging
- Life continuation (Progeny)
  - Reproduction
  - Sexual
    - Honey bee mating
  - Asexual
- Shelter
  - Hive
    - selection/building
    - Shifting
    - Defense

Drone disposal from hive

Dispensing (unmated and mated but alive) drones

If	*Winter*
Then	*Drones will be expelled*

Hive maintenance

If *Hive is over heated*
Then *There is a need for pollen and water*

If *There is a drought for food*
Then *Younger nurse bees also join the foraging process*

-------------- HB 97/64

Specialized skill

Releasing chemicals to keep working bees sterile Has control over whether an egg is fertilized when she lays it	Queen
Monitoring - Amount of nectar left in a patch - Quality of nectar - Distance from hive - Azimuthal angle between hive, Sun and patch - Conversion of nectar into honey in gut – Error in distance increases with magnitude	Employed forager

Work_ bees

- Food
  - Production of royal jelly
  - Feed of Queen, broods
  - Conversion of nectar, sugar into honey
  - Gather nectar, pollen, water, and propolis
- Hive building
  - build the comb from wax extruded from glands under their abdomen
  - Hexagonal walls of the honeycomb cells
- Come Hither" Pheromone
  - Signal entrance of hive
- Hive maintenance
  - Ventilation
  - Heat and cool as required
  - Darker brood comb areas
  - Clean out the cells
  - Empty brood cells
  - repair hive
- Brood care
  - Feed larvae
  - Cap pupae
- Empty brood cells
- Evaporate nectar into honey.
- Storing honey
- Production of wax in little flakes from
- glands under their abdomens

Communication				
From	Means	Direction	To	Activity
Forager	Round dance Waggle dance	→	Scout onlookers	Foraging
Work bees	Waggle dance	→	Decision group	New hive exploration
Work bees		←	Decision group	New hive selection
Queen	Mating dance	→	Drones	Before leaving for mating flight

Physical characteristics: The honey bees are light brown to black in color, oval-shaped and length is around 15 mm. The light (golden-yellow) and dark (brown) strips function as visual warning to predators that they sting.

2.2 Honey and common man vs. honey bees and science: The food of honeybees (nectar) is scarce in winter (a non-flowering) season. Looking at the life cycle of honeybees, concerted efforts are in the direction of conversion of nectar to honey, fine processing/storing/pumping preservatives etc. It is only to feed the members of hive during this harsh time. When Water is evaporated out of the nectar to an extent of 16%

sugar solution, it is called honey. The bees cap it over with wax. At this concentration, no fermentation takes place and can be stored long. The pollen contains protein and the percentage varies considerably.

The beneficial part to human beings in this entire scenario is the tasty high sugar containing, yet long non-fermenting honey collected by thousands of bees (which live 1 to 6 months, save the queen with 4-5 years of life span) from large number of flower patches spread over a few kilometers of area. The amount of nectar available in a flower is very small. Also, that carried by a bee in its whole life is less than half a gram compared to requirement (around two kilograms) for an averaged hive in winter. The taste, quality, shelf life and nutritional value vary with the country, breed of honey bee, environment, pollutants and many other factors.

A naive human being and the science perceived it with enthusiasm. Then efforts are successful to develop artificial honey hives for industrial production. The progressive understanding in depth brought noble prize to Karlvon Frishch and also added a feather in the cap of artificial intelligence/ Swam intelligence/E-man. Yet, all processes in honeybee life cycle are not yet completely mimicable. But, the tiny titbits of realised knowledge added jewels to optimization technology and applications in many critical areas of science/engineering both in civil/defense operations and environment/medical practices.

In honey bees there is a clear distinction in the role of different ones viz. queen, drones, foraging/ scouts/ onlooking workers. It is still, a controversial issue regarding the factors which render the bees into these distinct categories. Their life spans also differ significantly.

2.3 Natural (real) honey bee hive (comb)

A honey bee colony is a well organized social life system. A hive consists of only honeybees but of different categories [58] in terms of size, number, life span, functions (chart 2.2). Typically there is only single queen, many drones, and large number of workers. The different categories of workers are leaders, followers, and scouts. Each type has altogether targeted functionalities and even of widely varying life span say a month to 5 to 6 years. The basic functional operational behaviors of bees include foraging, dancing, mating and building/ maintenance/ defense of hive. The labor-intensive bees do specific jobs using communication methods at the individual and group level. The task is divided in cooperative and distributive manner and performed in parallel. Several types of dances adopted by foraging/ nest-search bees for communication are waggle dance, round dance, jostling dance, tremble dance, grooming dance, and jerking dance. A bee in each category of a honeybee species performs a single task of different nature. In a nutshell, from information technology stand point of view, a honey bee colony is a distributed agents (or creatures) system. It explores a large number of food sources at kilometers of distance all around (360^o) the hive.

Chart 2.2: Categories of bees in a honeybee hive

Honey Bees	#	Life span	Sex
Queen	1 or more	4 years	Female
Drones	≈100		Male
Workers	≈10 to 70K	6 weeks in summer 4–9 months in winter	Female

Real and artificial honeybees

Genetics: Female honey bees have 32 Chromosomes, 16 from mother (queen) and 16 from father (drone). On the other hand, males (drones) have 16 Chromosome from mother and born from unfertilized eggs byparthenogenesis[22].

Broods in nature: Broods developed from fertilized eggs form potential queens or workers [77]. On the other hand, drones are haploid individuals called fathers of honey bee colony, born from unfertilized eggs [5, 7, 14, 18]. The capabilities of the broods in general are improved [32] by work bees by feeding them royal jelly.

Artificial Brood care: Artificial worker bee employs specific local search heuristic to improve the solution. The number of workers attending a brood represents the number of local heuristics.

Queen bee: Queen (fig.2.2) is generally a single egg-laying long lived (5 to 6 years) honey bee. It is fed with royal jelly although its life. It attains maturity after a month of its birth. The bee then participates in mating flight drones in mid-air and in approximately a 15-meter height, in temperatures higher than 20°C, with wind speed lower than 28 km/h and during afternoon hours till the spermatheca is full (FactBase_Hb.2.1).

FactBase.Hb 2.1 [Hb-62]
Queen bee mating
✈ Mates with 7 to 20 drones in one mating flight
✈ Makes many mating flights on successive days until spermatheca is full
✈ Does not participate in further mating flights after start of reproduction
✈ Usually do not mate with drones from her home colony

Queen

Fig. 2.2: Honey Bee queen (bigger in middle) and caretaker work bees

The queen stores the entire spermatozoon in the spermatheca. The glands of queen excrete nutrients for the survival of almost 7,000,000 spermatozoa which are adequate for the rest of her life. Thus, it never involves in mating. A queen bee lays 1,500 to 2,000 eggs a day (approximately one egg per minute, day and night or 200,000 a year) and the variation depends upon the conditions. During the egg-laying, the queen bee chooses whether every egg that passes through her oviduct is to be fertilized or not. Thus, layed fertilized/unfertilized-egg hatches into, larva, pupate and adult bee. It does not do any chores including brood care. The offspring thus are males, female-workers, or new queens, depending on the time of year/ age of the hive and the queen is the mother of all the members of the colony. After the sperms in spermatheca exhausts, she produces unfertilized eggs and one of her daughters is selected as a queen in order to keep on egg-laying. The queen through pheromone secretion makes the female work bees to be sterile in the hive [32, 43]. Also, she produces chemical scents which regulate hive activity. Rarely more than one queen also is present during the active period (life cycle) of the hive. The metaphor is the queen is the first lady of the country and receives the utmost care and attention and may be thus referred by us, Homo sapiens as queen. When the queen becomes old, or departs to start another hive, she lays an egg in a large queen cell. The nurse bees feed the larva with royal jelly made from a gland on their heads. In around 16 days a new queen emerges. She destroys any rival queens, to continue to be a single queen of the colony.

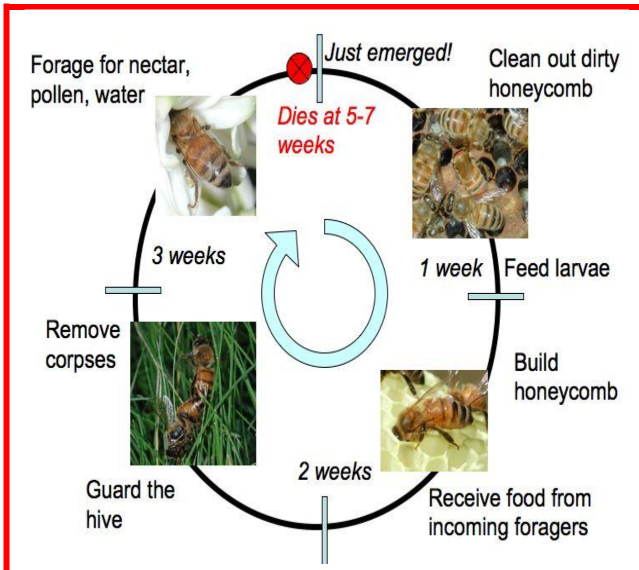
Artificial Queen bee: AQB (artificial queen) has a genotype, a set of genes which can be considered as a complete solution to the problem.

Drone in nature: They are males (fig. 2.3) and just function as agents to transmit and propagate their mother's gametes/genomes [77]. The number of drones is around 500 in a colony in spring and summer. They do not have any functional role except participating in mating flight with queen in air. In nature, drones are haploid. When there is no mutation, the genetic composition is unaltered. This enables females to act genetically as males.They are developed from unfertilized eggs. Drones become mature sexually within two weeks. A drone has big eyes i.e. twice the size of those of worker bees and queens, but no stings. The size of body is greater than that of worker bees, though usually smaller than the queen bee. The drones use enlarged eyes and also pheromones to find (virgin) queens with which to mate. Although heavy bodied, the drone flies fast enough to accompany the queen in mating flight. The drone dies just after mating with the queen. The left over drones are "kicked out" of hive in the autumn. They die of starving in cold winter

Fig. 2.3 Drone

Artificial Drones: In nature inspired model, a drone has a genotype which is a complete solution to the problem under investigation. It has a mask which covers half of the genes selected randomly. Thus, artificial drones have only half off a genotype. The non-masked genes constitute the sperm of the drone. Inbreeding is avoided by generating drones independent of the queen.

Worker bees: The worker bees are non-reproducing females (fig.2.4). The tasks of a worker bee are based on its age and the needs of the colony. They live for 6 weeks during summer times and 4–9 months in the winter. They perform [77] brood care, continuous follow-up of queen, maintenance and defense of hive. Further,



- ✓ Nurse bee (1-12 days)
- ✓ Clean own cell and others
- ✓ Feeding brood (larvae)

- ✓ 10 – 20 days
- ✓ Comb building
- ✓ House keeping
- ✓ Ripening honey
- ✓ Climate control
- ✓ Secreting/molding wax into cells
- ✓ Accept and store pollen and nectar from foragers

- House Security
  - ✓ Guard hive and its entrance
  - ✓ Orientation flights to learn surroundings

- Foraging Agent
  - ✓ Gathering pollen, nectar,
  - ✓ tree resin (that they turn into propolis)
  - ✓ water for the hive

Fig. 2.4: Life cycle of honey from egg to adult

they remove debris and dead bees, ventilate and guard the hive, feed the larvae, drones and queen by special substance or secretion of their salivary glands. Workers make the wax cells in which the queen lays eggs. In second half of her life, they work as foragers by initially leaving the hive for short flights in order to learn the location of the hive and the environment topology. They lay eggs in case of emergency of any sort.

KB. 2.1: Food source exploration	
If	Food source searched bee (i) > threshold
Then	It is a leading bee & Goes for exploration & Deploys more bees
If	Food source searched bee (i) is relatively low
Then	Gives up that source & Explores for another source
If	Food source searched bee (i) < threshold
Then	It follows leading bees and continues to explore
If	Searching times around a hive >> upper_limit & no patch worth for exploration found
Then	It abandons that source & explores for a new one

Artificial Worker bees*:* The capability of worker is restricted to heuristic improving the solution. Thus, it may be presumed that brood care only is mimicked.

Employed bee: In a general sense, all bees involved in exploring a food source are deemed as employed. Specifically, a bee going to the food source to get the nectar is called the employed bee [15]. It continues this task until the food source is exhausted. It is the same bee which in fact participated in exploring the source as a scout. The number of employed bees is equal to number of food sources around the hive. In other words, for every food source there is only one bee employed. The employed bees go to already explored food (nectar) sources of high/acceptable quality and with sufficient amount of nectar [45]. They bring the nectar from flowers to the hive. After every visit, they share the information with onlookers, rest bees, scouts (formerly scout bee makes to and fro trips between source and flower patch) about the food source through waggle dance on the dancing floor/area in the comb. Reassessing nectar amount is performed in the every trip. Some bees skip waggle dance in the hive and directly make a new trip after unloading the nectar, when they are confident that still there is lot more nectar left in the already visited flower patches.

An employed bee remembers position of neighborhood nectar source if it is more prosperous than the previous one and forgets the old location. Otherwise, she does not replace her memory new position. When all foragers complete search process, they share location, quality/quantity of food sources with decision makers (scouts, onlookers and rest bees) in the dance area.

Un-Employed bee: If the nectar amount decreases to a low level or exhausted, the foraging bee adons the food source and becomes unemployed. Later it act as an onlooker or scout squad.

Scout bees: A small (≈ eight) percent of population is act as scout bees and they explore continuously all through the season. When a food source is exhausted, employed bees in that mission become scout bees abandoning that source. The scout bee has no knowledge about the food sources in the search field

If	scout bee (j) finds a patch acceptable
Then	it deposits the nectar & perform waggle dance

and as such make random search always for a new food source near the hive from one patch to another [34] during the harvesting season [58]. When a scout bee finds nectar source, it returns and communicates the information through waggle dance to onlookers and other hive mates. The tiny bee remembers the location of patches precisely without any road map or aerial map (GPS). After the finalization of a new food source they again play the role of employed bees.

Onlookers: Another subset-swarm of bees, called onlookers remain and wait in the hive. They are the decision makers in arriving at the size of the swarm for each type of flower patch. Onlookers witness dances of the employed bees. The foraging waggle dance information by the employed bee is shared and scrutinized. Further, the relative quality of different patches is also analyzed. Good food sources (indicated by the bees dance) attract more onlooker bees compared to inferior sources. Thus the collective decision is an average of the individual onlooker in the process [45]. The onlookers search for better food source in the neighborhood of memorized food sources [42] based on the information from waggle dance of the employed/scout bees. A decision regarding the selection of food source is based on the probability expressed by the employed bees. A decision is made about the number of employed bees for a source and regarding abandonment of flower patch. But the decision even for abandoning a flower patch is collective (i.e. swarm) opinion. The details of methods adopted by the onlookers are not fully clear. Multiple numbers of information bits collected by identical non intelligent agents is received by a panel of identical judges who have to take an optimum decision. There is no interaction of employed/scout bees. The variation and information is mainly due to environment i.e. nectar source. One has to assume the equal capability of the bee in quantifying the parameters and also expressed in the form of waggle dance. In the second stage onlookers (they are not direct observers) perceive the dance and translate it into quantitative parameters. From a pool of n dances crucial decision is to be taken. Again the best decision of all onlookers is to be arrived. How it is done? In the third stage, this decision is to be expressed to the employed bees and also deploy appropriate number (resource management). What are the errors, precisions of biosensors, retention and translation in all three stages is not easy even with the state of art data to information processing. In a nutshell, onlookers tend to select good food sources from those founded by employed bees and further search the foods in the neighborhood of selected locations.

Foraging process

In a new hive, just started operations by a queen bee and first few nascent honey bees, they all play the role of detecting bees. At the start they do not have any prior knowledge about the landscape or flower patch locations. But on exploration, bees will be divided into onlookers, scouts, employed ones and saga continues. In a word, the food search is a swarm effort of is employed bees, onlookers, scouts and rest bees spread over few months for continuation of life in the winter (or non-flowering season) looking forward for next spring.

FactBase.Hb 2. 2: Foraging honey bee
Foraging
✈ Bees explore and travel up to 10km from hive to collect nectar
✈ $\cong 50$ bees in their life time make 2 table spoons (15ml; density 1.4) of honey
✈ The hive requires 60 pounds of honey during winter on average depending upon size

Food of honey bees

Royal jelly (RJ) is a milky secretion of nurse honeybees and has a role in reproductive caste determination of honey bees. It is a mixture of water, fats, sugars, low molecular mass compounds and proteins. The spectrometric analysis showed around 185 organic compounds and proteins make up approximately to 50% of dry weight of RJ. The major royal jelly proteins (MRJPs) share sequence homologies with yellow proteins of *Drosophila.* A few chosen larvae fed with surplus (copious amounts) of royal jelly throughout their larval development had prospects of becoming a queen. And, the queen is fed all through her life with royal jelly. In the first 5 to 6 days of honey bee's adult life, it consumes great amounts of pollen in order to obtain lipids, vitamins, minerals and protein necessary for completing its development and growth. The larvae those developing into workers are fed with very small amounts of royal jelly during the first three days and the rest of the period with royal jelly, pollen and honey.

Nectar is sugar in water (Glucose, Fructose and Sucrose) with some essential oils and tannins. It is also part of the honey bee diet between the tenth and the fourteenth day of their adult life. In the case of worker bees, the main dietary source is made up of carbohydrates, which are gathered as nectar from plants, trees and flowers.

2.4 Knowledge, memory, swarm effect in honeybee foraging in nature

The implicit objective of entire honey bee hive is storage of food in the form of non-decomposable honey for winter [26]. The natural honey is 80% sugar (glucose, fructose and sucrose), 16% water, 4% other stuff. Explicitly, the communication [43], species odors, life style/lifespan/eating habits all together result in exploring and exploiting nectar source from flowers even 10 miles away from the hive. The hierarchy in the species, their tasks and outcome in HB foraging is collection of nectar from flowers, conversion into honey and storage without any fermentation and so on. Production of royal jelly (food of broods), waxy materials (for repair of comb) and conversion of nectar into honey are specialized biochemical skills. Detecting flower patches, looking for a new hive are constrained search processes. Building hive with a perfect repetitive structure, fanning and sprinkling water droplets to maintain temperature and moisture for honey quality and preservation are physical processes executed by worker honey bees. Hive maintenance and defense again are distributed processing. Waggle dance is an astounding expression of remembered information by employed bees regarding location, quality and quantity of honey.

The honeybees have the capacity to remember the spatial location of food source and prospective hive location. It appears that it performs computation of angle between two vectors i.e., sun to hive and hive to food source [26]. The other guess is making calculations based on view points and land marks. Still it is a stigma which of the two is true. The bees use stimuli during the flight. The second one is that they encode the spatial information in their dances into their map of spatial memory.

The decision of Onlookers is a collective one. The scouts and employed bees collect information during exploration and nectar collection. In fact, the scout bees have long term memory. After first exploration of nectar source onlookers also visit the neighboring region. Self-organizing behavior in honeybees is in decisions in selecting the hive site, continuing foraging of a flower patch. Queen bee is always surrounded by number of workers. It is for feeding purpose and licking the queen although its movement is restricted to the nest except during mating flight.

- **Hive site selection**

The factors that honeybees try to consider in selecting site for a new hive bee are the size of the cavity to hold the honey comb, tightness of the cavity, weather conditions and construction time. It is laudable that the swarm of honeybees arrives at unified decision without conflicts in this multi-optimization vague task. Many bees explore in parallel the sites for the hive. Again dancing is the communication language to share the characteristics of explored sites with other bees. The best among many alternatives is selected by means of various coalitions. Inspection by scout bees prevents selection of poor sites. If a site is superior judged by scout bees than that advertised through dances, the latter is preferred.

Waggle dance of honey bees

Karlvon frishch [43] was awarded Nobel Prize for explaining the waggle dance of the forager honeybees. Waggle dance contains three vital pieces of information regarding flower patch viz. direction (the angle between the sun, hive and patch), distance and quality/approximate quantity of nectar. The waggle dance reflects the amazing capability of these stringed-insects to communicate with other bees. This dance is a miniaturized reenactment of foraging flight from the hive to the flower patch and is a tool rather than a behavioral pattern rigidly exhibited. The desirability or worth exploiting of a resource is proportional to the liveliness and enthusiasm in the dance. The duration of the dance lasts for several minutes to hours if the source is richer. Thus, waggle dance serves three diverse purposes, viz. hive selection, foraging and also mating. But, in some category of bees waggle dance is not that important. How a forager bee grasps the angle and the distance is worth exploring biological-phenomenon.

*Description of waggle dance:*Honey bee switches between a set of waggle (Fig. 2.5), turn-right and turn-left dances. The dance is a set of repetitive movements of the bee [77]. For us, humans, it appears as a

Fig. 2.5: Waggle dance of foraging honey bee

code language. But, how the small honey bee with its brain much smaller in size translates the information stored in its neural mess (system) into repeatable coded dance is a biological miracle. During the waggle dance, the bee walks roughly in a straight line while rapidly shaking its body from left to right [53]. The turning dances simply involve the bee turning in a clockwise or anti clockwise direction. From waggle dance, direction of the source with respect to the sun from hive is transferred to other bees.

2.5 Mathematical model for social forging of honeybees

Ideal free distribution (IFD) concept is useful to analyze how animals distribute themselves across patches of food and different habitats. IFD is a strict Nash equilibrium and is a special type of evolutionarily stable strategy. The word ideal emphasizes, the animals (insects, fish and birds) perfectly sense the quality of all habitats and seek to maximize the suitability. The term free indicates they do not have a preference to any habitat and moves anywhere.

In the case of honeybees, the foraging and getting honey to the hive is performed with an optimum management of its sources (bees). Quijano and Passino modeled social forging of honeybees using environmental model activities during expedition and unloading nectar, dance strength decisions, explorer allocation, recruitment on the dance floor and accounting for interaction with other hive functions. A differential equation model for dynamic labor force allocation of honeybees is developed and validated with a set of experimental conditions. Cox added the details on energetics to the model and Sumpter introduced a generic-NL- DE-model to represent social foraging processes in bees and ants. It seems that swarms of scouts and employees are deployed for a specific task.

3. Artificial honey-bee-foraging-algorithm (Hb_Fa)

3.1 Translation of biological process (HBFMH) into mathematical methods

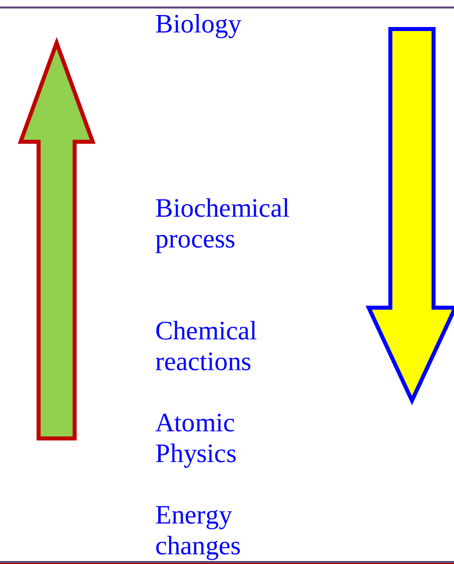
The inter-disciplinary swarm effort and rarely intelligence (nature mimicking)core modeler translates each sub step (process) of a biological/natural process into mathematical form using wisdom bits in bio-processes. The set of these micro steps form an algorithm. The implementation in software is the beginning of application for standard mathematical functions/equations for simulated data and real time field observations. With the notable success, the method will be applied to standard tasks in every discipline of science/engineering/commerce.

The behavior and traits of honey bees involve cognition of the flowers, remembering and recapitulating the direction, distance from the hive and communicating this data to other members of the hive (chart 2.3). The quality of honey is also sensed and transferred to the next batch of foragers. The communication includes waggle dance to transmit the information to onlookers in a small space of hive and in darkness.

Chart 2.3:Processes in life cycle of honeybee Foraging/mating ….

(a)

- ॐ Set of sequential/parallel macro processes
  - Large number of micro-process
    - Many Sub-micro-processes /Nano-processes
      - ✓ Molecular biochemical processes
      - ✓ Bonded/non-bonded/physical interactions
      - ✓ Atomic level/bond level
        - Energy change
          - Rearrangement/transfer/
          - Exchange/ production



(b)Activities in life cycle Natural honey bee		Equivalent method in mathematics/statistics/ computations
Foraging food (nectar in flower patches)		
Exploration	A number of scout bees explore food sources which are even 2 to 10 km without a priori information	Parallel, distributive
Nectar collection	Number of employed bees extracts nectar from flower patches from the same area (?) to exhaust the nectar quickly	Parallel, distributive
waggle dance by foraging HBs	No of onlookers witness the waggle dance • Decision to continue/discard a flower patch	Multiple experts
Skipping waggle dance	Time sense, reduction of waste process, quickening nectar collection (resulting in optimum resource – bees-utilization)	Avoiding tabu-list

	(c) Queen mating with drones	Equivalent method in mathematics/statistics/ computations
Driving off drones (in winter) from hive	Conserving food resources (No costly food wastage on sperm donors)	Leaving aside uninfluential variables/regions Ranges of variables of anti-model
Mating flight Choosing a drone flying with equal speed	Choice of a best spouse	Matching competence
Drone dying just after mating	Shrewd use of resources Protection of sperm in spermatheca from leakage	Use of one type of method once

	(d) Food distribution	Equivalent method in mathematics/statistics/ computations
Different type and quality of food Broods Drones Queen Worker bees	Optimum resource allocation based on need/availability/cost in terms of effort/time	Adaptive hardware/software deployment during execution of a job
Onlookers prioritizing exploitation of food source	Recruiting employed bees Rejecting food source	Collective decision

	(e) Shelter (hive) site selection/ hive design/ hive shifting/	Equivalent method in mathematics/statistics/ computations
Hive rejection	Foragers, decision makers	Collective decision

KB. 2.2.: Exploration and exploitation components

If Exploration and exploitation process are in same procedure (may be in different segments)

Then Algorithm is desirable

Domain	
Honey foraging	Optimization
Position of food source	Possible solution
Amount of nectar	Fitness (quality)
Number of bees	Number of solutions
Honeybee class	Type of method

3.2 Honey-bee-foraging-algorithm (HB_FA)

Karaboga et al. [15] proposed artificial bee colony (ABC) algorithm in 2005 from the inspiration of foraging tactics of honeybees in nature. The co-ordinates of position of a food source represent a possible solution of the optimization function. The quantity of nectar in the flower patch corresponds to the quality (fitness) of the associated solution. Over years, noteworthy modifications [24, 26, 68, 74-75, 84, 93] have been implemented widening the scope of algorithm for multi-objective optimization, clustering in diverse fields of engineering, science and technology. The basic assumptions, pseudo code and data structure follow.

Basic artificial bee colony (ABC) algorithm (Alg. 3.1): A randomly distributed initial population of solutions is generated. Each solution xi (i = 1, 2, . . . , N) is a D-dimensional vector of design variables. The functional values of all solutions for the object function are evaluated and sorted into ascending order. The follow up is repeated cycles of search process by employed, onlooker and scout bees. An employed bee produces a modification to the solution (in the neighborhood) depending on the local information. If the objective function value of the new solution is better than that of the earlier one, the artificial bee memorizes the new position and forgets the old one. Otherwise she keeps the position of the previous one in her memory. It is repeated for all employed bees. Then, they share the fitness function values of the approximate solutions and their position information with the onlooker bees. The onlooker bees evaluate the fitness information from all employed bees. An unanimous collective decision is the choice for solution with a probability related to its fitness value. An onlooker bee also produces a new solution and memorizes the new position, if its fitness value is better than the previous position. When needed scout bee comes to play and explores all together a new solution using random search. When the convergence criteria is satisfied or after a preset number of cycles (or CPU time), the solution of optimization function is displayed with details.

Alg. 3.1: Basic ABC and modification

Artificial Bee Colony (ABC) algorithm

Initiation

Do while Not converged | iter < iterMax

For All foragers
Position_Fitness_Comp

ABC_assumptions
- Only one source exhausted in each cycle
- Only one employed bee becomes a scout
- ✓ It is a negative feedback mechanism
- ✓ Fluctuation property in the self-organization

Chart 3.1 Variables and free parameters in Honey bee foraging algorithm

Fixed parameters
- Honey bee specific
- Optimization specific

Workbees(number,hive)
Foraging_bees(i, time)
Onlooker_bees(i, time)
Scout_bees(i, time)
Employed.foraging_bees
Unemployed.onlookers
Unemployed.scouts

Number of best empl
Number of onlooker employed bees
Number of onlooker employed bees
Number of scout bees

Limitations of ABC [75]
- − Frequency is fixed
- − Refinement of one parameter of the parent solution xi →
- − Slow convergence rate

Remedy: Control introduced

Remedial measures[75]
- \+ Controlled frequency of pe
- \+ Parameter modification →
- \+ Uniform random distri each parameter xij

Initial positions & Fitness function values
- Honey bees
- Foraging
- Onlookers
- Scouts

- Position_bee-Ap
- Fitnessvalue
- Fitnessvalue_Be

New positions & checks
- New position
- Check for crossing fence
- Remedial measures

- FitnessValue
- Ascending orde
- Best, best-of-bes

end
For All on-lookers
Roulette Wheel selection
Position_Fitness_Comp
End For

If Scout-bees
Initiation
Position_Fitness_Comp
End
Best solution

End while

Initiation of population of bees in Hb_Fa by Levy flight and patch environment: The initial values of approximate solution are randomly generated from user chosen/ default values of minimum and maximum ranges in all dimensions. Hussein et.al. [82] applied patch concept and Levy flight distribution to initialize foraging bees in Hb_Fa (FormulaeBase 3.1).Boltzmann selection is employed instead of roulette wheel and the initial group is rendered symmetrical.

<table>
<tr><td>FormulaeBase 3.1: Initiation of bee positions</td><td>Population of initial solution (food sources are randomly generated)
place each employed bee on a random position in the search space</td></tr>
<tr><td>Scout_bee
$$x_i^j = \text{xmin}^j + rand(0,1) * \left(\text{xmax}^j - \text{xmin}^j \right)$$ Formula 3.1</td><td>

```
function [xinit] =
x_init_forgBees(nbees,xmin,xmax)
[row,col]=size(xmin)

     xmin,xmax
for i = 1:nbees
     rand_10= rand(1,col);
for j = 1:col

         xinit(i,j) = xmin(1,j) +
rand_10(1,j) *(xmax(1,j) -xmin(1,j));
end
end
```

</td></tr>
<tr><td>Example
xmin =
0 0
xmax =
-1 2</td><td>xinit =
-0.9462 1.8129
-0.3927 0.0497
-0.6714 1.6743
-0.9715 0.1139
-0.4503 1.1649
-0.6866 1.4389</td></tr>
<tr><td>If nbees = 2; dimX = 8
LimitCycles =

16

>>LimitCycles_init
LimitCycles = 200; Default value assumed</td><td>

```
%
function [LimitCycles]=
LimitCycles_init(xpos)
if nargin ==0
      LimitCycles = 200;
      disp(' LimitCycles = 200; Default
value assumed')
else
      [nbees,dimX] = size(xpos)
      LimitCycles = nbees * dimX;
end
```

</td></tr>
<tr><td>Foraging bee initialization in Hb-Fa</td><td></td></tr>
<tr><td>Hb_Fa shortcoming
– Local optima
– Low convergence speed</td><td>Levy flight + HB_Fa
+ High-dimensional benchmarks
+ Better solution quality</td></tr>
</table>

Remedy	
Levy flight Patch environment	+ Higher convergence speed + Increased success rate

Fitness function: The object function (single or multiple transformed into a single) is task dependent and/or user chosen (FormulaeBase 3.2c). In nature inspired approaches (since proposal of genetic algorithm), fitness function (or simply fitness) had been popular respecting Darwinism and the same terminology is continued here. The fitness functions and calculation of fitness function values in Hb_Fa for current values of X are given in FormulaeBase 3.2. The goal again consists of multiple sub-goals and each sub-goal may be minimum, maximum or Pareto front and so on.

FormulaeBase 3.2: **FitnessFnValue**

FormulaeBase 3.2(b):Object Function value

```
%
%
function [objFnVal ] = objFnVal_om(x)
 objFnVal = objFn_om(x);
```

FormulaeBase 3.2(c): Object Function

```
function [zobjFnVal] = objFn_om(x)
     [row,col] = size(x);
for i = 1:row
zobjFnVal(i,1) = 0.;
for j = 1:col
             zobjFnVal(i,1) =
zobjFnVal(i,1) +(x(i,j).^2);
end
end
```

Example:	x =	objFnVal =
	1	1
	2	4
	3	9

$fitnessFn(xi) = \begin{cases} \dfrac{1}{1+f(Xj)} & if\ \ f(Xj) \geq 0 \\ 1+\lvert f(Xj) \rvert & otherwise \end{cases}$	Formula 3.2.1
$Goal\ = \ min(objFnValue)$	Formula 3.2.2

```
function [fitnessFnValue] =
fitnessFnValue_om(objFnVal)
     [row,col]= size(objFnVal);
     k = 0;
for i = 1:row
          k = k+1;
if objFnVal(i,1) > 0 | objFnVal(i,1)
== 0
             fitnessFnValue(k,1) =
1./[1+objFnVal(i,1)];
else
            fitnessFnValue(k,1) = 1+
abs(objFnVal(i,1));
end
end
```

Example:	objFnVal =	fitnessFnValue =
	1	0.5000
	4	0.2000
	9	0.1000

Example:	objFnVal =	fitnessFnValue =
	-2	3
	-3	4
	-4	5
	-5	6

```
function [zzworst,zzbest,zzworstset,zzbestset] = sortXY_om(fitnessFnValue,xpos)
[fitnessFnValue,xpos]
     zz = sortz([fitnessFnValue,xpos]);

      [fitnessFnValue_xpos] = zz;
      [row,col]=size(zz);
      nn = round(row*30/100);
if nn <1, nn=1,end;
zzworst = zz(1,:);
zzbest = zz(row,:);
zzworstset = zz(1:nn,:);
zzbestset = zz(row:-1:row-nn,:);
```

Example

```
6     5     4     3     2     1 %FitnessFnValue'

1     2     3     4     5     6 %xpos'
>>[zzworst,zzbest,zzworstset,zzbestset] =
sortXY_om(fitnessFnValue,xpos)
```

```
zzworst =
     1     6
zzbest =
     6     1
zzworstset =
     1     6
     2     5
zzbestset =
     6     1
     5     2
     4     3
```

Refinement of approximate solutions

The improvement of approximate solutions in Hb_Fa is multiphase and/ or hierarchical. Like in natural honey bee foraging, three steps viz. work_bees, on_looker and scout_bee participation in enhancing the quantity and quality of nectar is implemented in optimization process (FormulaeBase 3.3) as fitness function values.

Foraging (employed/work) bees: The refined solution considering neighborhood of current solution is calculated using uniform random number in different ranges ([0, 1]; [-1 1]) and corrections for betterment (FormulaeBase 3.3).

FormulaeBase 3.3: Refined (new) search positions

Employed_bee

$$xnew_{i,j} = x_{i,j} + randU_{i,j} * \left(x_{i,j} - x_{k,j}\right)$$ Formula. 3.3.1

$$xnew_{i,j} = x_{i,j} + \left(2 * randUm11 - 1\right) * Max\_Neighsize_j$$ Formula. 3.3.2

$$xnew_{i,j} = x_{i,j} + randU_{i,j} * \left(x_{i,j} - x_{k,j}\right) + \\ + randU0c * \left(xbestGlob_j - x_{i,j}\right)$$ Formula. 3.3.3

$xnew$	Refined solution (food source)
x	Approximate solution

```
function [xnewpos] = newPos_HB(x)

[nbees,colX] = size(x);
randnum = rand(nbees,colX);

%%   choice of k
%
for i = 1:nbees
for j = 1:colX
         [k] =
choiceOf_k(nbees,colX,i);

         xnewpos(i,j) = x(i,j) +
randnum(i,j)*  ((x(i,j)-x(i,k)));
end
end
```

```
function [k] =
choiceOf_k(nbees,colX,ith)
intnum = [1:ith-1 ith+1:nbees];
k = intnum(randi([1
numel(intnum)]));
```

$Max\_Neighsize$	Maximum neighbor size
$randUm11$	$uniform\,random\,number\,[-1\,to\,1]$
$randU$	$uniform\,random\,number\,[0\,to\,1]$
$randU0c$	$uniform\,rand\,number \in [0, const \geq 0]$

If	Constant increases from 0 to a constant value
Then	Exploitation increases
If	Constant >large value
Then	Weakens exploration
	g best term will drive the new candidate to move over global best soln. It will exploit eqn.2

$$xnew_{i,j} = \begin{cases} xcurmem_{ijk} + randU*\left(xcurmem_{ijk} - xrand_{ijr}\right) & if\ randU < ModRate \\ xcurmem_{ijk} & otherwise \end{cases}$$

Formula. 3.4.2

$xcurmem$	Current memorized position, Neighborhood solution (food source) $r \neq q$
$xrand$	Randomly chosen index

```
function [xnewpos] =
newPos_HB_2(x)
%   HB-118
ModRate = 2.4;

[nbees,colX] = size(x);
% randnum_m1To1
randnum = rand(nbees,colX);
randnum_01= rand(nbees,colX);
for i = 1:nbees
for j = 1:colX
        [k] =
choiceOf_k(nbees,colX,i);

if randnum_01 < ModRate
            xnewpos(i,j) =
x(i,j) + randnum(i,j)* ((x(i,j)-
x(i,k)));
else
            xnewpos(i,j) =
x(i,j);
end

end
end
```

Example:	xpos =	xnewpos =	xnewpos =
	1 2 3 4	0.9748 2.0000 3.0000 4.8541	0.3372 2.0000 3.0000 4.118 ModRate = 2.4000
		newPos_HB.m	newPos_HB_2.m

Example:
xpos =
1 3 4 6 7 8 9 10
2 4 5 7 8 9 10 11

```
xnewpos =
  -0.6364   3.0000   4.0567   7.0075   7.8358  11.3770  14.4728  15.2188
   2.0000   4.7193   6.5657   7.8783  13.4309  12.2793  10.8321  17.6264      % newPos_HB.m
```

```
ModRate =
   2.4000
xnewpos =
   0.0879   3.0000   4.2973   6.8947   9.0217  11.1553   9.4852  16.3359      % newPos_HB_2.m
   2.0000   4.6642   5.1861   7.2318  12.5686   9.6292  16.2179  15.8039
```

Check and remedial measures to prevent crossing boundaries: Measures are in operation to avoid the refined solution crossing the constraints (FormulaeBase 3.4) like minimum in the co-ordinates.

FormulaeBase 3.4: Prevention of crossing boundaries

Check for new position of Employed bee	
$$xnew_{i,j} = \frac{\left(\mathrm{xmax}^{j} - \mathrm{xmin}^{j}\right)}{2} \quad \vert if \;\; xnew_{i,j} < \mathrm{xmin}^{j}$$	Formula. 3.4.1

```
function [xnewpos_] =
check_newPos(xnewpos,xmax,xmin)
[nbees,colX] = size(xnewpos);
xnewpos,xmax,xmin
for i = 1 : nbees
for j = 1:colX
if xnewpos(i,j) < xmin(1,j)
            xnewpos_(i,j) =
(xmax(1,j) - xmin(1,j))/2;
end
end
end
```

Example:	xnewpos =	xmax =	xnewpos_ =
	-3 -4	-1 2	-0.5000 1.0000
	-4 -2	xmin =	-0.5000 1.0000
		0 0	

Onlooker bees: Based on fitness function values, the probability for selection of on looker bees is calculated. If probability (FormulaeBase 3.5) exceeds threshold, on looker bees comes into operation and the nearby flower patches are tested. It means the refined solution in the first phase is further fine-tuned.

FormulaeBase 3.5: Probability of fitnessFnVal

Onlooker bees

$$prob = \frac{fitnessFnVal(xi)}{\sum_{i=1}^{Nsol} fitnessFnVal(xi)}$$

Formula. 3.5.1

$$prob = \frac{0.9 * fitnessFnVal(xi)}{\sum_{i=1}^{Nsol} fitnessFnVal(xi)} + 0.1$$

Formula. 3.5.2

```
%
%
function [prob] = prob_om(fitnessFnVal)

fitnessFnVal_best = fitnessFnVal;
prob.onlooker    = fitnessFnVal./sum(fitnessFnVal);
prob.preference = 0.9*
fitnessFnVal./sum(fitnessFnVal_best)+ 0.1;
```

$finessFnVal\_best$	Quality of best solution among the current solutions

If	onlooker selected
Then	update solution

`

	fitnessFnVal	Prob. Onlooker	Prob. preference
Example:	1	0.1000	0.1900
	2	0.2000	0.2800
	3	0.3000	0.3700
	4	0.4000	0.4600

Scout bees: When the combined efforts of foraging and onlookers are inadequate to arrive solution of desired accuracy, the only choice is to start from square A i.e. random exploration with an another seed. It is executed under the name scout_bees search (FormulaeBase 3.6).

FormulaeBase 3.6: Scout bee search

Scout_bee [35, 58]

$$xinitSout_{i,j} = \left[\mathrm{xmin}^{j} \right]_{ABC} + \mathrm{costant} * \left(\mathrm{xmax}^{j} - \mathrm{xmin}^{j} \right)$$

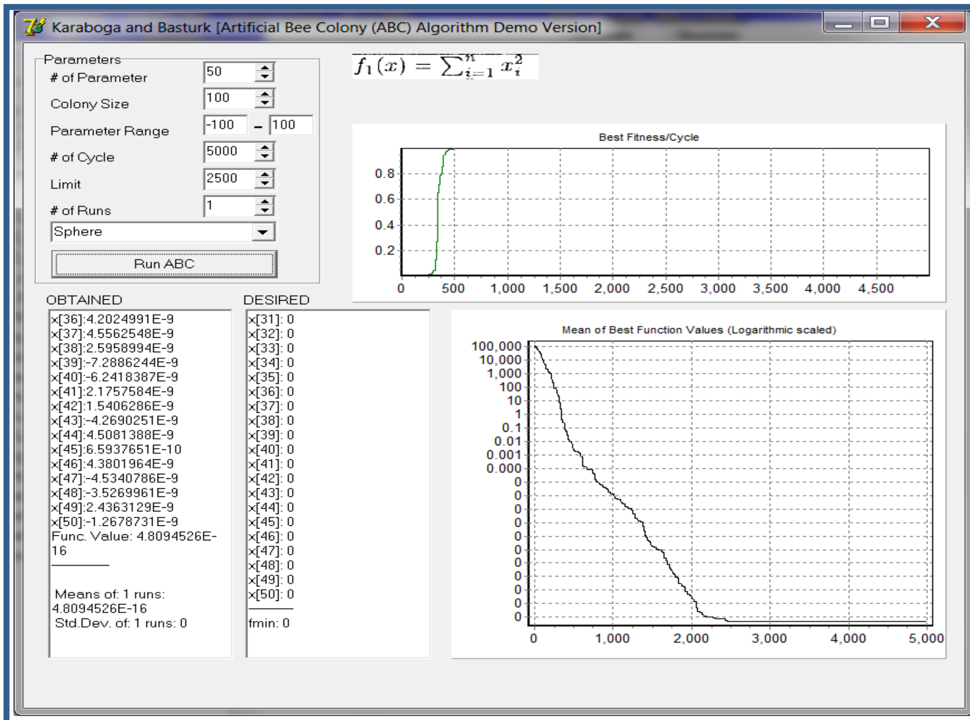
Formula. 3.6.1

If		then
constant=0		Exploration
Constant >high		Exploitation
Low<constant<high		Partial exploration & Partial exploitation

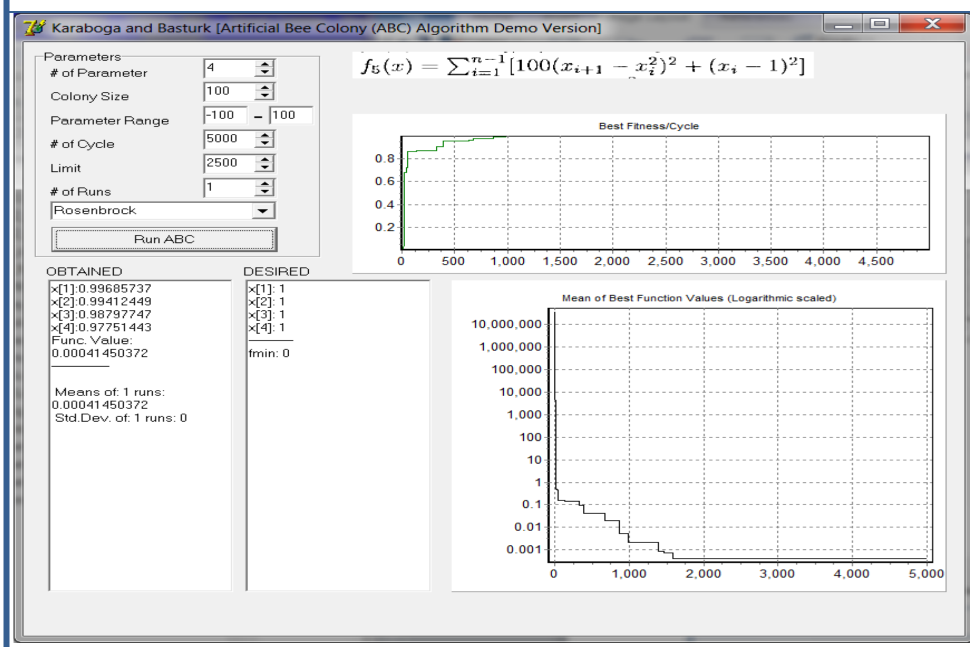
```
function [xinit_ScoutBees]=
scoutBee_init(nbees,xmin,xmax,locglob)
%
    exploration = 0; exploitation = 0;
exploreExploit = 1;
if exploration
        locglob = 0;
end
if exploitation
      locglob=1;
end
if exploreExploit
          locglob = 0.5;
end
for j = 1:col
         xinit_ScoutBees(:,j) =
xmin(1,j)*ones(nbees,1) +
locglob2*(xmax(1,j) -xmin(1,j));
end
```

3.3 Examples of ABC

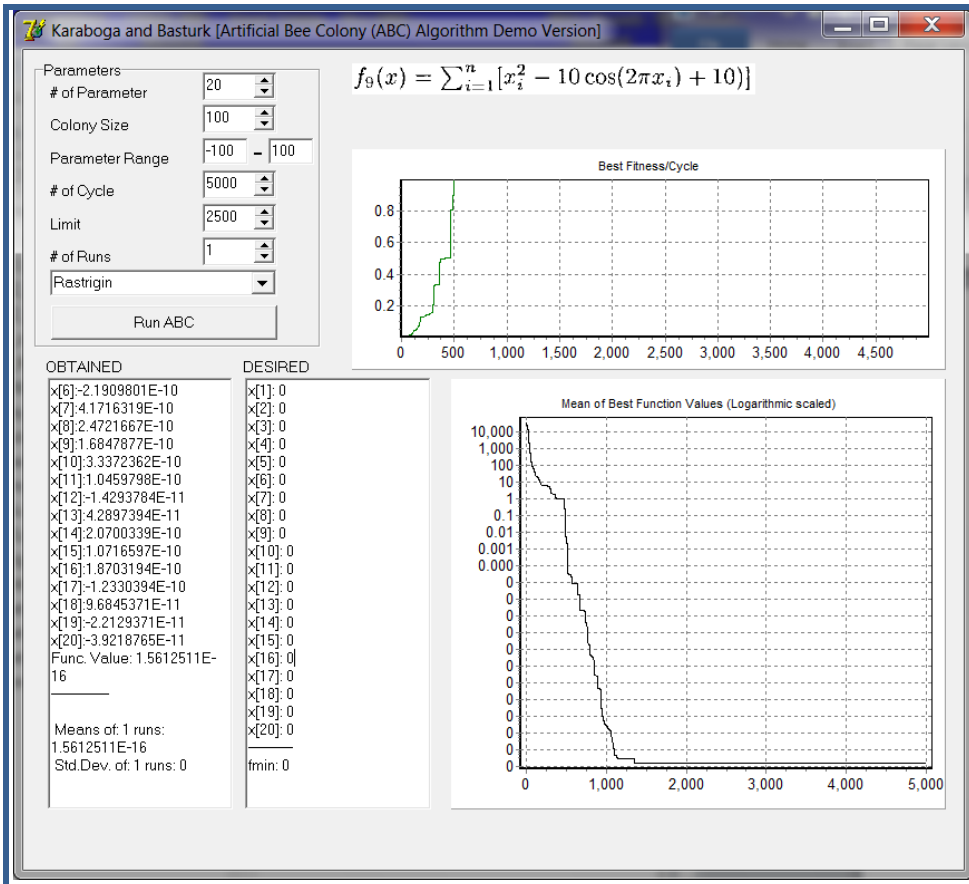
>> !ABC_demo2	



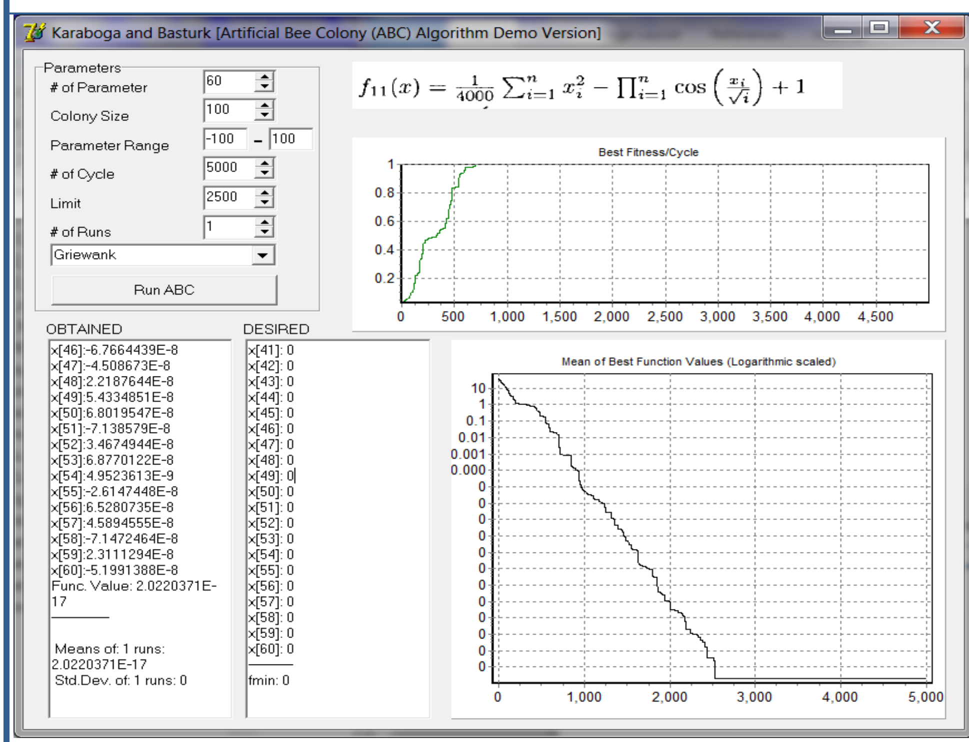
objFn	Sphere
xDim	50
xOpt	0.
Fmin	0



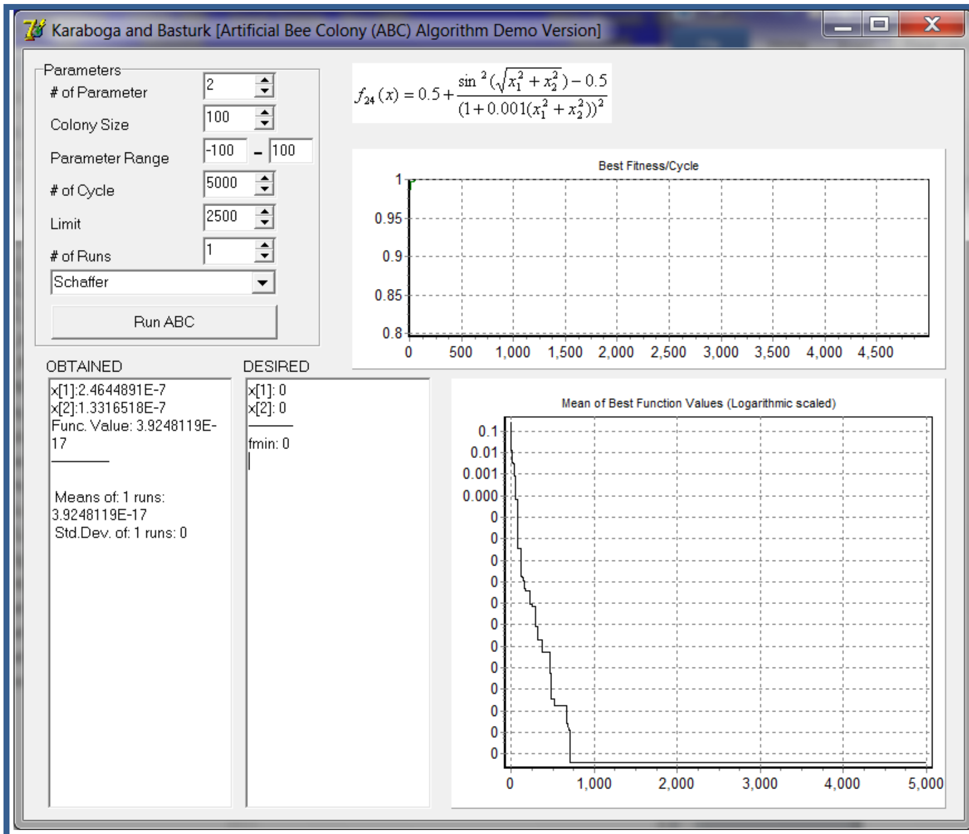
objFn	Rosenbrock
xDim	4
xOpt	1
Fmin	0



objFn	Rastrigin
xDim	20
xOpt	0
Fmin	0



objFn	Griewank
xDim	60
xOpt	0
Fmin	0



objFn	Schaffe
xDim	2
xOpt	0
Fmin	0

ABC with chaotic search: Xu [43] performed chaotic search (chart 3.1b) in the neighborhood of best solution arrived by ABC search process by each bee.

Chart 3.1b: Hybrid chaotic algorithm	
ABC + chaotic search + Better solution than that by ABC [HB 46/1578 ,HB 43/538]	**chaotic search** + Chaotic search by individuals of sub generations distribute ergodically in the search space. + Avoids premature convergence. + Speedy optimum + irregularity and ergodicity of the chaotic variable + jumps from local optimum

Bee Hive Algorithm: A protocol inspired from dance language and foraging behavior of honeybees is used.

Bee colony optimization: It looks like ACO. It differs from ACO in the fact that concept of pheromone trails is not in HB.

Bee Dance algorithm: The bee dance is transformed in to solution methods for optimization tasks (Alg. 3.2).

Alg. 3.2 Bee Dance Alg		
Initiation		

Do	until iter < iterMax		
	Do	While not converged	
		For	All elite bees
			Elite bees
			Dance_BestObjFnVal
		end	
	End	converge	
	For	all Non elite bees	
		Dance_BestObjFnVal	
	end		
	For	all non-selected bees	
		Dance_BestObjFnVal	
	end		
	Best_Bee_sofar		
End	iter		

Dance_BestObjFnVal
Bee dance
objFnValue
Best value

3.4 Applications of HB-Fa

The applications of honey bee foraging algorithm spread into engineering, science and mathematical sciences very fast. ABC and Virtual bee algorithms are applied to continuous/discrete high dimensional (multivariable), multimodal unconstrained/ constrained continuous/ mixed integer non-convex (concave) optimization tasks [15] with noteworthy success. It modeled water [18] resource management including ground water, heat exchange network synthesis, signal processing, designing low and higher order digital (unimodal and multi modal) IIR filters, multi-hydropower reservoir, economic load dispatch with valve-point effect, radial distribution of power systems, Optimized dam height, power plant installation capacity, releases from reservoir, communications, design of welded beam structure, camera calibration and electro–chemical machining process. Hb_Fa has edge over other algorithms in pattern classification/clustering in medical diagnosis, TSP task, parameter extraction in MESFET and training neural networks.

Design of two-channel quadrature mirror filters (QMF): Agrawal and Sahu [95] found a solution of design of two-channel quadrature mirror filters with linear phase using ABC algorithm and results are compared with PSO,DE and mathematical optimization algorithms (chart 3.2).

Chart 3.2: Optimization function

ObjFn = weighted sum (Terms)

Terms : [pass-band error;
stop-band residual energy of low-pass analysis filter;
square error of the overall transfer function at the quadrature frequency
amplitude distortion of the QMF bank]

Goal Min(ObjFn)

Applications
- Trains LVQ, MLP in PR
- MLP to model inverse kinematics of robot arm
- suitable for solving local and global optimization problems

Chart 3.3: Nature inspired algorithms in nuclear reaction research

- Simulated Annealing
- Genetic Algorithm
- Tabu Search
- Population-Based Incremental Learning
- Ant Colony Optimization
- Particle Swarm Optimization

Predictive control of Non-linear systems: Sarailoo et. al. [98] used honey bee foraging algorithm for solving open loop optimization problem. The object function is minimized with an aim of finding best continuous and discrete inputs subjected to constraints for a model system.

Nuclear power reactors

Maghali et al. [54] applied ABC with random keys for in-core fuel management optimization (ICFMO) in a pressurized water reactor (PWR) of nuclear power plant. The goal is maximum operation time of PWR by optimization of arrangement of fuel.
This task was rated as combinatorial multi-modal hard task and without rethought, heuristic procedures is only option. Chart 3.3 summarizes a few of earlier success stories in the design of loading pattern of fuel rods. LP (loading pattern) design experts' verdict was preferred although soft computing procedures are reported with acceptable success quotient. The boron concentrations in ppm over nine experiments with ABC-RK (50 bees) is better than results after 50,000 evaluations of GA and PSO. The diagnostic tests of accidents in PWR is complicated network of high dimensionality and ABC resulted in efficient prediction.

Bioinformatics

Protein sequence prediction: Benıtez and Lopes [33] applied sequential, parallel ABC algorithms in master-slave and hybrid hierarchical modes for Protein Structure Prediction (PSP) of four protein sequences (chart 3.4). Here, four synthetic 27 amino acids-long sequences are used as test proteins in the bioinformatics. Chart 3.5describes a few more applications of Hb_Fa.

Chart 3.4: Protein Structure Prediction	
Hardware	cluster of networked computers 124 processing cores
OS	Linux
software	ANSI-C
	Message Passing Interface (MPI) MPICH2 package for the communication between processes

Chart 3.5 Typical applications of Hb_Fa

Task	Compared with $$$
Two-sided Assembly line	ॐ Fuzzy logic
Clustering	ॐ HBF >> [PSO cooperative_PSO]
feedback controller design for a boost-type DC-DC converter	ॐ HBF >genetic algorithm.
Electric power plant	ॐ Binary_PSO ॐ GA
Image processing	ॐ PSO ॐ Hybrid cooperative- ॐ Comprehensive- learning based PSO algorithm ॐ Fast Otsu's method ॐ HBMO
Single reservoir operation	ॐ HBM>GA
leaf-constrained minimum spanning tree	ॐ GA, ACO ॐ Tabu search

3.5 Beneficial features and limitations (chart 3.6)

Chart 3.6 : Positive features of ABC algorithm

- + Robust compared to other multi-modal and m-D function solvers
- + Superior to deterministic simplex, stochastic (SAA, GA, ACO) algorithms in speed and accuracy
- + Neighbor production and selection schemes used in ABC algorithm make
- + Fast convergence
- + Simple and flexible
- + Inherently parallel
- + Self-improvement
- + Local search ability
- + Does not settle in local optimum
- + Very few control parameters
- + Has the ability to get out of a local minimum
- + Avoids solution of complex MIN-LP models
- + Easily scalable to large problems
- + Copes up with constraints like forbidden matches and imposed matches
- + Incorporation of safety and layout consideration

Limitation of Nature inspired algorithms

- – Artificial HBF or HBMA don't follow in-toto the real bees foraging or mating

- ✈ Onlooker uses the whole information of food sources of all the employed bees to determine best for further exploration which food source will be followed to conduct the extensive searches
- + Obviously, this treatment will reduce the diversity of the algorithm, thereby reducing global search ability of the algorithm

3.6 Comparison of HB_Fa with other algorithms: The performance of ABC is compared with a variety of algorithms (chart 3.7).

Chart 3.7: Comparision of ABC with other algorithms

ABC	#
Colony size	20
Maximum cycle/ Generation number (MCN)	1000
Limit value	1000

	ABC	PSO
Average	**13.13**	15.99
# evaluations	20,000	50,000

Classification techniques based on	Algorithm	Average
Bayesian based	Bayes Net	13.17
Function based	MLP, NN	**12.35**
	RBF-NN	26.93
lazy	KStar	14.71
meta-techniques	Bagging	13.30
	MultiBoostAB	22.92
tree-based	Naive Bayes Tree	14.68
rule-based techniques	Ripple Down Rule	15.38
	Voting Feature Interval	18.89

Chart 3.7(b) : Hb_Fa compared with	HB-114
• Genetic Algorithm (GA) • Differential Evolution (DE) • Particle Swarm Optimization (PSO) • Particle Swarm Inspired Evolutionary Algorithm (PS-EA)	→ Optimization → constrained → unconstrained problems
• training neural networks	→ tested on XOR → Decoder–Encoder

	→ 3-Bit Parity → Pattern classification

Table 3.1: Performance comparison of different optimal algorithms onmathematical function for 30 random runs

Algorithm	Mean value of the best objective function	Mean number of total iterations
GA	1.2342	1000×125
PSO	0.011151	1000×125
PS-EA	0.8211	1000×125
ABC	2.87×10−9	1000×125
Proposed algorithm	2.68×10−9	98645

Exhaustive comparison of ABC algorithm: Aydin [96] exhaustively studied ten recent ABC procedures and other state-of-the-art algorithms with test data sets. Here, best components of each step of honey bee algorithm are selected.

3.7 Modified Hb_Fa: The convergence rate of ABC is improved by integrating search iteration operator based on the fixed point theorem of contractive mapping in Banach spaces. The Newtonian law of universal gravitation increases exploitation capacity of onlooker phase in ABC. The addition of shift neighborhood and greedy randomized adaptive search heuristic improves the efficiency of ABC in specific applications like generalized assignment problem. The popular procedures EA with local search, ACO with hill climbing, hyper-heuristic memetic algorithm, informed GA, tabu search, graph-based hyper-heuristic and combination of multi-start large neighborhood search approach with local search methods gave a facelift to ABC foraging approach in solving real life tasks.

ABC with memory algorithm (ABCM): Li and Yang [106] proposed honey bee foraging algorithm with memory inspired by biological data of natural honey bees. It excels ABC, quick-ABC etc for typical bench mark test problems.

Balance-evolution artificial bee colony (BE-ABC): This modification in basic ABC increases the balance between exploration and exploitation rather than a greater focus on either of them [109]. It makes use of convergence information to reorient and increase in intensity in both phases. It includes overall degradation method to employ scout bees and prevent premature convergence. This procedure is applied to grey scale image recognition. The lateral inhibition (LI) model is used in pre-processing which widens the gray level gradients promoting image retrieval more efficiently.

3.8 Hybrid HB_FA algorithms

Levy flight distribution + ABC: Aydoğdu et. al. [104] analyzed design of steel space frames with a combined algorithm consisting of Levy flight distribution for the search by scout bees and original honey bee foraging principle. The results are found to be efficient and robust. This task is complicated due to discrete design variable and highly non-linear constraints.

Search heuristics + ABC: Yurtkuran and Emel [90] introduced six heuristic rules for operation of ABC to fill the gap of poor exploration (chart 3.8) and tested with increasing dimensions of benchmark test functions with remarkable results.

Chart 3.8: Operation of Heuristic rules in adaptive ABC
ABC + Good exploration – Poor exploitation ☎ **Remedy :** Heuristic rules

Neighborhood structure + Hb_Fa: Routing problem: Iqbal et. al. [101] hybridized ABC with two step constrained local search for neighborhood selection for multi-objective routing task.

Grenade Explosion + ABC: Zhang et. al. [91] hybridized grenade explosion method (good at exploitation) with ABC in employed bees search or in onlookers' decision phase. The hybrid algorithm is better than ABC, its variants on test functions. The robustness and efficacy of GE_ABC_onlookerBees is better than GE_ABC_employedBees.

Avalanche forecasting: Singh et.al. [100] developed a forecast model for avalanches due to snow flakes with Hb_Fa for Himalayan region (chart 3.9).

Chart 3.9: Avalanche forecasting

Input	Variables : snow-meteorological episodes of avalanche
Output	Avalanche forecast
ObjFn	Max(Forecast accuracy)
Earlier Methods	Nearest neighbors

Complexity	Multiple optima
Expt Design	uniform random sampling
Calibration	NN
Heuristic Method	Hb_Fa
Test data	two avalanche prone regions of Indian climatologically diverse

Detection of anomalies in TEC (Total Electron Content) seismic-ionosphere: Akhoondzadeh [92]investigated the relationship between strong earthquakes and seismo-ionospheric anomalies using Hb_Fa algorithm with several advantages (chart 3.10).

Chart 3.10: Hb-Fa for seismic-ionospheric anomalies

Earthquake	Time
Chile	27 February 2010 01 April 2014
Varzeghan	11 August 2012
Saravan	16 April 2013
Papua New Guinea	29 March 2015

Advantates of Hb-Fa

- Detection of discord patterns in a large non- linear data from a short time series data
- Efficient solution for multimodal and multidimensional optimization surfaces
- Simplicity
- Less control parameters

4. Honey bee mating in nature (HB_Min)

The honey bee mating process in real bees [32] consists of a number of different micro processes which are not easy to understand at molecular level. The entire process of honeybee mating and continuation of life cycle of honeybees is also very fascinating in nature. The single queen/ swarms of drones for reproduction, onlookers/ scouts/employed ones for food foraging and working bees for brood care/serving queen/maintenance of hive/ honey preservation/defense from invaders of hive, all play indispensable role in the natural life cycle of honey bees.

4.1 Mating flight: The queen performs a dance in the hive and the proceeds for a mating flight in the air. The queen initially has maximum flying speed. The drones from the same hive as well as from other hives participate in the SAGA [26].

KB. 4.1: Selection of Drone	
If	random probability < calculated probability,
Then	Drone inserts its sperm into queen's spermatheca & queen's speed is decreased.
If	queen's speed is decreased &
Then	Another drone from flying population selected

The drone widely opens its eyes to select the queen. From the set of drones, the one with similar speed has a chance (probability) of mating with queen. The probability with which a drone mates with the queen depends upon the speed of the queen and the fitness of queen as well as drone. During mating sperm of the drone is deposited in the vagina of the queen. The organ of the drone functions as a cap to reduce the loss of the sperm traveling into the "spermatheca" and forms the genetic pool [26]. The drone dies then and there. Although the speed of flying of the queen decreases, it continues mating with other drones one by one. The queen (honeybee) participates up to a maximum of 10 to 12 male bees (drones) sequentially during the mating flight in air. The queen returns to the hive, in other words, mating flight ends. This happensif the energy of the queen falls below a threshold level (which is close to zero) [14] or spermatheca is full. Sometimes, queen goes on several mating flights and the sperm in spermatheca is used for the rest of life.

Drone reproductive system: The reproductive organ of a drone is stored in the abdomen. A drone flying almost with equal speed with queen catches up and mounts her. Using the hind legs it removes any previous drone's endophallus.

Mating of Drones with queen:Using a contraction of abdominal muscles and hemostatic pressure, the drone everts its penis. And it looks like the force of explosion to push the reproductive organ out of the abdomen. Then it inserts tightly into the queen's reproductive tract. With contraction of abdominal muscles, drone ejaculates. Upon mating, the drone's endophallus and attached internal organs are ripped out of his abdomen. He is dead before he reaches the ground. In this process, the tip of drone's penis ruptures, and is left behind inside the queen. It serves as plug for preventing the leakage of sperm. The mating lasts 5-18 minutes. The part of his genitals remaining inside the queen's vagina is called the "mating sign". The next drone removes it and mates with queen. Sometimes, one sees flying queen with drone attached to her, hanging down in the air.

4.2 Fertilized egg formation: Afterwards it retrieves the sperm from a mixture pool in the spermtheca. Each time a queen lays fertilized eggs, she retrieves at random a mixture of the sperms accumulated in the spermatheca to fertilize the egg. A single egg is fertilized per crossover of randomly selected drones' sperm from the spermatheca of the queen and egg released from queen; the consequence is a single brood. The queen lays continuously around 1500 to 2000 eggs per day for next around two to three years.

4.3 Best gene continuation of Queen and best male selection with Haploid crossover for diversity

One parent, mother is always the best and fittest one (queen). This is queen is selected among the pool after feeding them large quantities of jelly. Once the bee is labelled as queen, it receives special attention all through its life span by a large number of worker bees. This is similar to concept royal blood in good olden times. Even among drones, those flying with similar (high) speed is chosen by the queen and thus male partner is also the best among available in that mating flight. This partially ensures the best gene is continued from mother and also best among males are responsible for progeny, a good sign for continuing high spirits through generations. The random picking up of sperm from spermatheca and cross over operation in the formation of avoid prototype (like cloning) and also ensure diversity at the level of genetic pool.

Haploid crossover: The haploid cross over in honeybees is known as uniform crossover in genetic algorithms (GAs) terminology. The unmarked and marked genes are represented as 'um' and 'm'. The marked genes in the genotype of a drone are complemented (substituted) with the corresponding gene from the queen. The resulting brood retains some of the genes of its mother and the rest of the drone, the sperm of which is picked randomly from the spermatheca. In turn, the drone inherits genes of its queen_mother, the best among that population.

4.4 Built-in Intelligence (SI) in honey bee mating Algorithm (BI_Hb_Mp): Honeybee mating saga is swarm based with respect to drones [55]. In single queen hives, there is no scope swarm intelligence from queen's side, of course even in multi queen hives.Since the drone dies immediately after mating, the question of it participating second time does not arise.The queen stores the sperm of different drones in her Spermatheca. The queen bee pickup part of the genotype of different drones randomly is a probabilistic chore.

The speed profile is like that of simulated annealing (SA). The point of discussion is the relation between speed of the queen and the quality of drone which in turn to reflect the quality of sperm [77].

Open question Sabar [77]: It is interesting to probe into what would be the change in flying speed/height of drone with the changing quality of the sperm?

5. (Artificial) honey bee mating algorithm (Hb_Ma) or Hb_Ma with artificial bees (Hb_Ma_ab)

HB_MA is an instance of meta-heuristic in swarm intelligence consisting of a number of different micro mathematical procedures [26]. Broadly speaking, it is a ternary hybrid artificial intelligence algorithm-2 (AI-2) [32] employing SA, GA and local search operated in sequential manner and thus obviously loose coupled. However, the outcome of HB_MA surmounts the deficiencies of the individual components enabling the use to arrive at optimal solutions for complex problems [18]. The applications grew at a fast pace in many disciplines and modifications to basic version and hybridization with efficient procedures cropped up.

5.1 Translation of Honey bee mating into mathematical model

At the start of the flight the queen flies with maximum speeds. She selects a drone randomly from the population. The mating probability is calculated based on the object function values of the queen and the selected drone. The random number between zero to one is the calculated probability. The decrease of speed of flying of honeybee queen during mating with drones is translated into SAA. Mathematically it is conceived as a set of transitions in a state-space where the queen moves between different states of varying speeds. The encountering of a drone is represented by the probability of state. The breeding process is mapped to genetic algorithm (GA). The feeding of broods and queen bees is like local search methods. Further, the brood care by worker bees is like a local search phase to improve the search or in other words helps to move towards optimum [42].

5.2 Key-features in Hb_Ma from mathematical optimization stand point: Queen is the best solution arrived till that point. Drones are similar/definitely inferior solutions in the feasible solution space. Worker bee plays the role of a heuristic [80]. It improves the solution locally. In the artificial HB_MA, the new solution (brood) has a chance to escape from the local optimum. All other broods and former queen are destroyed. Another mating flight is initiated with a new queen and same pool of drones. Although, Saber

[77] used cross over operator in HB_MA, many others dropped it. The drone is selected based on the fitness using equations 2 and 3.

Initiation Hb_Ma

Queen speed and energy: The initial speed of artificial queen bee at the start of mating flight is randomly generated using chosen/default minimum and maximum values (FormulaeBase 5.1, chart 5.1).

FormulaeBase 5.1: Speed of queen in mating flight

$$speed_{queen} = speed\_\min + rand(.)* (speed\_\max - speed\_\min)$$

Formula 5.1.1

Spermatheca: The sperm of i^{th} drone matedis randomly selected from queen's spermatheca. An integer number (m) between 1 and n is randomly generated.

Chart 5.1: Variables used Hb_Ma

Number of queens	1	NQueens
Number of drones	100 ;15	NDrones
number of workers (caretaker bees)	10	*NWorkers*
Capacity of spermatheca	20 ; 15;50	SpermathecaSize
Number of broods	60	NBroods

Speed of queen at the start of a mating flight	1;
Speed of queen at the end of a mating flight	0.2 randU[0.5,1]
Speed reduction schema (a)	0.98 ,0.93

Mutation ratio (Pm)	0.01
Mutation variation (e)	0.5
CrossOverType	[one_point; Two_point;]
Iteration Max	200

Probability of queen mating with drone: The probability of mating (FormulaeBase 5.2) is high at the start of queen's mating flight (higher speed) or when fitness of drone is comparable to that of queen. This function mathematically is similar to exponential function of simulated annealing algorithm with decreasing values.

FormulaeBase 5.2 : Probability of mating of queen with drone

$$\Delta f = [fitnessFnValue(queen) - fitnessFNValue(drone)]$$

Formula.5.2.1

$$prob(Q\_D) = \exp\left[\frac{-abs(\Delta f)}{speed(t)}\right]$$

Formula.5.2.2

$prob(Q\_D)$	Probability of a successful mating i.e. probability of adding sperm of drone D to Spermatheca of queen Q
$Abs(\Delta f)$	Absolute difference between the fitness of D and the fitness of Q

If	fitness (drone) ; fitness (queen)	OR
	queen's flight speed is high	
Then	$prob(queen\_drone)$ is high	

Speed and energy of queen bee with time: After successful mating with a drone or a natural transition in space, the queen's speed (FormulaeBase 5.3) and energy decrease. Then there is a chance that another drone compatible with this speed participates in mating.

FormulaeBase 5.3: Decay of speed of queen in mating flight	
$speed\_queen(t+1) = randU10 * speed(t)$ Formula.5.3.1	Speed_queen(t): speed of the queen at time t. fac: amount of energy reduction after each transition
$fac = \frac{0.5 * Energy_{initial}}{Speed}$ $Energy(t+1) = Energy(t) - fac$ Formula.5.3.2	

Broods: A large number of broods are continuously generated (FormulaeBase 5.4). The sperm of mated drones stored in queen's spermatheca is picked up randomly.

FormulaeBase 5.4(a): Brood generation [55]		
$sperm(i,:) = \begin{bmatrix} sperm(i,1) \\ sperm(i,2) \\ \\ sperm(i,n) \end{bmatrix}$	$Xbest = \begin{bmatrix} xbest(1) \\ xbest(2) \\ \\ xbest(n) \end{bmatrix}$	For i = 1: nchaos $brood(j) = mean(Xbest) + (Xbest - sperm(i))$ end

Improved brood generation: The sperm from three drones [Sperm1; Sperm 2; Sperm 3] are randomly selected from the queen's spermatheca. FormulaeBase 5.4(b) and 5.4(c) depicts calculation of improved drone positions.

Initial population for CLS:

Chaos ques generate non-repeatable exhaustive set of states (positions) in any domain. Thus, chaotic search is competing with statistical random sequences even in optimization tasks. A way of characterizing chaos is through ergodicity, randomicity and regularity. The best solution (queen's place) is taken as initiation for chaotic series. It is scaled between zero and one.

5.4(b): chaotic approach in refinement of solution vector	
	xmin j: jth value of xminimum x max j: jth values ofxmaximum xj: position of the jth variable

$$X(0,cls)=\begin{bmatrix} x(1,cls,0) \\ x(2,cls,0) \\ \\ x(n,cls,0) \end{bmatrix}$$

$$Cx0=\begin{bmatrix} cx0(1) \\ cx0(2) \\ \\ cx0(n) \end{bmatrix}$$

$$Cx0(j)=\frac{x(j,cls,0)-x(j,\min)}{x(j,max)-x(j,\min)}$$

for	i = 1: nchaos
	$X(i,cls)=[x(cls,i,1) \quad x(cls,i,2) \qquad x(cls,i,n)]$
end	
for	j= 1: n
	$x(cls,j)=x\min(j)+cx(j,i-1)*[x\max(j)-x\min(j)]$
end	

Generation of chaos population: For a set of chaotic variables, the object function values are calculated. The best solution amongst them replaces one randomly selected drone. Tent equation, a popular one in chaotic field, is used in chaotic local search embedded in improved honey bee mating optimization procedure.

5.4(c): Chaotic solution refinement

$$ChaosX=\begin{bmatrix} chaosx(1,:) \\ chaosx(2,:) \\ \\ chaosx(i,:) \end{bmatrix}_{Nchaos}$$

$$chaosx(i,:)=[chaosx(i,1) \quad chaosx(i,2) \quad chaosx(i,j)$$

Xchaosji	jth chaotic variable,
Nchoas	number of individuals for CLS
randU10	random number between [0,1].

```
For     i = 1: nchaos
        For     j = 1: Xcol
                If      0 < cx(i,j)  <= 0.5
                Then    Chaos(i+1,j) = 2 * chaos(I,j)

                If      0.5 < cx(i,j)  <= 1.0
                Then    Chaos(i+1,j) = 2 *(1- chaos(I,j))

                If      cx(j,0) ∉ [0.25,0.50,0.75]
                Then    cx(i,j) ∈ [0.0,1.0]
        end
end
```

$$cx(0,j)=rand(.)$$

Improvement of broods with heuristic functions: The worker (caretaker) honey bees represent a set of different heuristics helpful in breeding. Each heuristic has a fitness value that represents the amount of improvement in a brood's genotype as a result of applying the heuristic to that brood. Typical heuristics used are in Heuristic 5.1(a). Niknam [19] used a set of heuristics and mutation operators to enhance the performance of solution. An ithbrood is randomly selected. Two random numbers (randint1 < randint2) are generated. The position of brood is heuristically refined (Heuristic 5.1b).

Heuristic 5.1(a): Heuristics in improvement of solution of optimization function	
☞ Random flip	☞ Randomly chooses a variable and

Heuristic 5.1(b): Brood refinement

	changes its value to its complement (*i.e.* Changing 0 to 1 and 1 to 0)
Random new	Replaces the brood's genotype with a new randomly generated genotype
Crossover	The crossover point(s) is (are) chosen at random
1-point	1-point and 2-point crossover heuristics, crossover the brood's genotype with a randomly generated genotype
2-point	
Greedy SAT	
Random walk	

```
For   i=1:nbrood
   For   J = 1:ndim
         If    J <randint1
         Then  Brood(i,j) = brood(i,j)

         If    randint1 <= j <= randint2
         Then  Brood(i,j) = xmin(j) + rand10 * [xmax(j)-xmin(j)]

         If    j > randint1
         Then  Brood(i,j) = brood(i,j)
   end
end
```

Alg.5.1: Artificial Honey bee mating (Hb_Ma) Algorithm [80]

```
      Mating flight
Do    while not converge

      Best solution (queen combines probabilistically with
      randomly selected solution (Drone))
      Cross over, mutation → generation of broods
      Local search (brood care)
      If        fit_brood >fit_queen

      Then      queen ← fit_brood

      Reject remaining solutions (kill broods)

end   Do

      If        less than the calculated probability the drones
                sperm is stored in the queens spermatheca
      Then      the queen speed is decreased
      Z^ith brood is generated
```

5.3 Positive features &Shortcomingsof Hb_Ma

The advantages and limitations of honey bee mating algorithm are briefed in chart 5.2.

Chart 5.2: Positive features and limitations of HB_Mating Algorithm

- + Efficient for non-smooth and non-continuous object functions
- + Simultaneously explores and exploits solution space
- + Exploration is through queen's transition in this space
- + Exploitation is in local search at each iteration
- + SAA, GA and local search are implicitly executed sequentially
- + HB_MA-Saber
- + Diversity maintained
  - The mated drones are discarded
  - New broods are inserted for the next mating flight
- + Number of parameters need to be setMA
- + Maintains part of elitism, cross over operation with drone sperm
  - + Avoids true replicate species (like cloning)MA

Shortcomings_ HB_Mating Algorithm [77]

- Tendency to converge prematurely
  - Reason : Initial population was never updated or modified during mating and also breeding process
    - Remedy: Chaotic search in the neighborhood of the best solution at each iteration
- It falls into a near optimum in a limited run time
  - Remedy: chaotic local search improves mating process of HB_MA
- The basic algorithm gets trapped in local optima
- Optimum may be missed
- The solution may be infeasible due to violation of resource constraints
  - Remedy: Local search (by worker bee) tends to local optimal solution
- Large number of iterations to global optimum
  - Remedy: Chaotic search in the neighborhood of the best solution at eachiteration

5.4 Hb_Ma_applications(chart 5.3)

Bozorg Haddat [51] established the superiority of Hb_Ma in optimizing standard mathematical functions. It is superior to many analytical methods and nature inspired algorithms like GA. The heuristics of Hb_Ma along with the problem specific constraints for multi-dimensional large space also results in best possible solution [32].

Chart 5.3:Hb_Ma _applications

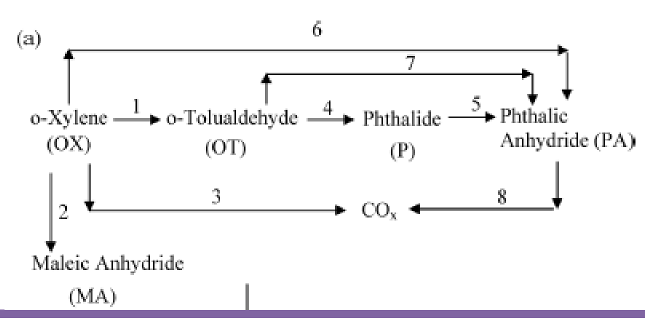
- Scheduling problems – constrained/unconstrained
  - Science, commerce, engineering
  - Non-linear
  - Continuous decision and state variables
  - Time series forecasting
- NLopt (constrained/unconstrained) 3-SAT

Quick Hb_Fa: Karaboga and Gorkemli [84] modified Hb_Fa improving the behavior of onlooker bees more accurately based on neighborhood radius. The effect of neighborhood radius, colony size and effect of parameters is tested on a set of bench mark problems.

Chemical engineering

Synthesis of phthalic anhydride (PA) in industrial reactor: Ramtekeand Gupta [27]applied Alt-NSGA-II-aJG algorithm for industrial phthalic anhydride production using gas-phase catalytic oxidation of *o*-xylene in an multi-bed industrial reactor system. In the optimization process, the reaction scheme, Langmuir-Hinshelwood-Hougen-Watson (LHHW) rate expressions, kinetic model equations, and adsorption parameters are used. The bi-conflicting optimization functions, constraints and bounds are in chart 5.4. Further intricate details are omitted here. The optimal point (f1:1.17161; f2:1.02) with Alt-NSGA-II-aJG is distinctly superior to (*f*1:1.17162; *f*2:0.795) by NSGA-II-aJG.

Chart 5.4: Synthesis of phthalic anhydride		
Nine catalyst zones 20 decision variables		(see scheme below)
Multi_objFns	max $f1(\mathbf{u})$) $=XPA$	
	min $f2(\mathbf{u})$) = $Lcat$	



Simulation of Cancer: Ramtekeand Gupta [27]studied the initiation and growth of cancer with Alt-NSGA-II-aJG. The carcinogenesis process can be simulated, although the mechanics of the algorithm does exactly match with natures' evolution.

The normal rate of mutation is of per gene per cell division is around 10^{-7}. But, solution of real-life optimization tasks in science and engineering require much higer values. Similarly, onset of cancer is less probable in the life time of human beings under normal conditions. But cancer gets initiated and progresses in multiple stages to show its presence sufficient enough to cause damage to normal metabolism.

5.5 Comparison of Hb_Ma with other nature inspired Algs.

This algorithm is distinct in the sense that the quality of one parent (queen) is same. In standard GA both parents are chosen randomly. Elitist dropping is not to continue domination, while elitist retaining is to continue royal blood and in Hb_Ma it is built in. It is interesting to think of the diversity measure between genotype of queen and drones. Chart 5.5 incorporate honey bee mating algorithm applications and comparison of its efficiency with other procedures.

GA

– In GA two parents are selected randomly by the same selection procedure
  - ✓ Remedy: Use of Mimetic algorithm in GA includes (local search) for exploitation.

– In GA there is no local search

Remedy: Hb_Ma +chaotic search

+ Chaotic search in neighborhood of best solution at eachiteration

Chart 5.5: Typical applications of Hb_Ma and comparison with other algorithms

Hb_Ma + $$$_	Field	Sub-disciplinei	Compared with
Hb_Ma + Discrete PSO	Electrical	MOO ✈ Distribution Feeder Reconfiguration ✈ Real power loss ✈ Deviation of nodes' voltage ✈ # switching operations ✈ Balance of loads on feeders ✈	ॐ Original DPSO ॐ HBMO
Hb_Ma + Maximum entropy based thresholding	Image		ॐ PSO ॐ Cooperative-comprehensive learning based PSO algorithm ॐ Fast Otsu's ॐ Exhaustive search
Hb_Ma + k-means	Clustering		ॐ GA ॐ SA ॐ TS ॐ ACO

Chart 5.5b: Typical applications of Hb_Ma

Algorithm	Field	Sub-discipline
Hb_Ma + snake algorithm	Shape of profiles	✈ Detection of concave region connected with the control points of active contour
Hb_Ma	Electricity Generators	Minimization voltage profile ○ Costs ○ Emission ○ Losses of distributed system
Hb_Ma + Chaotic	Electric Energy	MOO (Multi object optimization) ✈ Active power values of DGs ✈ Reactive power values of capacitors ✈ Tap positions of transformers for the next day ▶ Multi-objective daily Volt/Var control in distribution systems • Distribution companies • Electrical energy losses • Voltage deviations for the next day
Hb_Ma + MOO-modified	Electrical energy	MOO Min(.) ✈ Electrical active power losses ✈ Voltage deviations ✈ Total electrical energy costs ✈ Total emissions of RESs and substations ✈ Energy_ renewable
Hb_Ma	Energy sources	MOO ✈ Pareto- non-dominated solution ✈ Fuzzy clustering ✈ Fuzzy-based decision maker
Hb_Ma + MO_EA	Electric power	MOO ✈ Distribution feeder reconfiguration ✈ Real power loss ✈ Number of the switching operations ✈ Deviation of the voltage at each node

5.6 Hybrid Hb_Ma algorithms

SAA + Neighborhood structure + Hb_Ma: Yuan et.al. [99] used a combination of SAA and honey bee mating algorithm in solving of two sided assembly lines balancing NP hard task in industry. The different neighborhood structures in SAA for work-bees in improving broods strikes a balance between intensification and diversification in search region of object function hypersurface. This hybrid algorithm is superior to mixed integer programming and SA.

Chaotic Local Search + Hb_Ma: Ghasemi et.al. [107]proposed an online Learning HBMO for optimal dispatch between thermal and wind units (chart 5.6). When the optimization reaches a predefined threshold, in terms of fitness values and co-ordinates of solutions, two neural networks are trained. Chaotic Local Search (CLS) operator enhances local search efficiency and a data sharing model determines non-dominated solutions which are stored in external memory. From Pareto solution, the best solution was picked up by decision making method named 'Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)'. The model is tested with IEEE 30-bus 6-unit, the IEEE 118-bus 14-unit, and 40-unit with valve points.

Chart 5.6: Wind/Environment/Economic Dispatch (WEED) by hybrid Hb_Ma

Task

Wind/Environment/Economic Dispatch (WEED)

MultiObjFn

optimal dispatch between thermal and wind units

Model

2 m-point to estimate the uncertainty of wind power

Meta-heuristic optAlg.

Hb_Ma

- − Convergence to local optima
- + Fine performance

Ghasemi_algorithm

- ➢ Online Learning HBMO
- ➢ Chaotic
- ➢ Neural networks
- ➢ Local Search
- ➢ 'Technique for Order Preference by Similarity to ideal Solution
- ➢ Pareto optimal solution

Chart 5.7: Comparison of hybrid algorithm LBG + Hb_Ma

Linde–Buzo–Gray (LBG), vector quantization (VQ)

- + lower PSNR value
- − Local optimal codebook
- − Depends on the appropriate codebook

Remedy

- o Particle swarm optimization (PSO)
- o Firefly algorithm (FA)
- + Efficient codebook
- − Instability in convergence if
- • Particle velocity is high
- • Non-availability of brighter fireflies in the search space

Bat Algorithm + Linde–Buzo–Gray (LBG)

- o Uses on initial solution of LBG
- + Efficient codebook
- + Less computational time
- + Very good PSNR
- o Automatic zooming
- + Pulse emission rate
- + Loudness of bats

no significance difference

PSNR

LBG, PSO-LBG,
Quantum PSO-LBG,
HBMO-LBG
FA-LBG
BA-LBG approx. equal to PSO

Average convergence speed

BA-LBG > 1.841 * [HBMO-LBG ; FA-LBG]

Linde–Buzo–Gray (LBG) + Hb_Ma: BA-LBG has high PSNR compared to LBG, PSO-LBG, Quantum PSO-LBG, HBMO-LBG and FA-LBG, and its average convergence speed is 1.841 times faster than HBMO-LBG and FA-LBG (chart 5.7).

Solar cell characterization: Oliva et.al. [89] applied Hb_Fa in the optimization of parameters of current-voltage modeling of solar cells (chart 5.8). The precise/accurate modeling of current vs voltage profiles of solar cells are indispensable to achieve higher performance of solar energy system. It is noticed that parameters of model cannot be extracted from data sheet specifications. So, more complex models for optimized parameters are developed here to arrive at robust and accurate solar cell performance.

Chart 5.8: Hb-Fa in parameter optimization of solar cell models

Optimum of parameters of Solar cell models of current vs voltage
ObjFn
- Multi-model
- Several Local sub-optima
- Premature convergence

Error in waggle dance of foraging honeybees: Preece and Beekman [83] analyzed in detail the available reports for bees' dance error and proposed that bees dance as best as they can and the error is non-adaptive. It is almost constant as the distance to the resource increases.

Design of power system stabilizer: Shayeghi and Ghasemi [87] estimated parameters of optimal power system stabilizers using Parallel Vector Evaluated Improved Honey Bee Mating Optimization (VEIHBMO) (chart 5.9).

Chart 5.9: Parameters of power system stabilizers

Input
- Feed back signal of a remote machine
- For each machine
- Signal ratios of local and remote input signal
- End
- Goal
- Multi objective optimization
- Integral square time of square erro
- Eigen values based comprising the damping factor
- Two competing and non-commensurable fitness functions
- Application
  - power systems

Chart 5.10: Electrical and thermal energy expansion planning in a network

Multiple.ObjFns
1) Loss of real energy
2) Deviation of voltage
3) Cost of installation equipment
- incommensurable

Hybrid Hb_Ma
- ⊥ Global search + Hb_Ma
- ⊥ Point Estimate Method
- + probabilistic load flow

k-means algorithm for clusters
- Tendency to converge to local optima
- Depends on approximate values of cluster centers
- Remedy: modified cohort intelligence + k-means

Method Test data

–
– 4-machine two-area
– 6-machine five-area
– Performance
– Time * absolute value of error
– Eigen values
– Figure of demerit

Hybrid Hb_Ma

⊥ UCI Machine Learning Repository

Methods compared

- K-means
- K-means ++
- GA
- SAA
- ACO
- HB_Ma
- PSO
-
- Tabu search TS
- Cohort intelligence CI
- Modified CI MCI

Discrete HB_Ma: Fatnassi et. al. [105] analyzed routing of battery-operated automatically guided personal rapid transit systems (PRT) electric vehicles with discrete honey bee mating algorithm. The extensive testing with 1320 simulated random cases are statistically evaluated for this algorithm.

Optimization of electrical and thermal energies: Abbasi and Seifi [88] reported simultaneous optimization of electrical and thermal energy equipment in expansion planning of a network using modified Hb_Ma (chart 5.10). The hybrid procedure with global search capability and point estimation for energy expansion planning passes through the tests of feasibility and effectiveness with real time case studies.

Optimized dispatch of reactive power: Ghasemi et.al. [85] used chaotic Hb_Ma for optimal dispatch of reactive power from generators feasibility and arrived at Pareto optimal design (chart 5.11).

Chart 5.11: Multi-conflicting-objective dispatch of reactive power by hybrid Hb_Ma

Task: settings of variables
⊥ Continuous and discrete
✈ Tap positions of tap changing transformers
✈ Generator voltages
✈ Amount of reactive compensation devices

Multiple objectives
1) Voltage deviation
2) Total voltage stability
3) Real power loss.
– Conflicting
– Non-commensurable

Hybrid Hb_Ma
1 Chaotic
2 Parallel Vector
3 Honey Bee Mating Optimization
4 Pareto dominance

Positive features of Hybrid Hb_Ma
+ excellent convergence
+ superior to MOO.ALgs.
+ Multi objective
+ Evaluated Interactive
+ Generates solutions

✓ Dominated
+ Non-dominated

Fuzzy sets + Hb_Ma: Niknam [55] proposed hybrid modified HB_MA. It solves MOO, wherein the object functions are modeled with fuzzy sets. The additional feature of this contribution is a pareto-optimal solution is calculated.

Greedy search + Hb_Ma: Marinakis et.al. [64]hybridized HB_MA with multiple-phase-neighborhood-search-greedy-randomized-adaptive-search-procedure in one method and with expanding-neighborhood – search – strategy in another hybrid version. A new cross over operator and the different group of operators are introduced.

Alg. 5.2 Hybrid Honeybee and parallel CSO	
Phase 1:	The size of population is small. Iterate it < it_max Parallel CSO End it
Phase 2:	Clone randomly the population Add to the initial population ABC algorithm (iterative) Sequential implementation of parallel CAT and ABC

Alg. 5.3: Alt-NSGA-II-aJG[27]

Binary-Coded Altruistic Elitist Nondominated Sorting Genetic Algorithm with aJG Operation		
Generation =0		
Do	while generation < generation_max	
		Generate Nparent strings
	Do	Until Convergence | stopping criteria
		Classify strings into non-dominated ones
		Evaluation of crowding distance of a string in any front
		Altruism
		Generation of a mating pool
		Crossover
		mutation
		aJG operation
		Elitism
	Continue Do Until	
Continue Do while		

binary-coded elitist	
genetic algorithm	GA
nondominated sorting GA	NSGA-II
jumping gene5 adaptation	aJG.
Altruistic behavior of honey bee colonies	**Alt-**

Generation of a mating pool

One queen adaptation

Multiple queen adaption

Second string picking up

- Repeat this procedure to select a second (*j*th) string.

Selection of better string for Nqueens

- For all Nqueens
- betterString(queen,i,j)←Select better of two strings
- end

% 90% of betterString(queen,i,j) have *I*rank = 1

String of front 1

- For I = Nqueens +1:NP
- Select two strings randomly
- end

One queen adaptation

one-good-queen

Solution with NSGA-II-aJG

Best_solution: select one of the solutions of the final Pareto optimal front

good queen ← Best_solution

Multiple_Queen_procedure

One-Bad-queen-Alt-NSGA-II-aJG

Queen at the starting generation

Multiple_Queen_procedure

Multiple-Queen Adaptation

integral random number IRN([1 to Nparents])
Select a random string
RN ← RandU([0 to1])

if RN lies in between [0 to 0.9] &
String selected (IRN) is from rank =1
then Discard it &
Repeat with new IRN/RN

if RN lies in between [0.9 to 1.0] &
then Accept the selected string irrespective of its *I*rank
greater than 90% probability that selected string has a rank of 1.

Crossover

Generate an RN in [0, 1]

Simple Crossover for the One-Queen Adaptation

Simple Two-Mate Crossover

New Crossover for the Multiple-Queen Adaptation

Two-Mate Crossover

Three-Mate Crossover.

Mutation operation

- For all strings
- Select a string
- If prob(mutation) > randN([0,1])
- Alter selected binary number from 0 to 1 or 1 to 0
- end

Fixed-Length JG Operation (aJG)	Elitism
For all strings	Copy Nparents and daughters. Total number = 2* Nparents
Select a string	Classification into non-dominated fronts
If prob(jump)>rand([0,1])	Pick up Nparents with lowest front numbers
Calculate beginning of aJG by integer random number (IRN)in the range [1, lchr]	Calculate crowding distance
End of aJG is at INR +*f*b	
Generate randomly distributed new binaries (RandBinaries)	
Replace between aJG to INR +*f*b RandBinaries	

6. State-of-Knowledge

Science: The continual increase in sophistication of instrumentation, experimental designs, refined/modified/new theories and computational revolution with support of software/hardware has direct consequences in addition/deletion/modification/fine-tuning of fact-base. The outcome is unification and /or diversification of sub-disciplines into super-specializations and mega theory/model under one roof respectively. In this high ended intellectual paradigm, it is not a new item if a theory is proved again or experimental evidence is arrived at. It just adds a tiny grain to the human perception of Himalayan ranges, a spec in nature. But, it upholds the reputation of the long lived theory and instrumental for promotion of breadthwise research. If a theory is refuted, disproved, experimental data/information contradicts, theoretical postulate/ prediction/projection is disproved, then it opens a new science window tending towards realizing true nature. The pre requisite is thorough investigation of both truth and falsehood values of original theory as well as reasons for refutation. The support is tested under six sigma limits for experimental evidence and rigorous logical and mathematical rigor with billions of simulated results in almost exhaustive limits. The simple, but challenging and brain storming future is in rewriting the established/coveted/sought after theories of yester years. Broadly speaking, one gets convinced with axiom 'change is law of nature' and so science in this dynamic evolving universe of 13.7 billion years young. Mostly these efforts raise more queries rather than answers.

Mathematics/statistics: The deterministic, probabilistic, possibility, fuzziness in happening/not-happening of incidence/phenomena continues to play a vital role in mathematical sciences.The algebraic/Boolean/tensor operators, differentiation/integration with finite/infinite limits enhanced the power of mathematical probes. The two way transformation of integer (binary/multiple discrete), real, (extended) complex numbers, and transformation in either direction of Euclidian/polar/Reman orthogonal/projected/ discipline (physical/chemical) specific spaces increased the applications of many micro- to mega-goals of real life tasks. The unique/ multiple deterministic/probabilistic, dominated/non-dominated/Pareto (front) optimal methods result in wide spectrum of solutions for solvable equations. The direct/indirect combinatorial polynomial/non-polynomial, exhaustive approaches for single/multiple unconstrained/constrained object function of (in)equations created a luxury suite of search algorithms for finding roots/ (local/global) optima created sets of laser sources to probe more into nature of nature.

Nature inspired algorithms (NIAs): These procedures emerged with mapping of at least partial processes in living species or non-living systems into mathematical frame (chart 6.1). The chemical/physical/geological processes influenced mathematicians more than half a century ago. In the last two decades, foraging (chart 6.2), nest building, mating, migration of birds, insects, cats/ lions/ rats continues to be a perineal flow of inspiration, emerging another computational world called Mathematics II. The earlier mathematics/statistics/fuzzy systems in a nutshell being encapsulated as mathematics-I. This revolutionary evolution is similar to Computer science I and II and physics as atomic/nuclear/particle physics. Chart 6.3 describes research mode representation of honey bee (foraging and mating) algorithms with advances and leading to different algorithm flows.

Chart 6.1: Evolution of Mimics of Algorithms of Nature

$$$	Alg	Abbr eviation
Statistical	Algorithms	sa
Real	intelligence	ri
genetic	Algorithms	ga
Mathematical	Algorithms	ma
Probability	Algorithms	pa
Possibility		
Deterministic	Algorithms	da
Nature	intelligence	ni
Swarm	Algorithms	sa

Chart 6.2: OOP representation of foraging tactics in nature and corresponding E-man modules

Foraging _in_nature	: [	Flies {Honeybee}, Ant, Amphibian {Frog}, {Cat}, Vultures {Bat, Eagle}]
Eman_foraging		**Eman_foraging_alg**
Eman_flies	: [	HB Foraging algorithm (HBFA), HB Foraging Programming(HBFP)]
Eman_Ant	: [	Ant colony]
Eman_ Frog	: [	Frog leap, Shuffled frog leaping]
Eman_ cat	: [	cat]
Eman_Vultures	: [	Bat, Eagle]

Swarms and swarm intelligence: The swarm behavior is in living/moving/working together of unintelligent agents for benefits in food search, defense, propagation of best genes to posterity etc. If intelligence is exhibited by a swarm of unintelligent species with no leader/ no goal, it is termed as swarm intelligence. Thus, it is more precious and rare and becomes apt when focussed research results on grazy boundaries on knowledge based processes, adaptability/evolution and intelligence(KB. 6.1) are unambiguous.

KB. 6.1: Multiple optima and Swarm search (MOSS)	
If	objective function has only one optimum
Then	(swarm) SI members converge to that of optimum
If	objective function has multiple optima
Then	swarm capture then in its final population
	SI: (ACO, GA,PSO)

The success in solving complex and combinatorial tasks with NIAs is astounding compared to gradient methods. Most of these procedures don't employee gradient/hessian information and come under derivative free direct methods. Most of them (SAA, GA, HBA etc.) are global search Meta heuristic procedures. In recent times the binary/ternary hybridization even with local search methods raised their figure of merit very high. But one point to note at this juncture is that still there are gaps in compiling not only the natural processes but in translation to mathematical space. This explains the reasons why science and technology is still far behind leave alone in producing but mimicking even tiny natural trait.

Chart 6.3: State-of-knowledge of research mode modules of artificial honey bee algorithm

Honey bee algorithm (E-Man --- NIA ----Swarm Alg)	
• Hb_Fa	• Honey bee foraging algorithm
• Hb_Ma	• Honey bee matingalgorithm
•	

Hb_Fa		
Name	Proposer	year
ABC	Karaboga	2007
Virtual bee algorithm	Yang	2005
Bee colony optimization algorithm	Teodorovic	2005
Bee hive algorithm	Weddle	2004
Bee swarm optimization	Brias	2005
Bee algorithm	Pham	2006

Initiation
• Random
• Levy flight
•

Refinement by foraging artificial honey bees
• Scout
• Onlookers
• Foragers

Check for boundary crossing
• Lower and upper limits
• Mod Rate
•

Probability of fitnessFnVal
• Simple
• Prefernece
•

Honey bee mating algorithm **Hb_Ma**

Advances
Neighborhood radius

Data type	Hb_Ma	
Discrete		

Fuzzy sets		
Fuzzy rules		

Iniiation of broods
Random
Chaotic

Brood improvement
Heuristics

Hybrid Hb_Ma
Binary
Ternary
Quaternary

Ternary	Hybrid Hb_Ma
$$$_ ###_HB_Ma	
SAA	Neighborhood structure

Quaternary	Hybrid Hb_Ma	
Alt-NSGA-II-aJG		

Binary
$$$_HB_Ma
PSO
Maximum entropy
k-means
snake
Chaotic
EA
Linde–Buzo–Gray (LBG)
Parallel Vector Evaluation
Greedy search
Parallel CSO

Discrete HB_Ma
Continuous

Hb_Ma
Threshold Acceptance (TA)
Multiple-descendant honeybee mating optimization

7. Future Trend

It is a dream at the moment that a computer replicating even brain of a rat in its life cycle. However, the fruits of upward gradient of realization of science are evident in the production of artificial cell on one hand, humanoid robots/sucker game robots and blue chip in chess on other hand. A lookup table of algorithms, standard mathematical/statistical tasks and disciplines throw light on a panoramic view. The implementation of software on a chip popularizes the method and becomes a tool like a toy robot medical instrument or domestic/industrial appliances.

The migration between of honey bee hives leads to beneficial effect due to coevolution. Larger colonies have positive edge over smaller swarms. The different topologies viz. hypercubes, toroidal mesh and fully connected also play a role on the end result. A comparative study of parallel versions of ACO, PSO, Firefly and mosquito with latest modified modules on use of reconfigurable computing will open a new window in the direction of computational artificial human brain.

REFERENCES

[1] R. E. Page, Jr *Genetics*,**1980,**96,265-273.
The evolution of multiple mating behavior by honey bee queens (apis mellifera l.)

[2] Y. Lensky P. Cassierp M. Notkin C. Delorme-Joulie M. Levinsohn, *J. Insect Physiol.*,**1985,**31,4.
Pheromonal activity fine structure Of the mibular gls of honeybee Drones (api!3 mellifera l.) (insecta Hymenoptera apidae)

[3] T. D. Seeley S. C. Buhrman, *Behav Ecol Sociobiol*,**2001,**49,416–427.
Nest-site selection in honey bees: how well do swarms implement the “best-of-N ” decision rule?

[4] J. Teo H. A. Abbass,*Int. J Comput. al Intel. Appl.*,**2003,**3 (2), 199-211.
A true annealing approach to the marriage in honey-bees optimization algorithm

[5] O. B. Haddad A. Afshar M. A. Mariño, *Ninth Int. Water Techn. Conf. IWTC9 Sharm El-Sheikh Egypt*,**2005,**1053-63.
HBMO in Eng. optimization

[6] V. Albertova S. Su A. Brockmann J. Gadau S. Albert, *J. Agric. Foood Chem.*,**2005,**53,8075-8081.
Organization Potential Function of the mrjp3 Locus in Four Honeybee Species

[7] O. B. Haddad A. Afshar, B. J. Adams, *Ninth Int. Water Techn. Conf. IWTC9 Sharm El-Sheikh Egypt*,**2005,**999-1008.
HBMO in optimal reservoir operation

[8] T. D. Seeley P. K. Visscher K. M. Passino, *American Scientist*,**2006,**94,220-229.
Group Decision Making in Honey Bee Swarms

[9] K. M. Passino T. D. Seeley, *Behav Ecol Sociobiol*,**2006,**59,427–442.
Modelling analysis of nest-site selection by honeybee swarms: the speed accuracy trade-off

[10] H. F. Wedde M. Farooq, *J Syst. Architecture*,**2006,**52,461–484.
A comprehensive review of nature inspired routing algorithms for fixed telecommunication networks

[11] D. C. Gilley G. DeGri-Hoffman J. E. Hooper, *J Insect Physiology*,**2006,**52,520–527.
Volatile compounds emitted by live European honey bee (Apis mellifera L.) queens

[12] M. Fathian B. Amiri A. Maroosi, *Applied Maths. Comput.*,**2007,**190,1502–1513.
Application of honey-bee mating optimization algorithm on clustering

[13] P. Curkovic B. Jerbic, *Int J Simul Model*,**2007,**6,154-164.

[14] A. Afshar O. Bozorg Haddad M.A. Marino B.J. Adams,*J Franklin Institute*,**2007,**344,452–462.

[15] D. Karaboga B. Basturk, *J Glob Optim*,**2007,**39,459–471.
A powerful efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm

[16] B. Amiri M. Fathian, *J theoretical Applied Inform. Techn.*,**2007,** 70-86.
Integration of self organizing feature maps honey bee mating optimization algorithmfor market segmentation

[17] S. D Kocher Freddie-Jeanne Richard D. R Tarpy, C. M Grozinger, *BMC Genomics*,**2008,**9,1-15.
Genomic analysis of post-mating changes in the honey bee queen(Apis mellifera)

[18] O. B. Haddad A. Afshar, M. A. Marino, *Water Resour Manage*,**2008,**22,1709–1722.
Design-Operation of Multi-Hydropower Reservoirs: HBMO Approach

[19] T. Niknam J. Olamaie R. Khorshidi, *World Applied Sci. J*,**2008,**4 (2), 308-315.
A Hybrid Algorithm Based on HBMOFuzzy Set for Multi-Objective Distribution Feeder Reconfiguration

[20] K. M. Passino T. D. Seeley P. K. Visscher, *Behav Ecol Sociobiol*,**2008,**62,401–414.
Swarm cognition in honey bees

[21] P. Navrat M. Kovacik A. Bou Ezzeddine V. Rozinajova, *Web Intel. Agent Syst.: An Int. J*,**2008,**6,441–452.
[22] Ping-Feng Pai Shun-Ling Yang Ping-Teng Chang, *Expert Syst. with Appl.*,**2009,** 36, 10746–10751. Forecasting output of integrated circuit industry by support vector regression models with marriage honey-bees optimization algorithms
[23] T. Niknam, *Energy Conversion Manag.*,**2009,**50,2074–2082. An efficient hybrid evolutionary algorithm based on PSO HBMO algorithms for multi-objective Distribution Feeder Reconfiguration
[24] N. Karaboga *J Franklin Institute*,**2009,** 346, 328–348. A new design method based on artificial bee colony algorithm for digital IIR filters
[25] K. Sundareswaran, V. T. Sreedevi, *Electric Power Components Syst.*,**2009,**37,465–477. Design Development of Feed-back Controller for a Boost Converter Using a Colony of Foraging Bees
[26] D. Karaboga, B. Akay, *Art. Intel. Rev.*,**2009,**31,61–85. A survey: algorithms simulating bee swarm Intel.
[27] M. Ramteke, S. K. Gupta, *Ind. Eng. Chem. Res.*,**2009,** 48, 9671–9685. Biomimicking Altruistic Behavior of Honey Bees in Multi-objective Genetic Algorithm
[28] Han Xue Xun Li Hong-Xu Ma, *Int. J Automation Computing*,**2010,**7 (1),115-122. Rom Fuzzy Chance-constrained Programming Based on Adaptive Chaos Quantum Honey Bee Algorithm Robustness Analysis
[29] S. D. Kocher D. R. Tarpy, C. M. Grozinger, *Insect Molecular Biology*,**2010,**19 (2),153–162. The effects of mating instrumental insemination onqueen honey bee flight behaviour gene expression
[30] H. Li K. Liu, Xia Li, *Z. Cai et al. (Eds.): ISICA 2010 CCIS 107*,**2010,**198–207. A Comparative Study of Artificial Bee Colony Bees Algorithms Differential Evolution on Numerical Benchmark Problems
[31] D. Vera J. Carabias F. Jurado N. Ruiz-Reyes, *Applied Energy*,**2010,**87,2119–2127. A Honey Bee Foraging approach for optimal location of a biomass power plant
[32] Qin-Ma Kang Hong He Hui-Min Song Rong Deng, *J Syst. S tware*,**2010,**83,2165–2174. Task allocation for maximizing reliability of distributed computing Syst. using honeybee mating optimization
[33] C. M. V. Benıtez H. S. Lopes *M. Essaaidi et al. (Eds.): Intelligent Distributed Computing*,**2010,**IV SCI 315,255–264. Parallel Artificial Bee Colony Algorithm Approaches for Protein Structure Prediction Using the 3DHP-SC Model
[34] K. Guney M. Onay, *Expert Syst. with Appl.*,**2010,**37,3129–3135. Bees algorithm for interference suppression of linear antenna arrays by controlling the phase-only both the amplitude phase
[35] G. Zhu S. Kwong, *Applied Maths. Comput.*,**2010,**217,3166–3173. Gbest-guided artificial bee colony algorithm for numerical function optimization
[36] S. Sundar A. Singh, *Inform. Sci.*,**2010,**180,3182–3191. A swarm Intel approach to the quadratic minimum spanning tree problem
[37] Ming-Huwi Horng, *Applied Maths. Comput.*,**2010,**215,3302–3310. A multilevel image thresholding using the honey bee mating optimization
[38] L. Özbakir A. Baykasoglu P. Tapkan,*Applied Maths. Comput.*,**2010,**215,3782–3795. Bees algorithm for generalized assignment problem
[39] D. T. Pham Ebubekir Koc,*Int. J Automation Computing*,**2010,**7 (3),399-402. Design of a Two-dimensional Recursive Filter Using the Bees Algorithm
[40] Ming-Huwi Horng,*Expert Syst. with Appl.*,**2010,**37,4580–4592. Multilevel minimum cross entropy threshold selection based on the honey bee mating optimization
[41] C. Zhang D. Ouyang J. Ning *Expert Syst. with Appl.*,**2010,**37,4761–4767.

An artificial bee colony approach for clustering
[42] Y. Marinakis M. Marinaki G. Dounias, *Nat Comput*,**2010,**9,5–27.
Honey Bees Mating Optimization algorithm for large scale vehicle routing problems
[43] C. Xu H. Duan F. Liu, *Aerospace Science Techn.*,**2010,**14,535–541.
Chaotic artificial bee colony approach to Uninhabited Combat Air Vehicle (UCAV) path Planning
[44] H. Zhao Z. Pei J. Jiang R. Guan C. Wang, X. Shi, *Y. Tan Y. Shi K.C. Tan (Eds.): ICSI 2010 Part I LNCS 6145*,**2010,** 558–565.
A Hybrid Swarm Intelligent Method Based on Genetic Algorithm Artificial Bee Colony
[45] S. L.Sabat S. Udgata A. Abraham *Appl. Artificial Intel. Eng.*,**2010,**23,689–694.
Artificial bee colony algorithm for small signal model parameter extraction of MESFET
[46] Ming-Huwi Horng Ren-Jean Liou Jun Wu *Expert Syst. with Appl.*,**2010,**37,7015–7025.
Parametric active contour model by using the honey bee mating optimization
[47] K. M. Passino, *Int. J Swarm Intel. Research*,**2010,**1 (2),80-97.
Honey Bee Swarm Cognition
[48] O. B. Haddad M. Mirmomeni, M. A. Mariño, *Civil Eng. Environmental Syst.*,**2010,**27 (1), 81–94.
Optimal design of stepped spillways using the HBMO algorithm
[49] N. Quijano K. M. Passino *Eng. Appl. Art. Intel.*,**2010,** 23, 845–861.
Honey bee social for aging algorithms for resource allocation: Theory application
[50] A. L. Nevai K. M. Passino P. Srinivasan*J oretical Biology*,**2010,** 263, 93–107.
Stability of choice in the honey bee nest-site selection process
[51] O. Bozorg Haddad M. Mirmomeni M. Z. Mehrizi M. A. Mariño, *Comput Optim Appl.*,**2010,** 47, 97–128.
Finding the shortest path with honey-bee mating optimization algorithm in project manag.problems with constrained/unconstrained resources
[52] D. vanEngelsdorp M. D. Meixner *J Invertebrate Pathology*,**2010,**103,S80–S95.
A historical review of managed honey bee populations in Europethe United States the factors that may affect them
[53] E. Fox E. B. Sudderth M. I. Jordan, A. S. Willsky *IEEE TRANSACTIONS ON SIGNAL PROCESSING*,**2011,**59 (4).
Bayesian Nonparametric Inference of Switching Dynamic Linear Models
[54] Ioná Maghali Santos de Oliveira R. Schirru,*Annals Nuclear Energy*,**2011,**38,1039–1045.
Swarm Intel. of artificial bees applied to In-Core Fuel Manag. Optimization
[55] T. Niknam H. Z. Meym H. D. Mojarrad, *Energy*,**2011,**36,119-132.
An efficient algorithm for multi-objective optimal operation manag.of distribution network considering fuel cell power plants
[56] L. Özbakır P. Tapkan, *Expert Syst. with Appl.*,**2011,**38,11947–11957.
Bee colony Intel.in zone constrained two-sided assembly line balancing problem
[57] T. Davidovic D. Ramljak M. Selmic D. Teodorovic *Computers & Operations Research*,**2011,** 38, 1367–1376.
Bee colony optimization for the p-center problem
[58] Ming-Huwi Horng, *Expert Syst. with Appl.*,**2011,**38,13785–13791.
Multilevel thresholding selection based on the artificial bee colony algorithmfor image segmentation
[59] Ming-Huwi Horng Ting-Wei Jiang, *Expert Syst. with Appl.*,**2011,**38,1382–1392.
Image vector quantization algorithm via honey bee mating optimization
[60] Ming-Huwi Horng Ren-Jean Liou, *Expert Syst. with Appl.*,**2011,**38,14805–14811.
Multilevel minimum cross entropy threshold selection based on the firefly algorithm
[61] Zhi Deng Huaxi Gu Haizhou Feng Baojian Shu, *Y. Tan et al. (Eds.): ICSI 2011 Part I LNCS 6728*,**2011,**285–292.
Artificial Bee Colony Based Mapping for Application Specific Network-on-Chip Design
[62] T. Niknam,*Expert Syst. with Appl.*,**2011,**38,2878–2887.

An efficient multi-objective HBMO algorithm for distribution feeder reconfiguration
[63] T. Niknam E. T. Fard N. Pourjafarian A. Rousta *Eng. Appl. Artificial Intel.*,**2011,** 24, 306–317.
An efficient hybrid algorithm based on modified imperialist competitive algorithm K-means for data clustering
[64] Y. Marinakis M. Marinaki G. Dounias *Inform. Sci.*,**2011,**181,4684–4698.
Honey bees mating optimization algorithm for the Euclidean traveling salesman problem
[65] T. Niknam S. I. Taheri J. Aghaei S. Tabatabaei M. Nayeripour, *Applied Energy*,**2011,** 88, 4817–4830.
A modified honey bee mating optimization algorithm for multiobjective placement of renewable energy resources
[66] Wei-Chiang Hong,*Energy*,**2011,** 36, 5568-5578.
Electric load forecasting by seasonal recurrent SVR (support vector regression) with chaotic artificial bee colony algorithm
[67] M. Wilhelm M. Chhetri J. Rychtár O. Rueppell, *Bull Math Biol*,**2011,**73,626–638.
A Game Theoretical Analysis of the Mating Sign Behavior in the Honey Bee
[68] D. Karaboga C. Ozturk,*Appl. S t Comput.*,**2011,**11,652–657.
A novel clustering approach: Artificial Bee Colony (ABC) algorithm
[69] T. Niknam, *Applied Energy*,**2011,**88,778–788.
A new HBMO algorithm for multiobjective daily Volt/Var control in distribution Syst. considering Distributed Generators
[70] W. Gao S. Liu, *Inform. Processing Letters*,**2011,**111,871–882.
Improved artificial bee colony algorithm for global optimization
[71] T. Niknam H. D. Mojarrad H. Z. Meym B.B Firouzi *Energy*,**2011,** 36, 896-908.
A new honey bee mating optimization algorithm for non-smooth economic dispatch
[72] T. Niknam H. D. Mojarrad H. Z. Meym B. B. Firouzi *Energy*,**2011,**36,896-908.
A new honey bee mating optimization algorithm for non-smooth economic dispatch
[73] Ming-Huwi Horng, *Expert Syst. with Appl.*,**2012,**39,1078–1091.
Vector quantization using the firefly algorithm for image compression
[74] D. Karaboga C. Ozturk N. Karaboga B. Gorkemli, *Inform. Sci.*,**2012,**209,1–15.
Artificial bee colony programming for symbolic regression
[75] B. Akay D. Karaboga,*Inform. Sci.*,**2012,**192,120–142.
A modified Artificial Bee Colony algorithm for real-parameter optimization
[76] V.J. Manoj Elizabeth Elias, *Inform. Sci.*,**2012,**192,193–203.
Artificial bee colony algorithm for the design of multiplier-less Non uniform filter bank transmultiplexer
[77] N. R. Sabar M. Ayob G. Kendall R. Qu, *European J Operational Research*,**2012,**216,533–543.
A honey-bee mating optimization algorithm for educational timetabling problems
[78] M. Malekzadeh A. Khosravi S. Alighale H. Azami
D.-S. Huang et al. (Eds.): ICIC 2012 LNCS 7389,**2012,**95–102.
Optimization of Orthogonal Poly Phase Coding Waveform Based on Bees Algorithm Artificial BeeColony for MIMO Radar
[79] R. Venkata Rao V. Patel, *Eng. Optimization*,**2012,**44 (8),965–983.
Multi-objective optimization of combined Brayton inverse Brayton cycles using advanced optimization algorithms
[80] S. J. Sadjadi R. Soltani
Expert Syst. with Appl.,**2012,**39,990–999.
Alternative design redundancy allocation using an efficient heuristic a honey bee mating algorithm
[81] E. Cuevas F. Sención-Echauri D. Zaldivar, M. Pérez*I. Zelinka et al. (Eds.): H book Optimization,ISRL 38*,**2013,**965–990.
Image Segmentation Using Artificial Bee Colony Optimization
[82] W. A. Hussein S. Sahran S. N. H. S. Abdullah *Appl. S t Comput.*,**2014,***23*,104-121.

Patch-Levy-based initialization algorithm for Bees Algorithm
[83] K. Preece M. Beekman *Animal Behaviour*,**2014,***94*,19-26.
Honeybee waggle dance error: adaption or constraint? Unravelling the complex dance language of honeybees
[84] D. Karaboga B. Gorkemli *Appl. S t Comput.*,**2014,***23*,227-238.
A quick artificial bee colony (qABC) algorithm its performance on optimization problems
[85] Ali Ghasemi K. Valipour A. Tohidi *Int. J Electrical Power & Energy Syst.*,**2014,***57*,318-334.
Multi objective optimal reactive power dispatch using a new multi objective strategy
[86] G. Krishnasamy A. J. Kulkarni R. Paramesran *Expert Syst. with Appl.*,**2014,***41* (13),6009-6016.
A hybrid approach for data clustering based on modified cohort Intel. K-means
[87] H. Shayeghi A. Ghasemi *Int. J Electrical Power & Energy Syst.*,**2014,***62*,630-645.
A multi objective vector evaluated improved honey bee mating optimization for optimal robust design of power system stabilizers
[88] Ali R. Abbasi Ali R. Seifi *Energy Conversion Manag.*,**2014,***83*,9-18.
Energy expansion planning by considering electrical thermal expansion simultaneously
[89] D. Oliva E. Cuevas G. Pajares *Energy*,**2014,***72*,93-102.
Parameter identification of solar cells using artificial bee colony optimization
[90] A. Yurtkuran E. Emel *Applied Maths. Comput.*,**2015,***271*,1004-1023.
An adaptive artificial bee colony algorithm for global optimization
[91] C. Zhang J. Zheng Y. Zhou *Neurocomputing*,**2015,***151* (3),1198-1207.
Two modified Artificial Bee Colony algorithms inspired by Grenade Explosion Method
[92] M. Akhoondzadeh *Advances in Space Research*,**2015,***56* (6),1200-1211.
Application of Artificial Bee Colony algorithm in TEC seismo-ionospheric anomalies detection
[93] H. Habbi Y. Boudouaoui D. Karaboga C. Ozturk *Inform. Sci.*,**2015,***295*,145-159.
Self-generated fuzzy Syst. design using artificial bee colony optimization
[94] X. Song H. Gu Li Tang S. Zhao X. Zhang L. Li J. Huang *Computers & GeoSci.*,**2015,***83*,219-230.
Application of artificial bee colony algorithm on surface wave data
[95] S.K. Agrawal O.P. Sahu*Swarm Evolutionary Comput.*,**2015,***21*,24-31.
Artificial bee colony algorithm to design two-channel quadrature mirror filter banks
[96] D. Aydın *Appl. S t Comput.*,**2015,***32*,266-285.
Composite artificial bee colony algorithms: From component-based analysis to high-performing algorithms
[97] B. Ranjbar-Sahraei K. Tuyls I. Caliskanelli B. Broeker D. Claes S. Alers G. Weiss *Biomimetic Technologies*,**2015,**273-299.
Bio-inspired multi-robot Syst.
[98] M. Sarailoo Z. Rahmani B. Rezaie *Neurocomputing*,**2015,***152*,294-304.
A novel model predictive control scheme based on bees algorithm in a class of nonlinear Syst.: Application to a three tank system
[99] B. Yuan C. Zhang X. Shao Z. Jiang*Computers & Operations Research*,**2015,***53*,32-41.
An effective hybrid honey bee mating optimization algorithm for balancing mixed-model two-sided assembly lines
[100] A. Singh B. Damir K. Deep A. Ganju *Cold Regions Science Techn.*,**2015,***109*,33-42.
Calibration of nearest neighbors model for avalanche forecasting
[101] S. Iqbal M. Kaykobad M. S. Rahman *Swarm Evolutionary Comput.*,**2015,***24*,50-64.
Solving the multi-objective Vehicle Routing Problem with Soft Time Windows with the help of bees
[102] M. Garbuzov A. Madsen F. L.W. Ratnieks *Acta Oecologica*,**2015,***62*,53-57.
Patch size has no effect on insect visitation rate per unit area in garden-scale flower patches
[103] C. Karri U. Jena*Eng. Science Techn.*,**2015**.
Fast vector quantization using a Bat algorithm for image compression
[104] İ. Aydoğdu A. Akın M.P. Saka *Advances in Eng. S tware*,**2016,***92*,1-14.

Design optimization of real world steel space frames using artificial beecolony algorithm with Levyflight distribution

[105] E. Fatnassi O. Chebbi J. Chaouachi *Swarm Evolutionary Comput.*,**2016,***26*,35-49.
Discrete honeybee mating optimization algorithm for the routing of battery-operated automated guidance electric vehicles in personal rapid transit Syst.

[106] X. Li G. Yang *Appl. S t Comput.*,**2016,***41*,362-372.
Artificial bee colony algorithm with memory

[107] A. Ghasemi M. Gheydi M. J. Golkar M. Eslami *Appl. S t Comput.*,***2016,****43*,454-468.
Modeling of Wind/Environment/Economic Dispatch in power system solving via an online learning meta-heuristic method

[108] Ahmed Al-Ghamdi N. Adgaba A. Getachew Y. Tadesse *Saudi J Biol. Sci.*,***2016,****23 (1)*,92-100.
New approach for determination of an optimum honeybee colony's carrying capacity based on productivity nectar secretion potential of bee forage species

[109] B. Li *Optik - Int. J for Light Electron Optics*,**2016.**
An Evolutionary Approach for Image Retrieval Based on Lateral Inhibition

[110] C. Korat, P. Gohel,*International Journal of Advanced Research in Electrical, Electronics Instrumentation Engineering* **2015,**4(8), 2320 – 3765.
A Novel Honey Bee Inspired Algorithm for Dynamic Load Balancing In Cloud Environment

[111] H. Awadh. A. Bahamish, R. Abdullah, R. A. Salam,*Proc. 2nd IMT-GT Reg.Conf.Math. Statist.Appl.Univ. Sains Malaysia, Penang*, **2006,** 1-8.
Protein conformational search using honey bee colonyoptimization

[112] S.L. Hoa, S. Yang, *International Journal of Applied Electromagnetics Mechanics*, ***2009,****3*, 181–192.
An artificial bee colony algorithm for inverse problems

E-man

[113] K RamaKrishna and R Sambasiva Rao, J. Applicable Chem., 2015, 4(6): 1597-1690.
Evolution of Mimics of Algorithms of Nature (E-man) Part 6: Research Tutorial on bat and Mosquito algorithms.

[114] K. RamaKrishna, G. Ramkumar and R. Sambasiva Rao, *J. Applicable Chem.*, **2013,** 2, 6, 1413-1458.
Evolution of Mimics of Algorithms of Nature (E-man) Part 5: Tutorial on Big_Bang–Big_Crunch algorithm.

[115] K. RamaKrishna, Ch. V. Kameswara Rao and R. Sambasiva Rao, *J. Applicable Chem.*, **2013,** 2, 5, 1007-1034.
E-man Part 4: Tutorial on prospects of charged system search (CSS) algorithm in chemical sciences.

[116] K. RamaKrishna, Ch. V. Kameswara Rao, R. Sambasiva Rao, *J. Applicable Chem.*, **2013,** 2, 4, 698-713.
Eman-Part III: Tutorial on gravitational algorithm in Structure activity relationships (SXR).

[117] K. Viswanath, R. Sambasiva Rao, Ch. V. Kameswara Rao, K. Rama Krishna, B. Rama Krishna and G. E. G. Santhosh, *J. Applicable Chem.*, **2012,** 1, *1*, 109-124.
Eman (Evolution of Mimics of Algorithms of Nature)-Part II: Application of neural networks for classification of bauxite.

Swarm Intelligence

[118] K. RamaKrishna, R. Sambasiva Rao,*J. Applicable Chem*., 2014, 3 (2) 449-492.
Swarm_Intelligence (SI)-State-of-Art (SI-SA), Part I: Tutorial on Firefly algorithm

Neural Networks

[119] K RamaKrishna, Ch. V. Kameswara Rao, V.Anantha Ramam, R. Sambasiva Rao, *J. Applicable Chem*., **2014**, 3 (6) 2209-2311
Mathematical Neural Network (MaNN) Models, Part VI: Single-layer perceptron [SLP] and Multi-layer perceptron [MLP] Neural networks in ChEM- Lab.

[120] M Venkata Subba Rao, V Ananta Ramam, V Muralidhara Rao, R Sambasiva Rao, *Asian J Chem*., **2010**, 22, 5937-5950.
Neural network modelling used as a chemometric tool for kinetic investigations
[121] I.Suryanarayana, A Braibanti, R Sambasiva Rao, V Ananta Ramam, D Sudarsan, G Nageswara Rao,*Fisheries Research*,**2008**, 92, 115-139.
Neural Networks in Fisheries Research

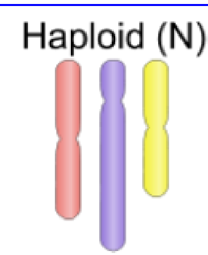
Appendix 0: DefBase-honeybee

			→	→	
D					→ Data
ID				Intelligence	→ Data
CID		Conscience		Intelligence	→ Data
CID		Chemistry		Instrument	→ Data
KID			Knowledge	Intelligence	→ Data
MIND		Method/ Mind	Intelligence	Natural genotype	→ Data
			←	←	← Data

Vocabulary of SI	Abb	Definition
Swarm behavior	SB	The three important components for survival of species are food, defense from predators and harsh environment. When larger number of same species stay together the chances of survival increase. In evolution, flocks of birds, parliament of owls, herds of land animals, fish schools and various social insects (bees, wasps, ants, termites) adapted this approach of swarm behavior. The swarm behavior is exhibited in distributed functioning, self-organizing and autonomy
Swarm processing	SP	A task beyond the scope of an individual, a larger number of individuals of same species perform it and is called swarm processing. Always, it need not be praised as swarm intelligence Examples: • A colony of honey bees requires 60 lbs of honey for survival in the winter. But, each bee carries only 20 gms in its whole life time of foraging. • Ant bridge, Ant hill • Wasp
Swarm intelligence	SI	Many a time, there is no leader and every individual can execute a bit of process. If the swarm in total exhibits intelligence, it is referred as swarm intelligence Examples: • Flock of birds flying to placed never visited • Fireflies
Artificial Swarm	AS	Artificial swarms consists of o Micro-robots o Artificial neurons (10,000 or more) o Mathematical object mimicking at least partially the behavior of natural swarms (birds, fireflies, mosquitoes, honey bees, fishes etc. → The artificial swarm behavior is exhibited in systems functioning in distributed mode with autonomous and self-organizing features → The decentralized multi agent systems consisting of physical machines (robots) or virtual (artificial) ones. They execute their bit of job and communicate among themselves and also others in the hierarchy. They cooperate, collaborate, exchange information and knowledge and intelligence bits (if any) and continue their bit or

		modified chores in the adaptive systems
Artificial Swarm intelligence	ASI	If artificial swarm of a category exhibits the intelligence compared to individual components of swarm, it is Artificial Swarm intelligence (ASI) Application: The practical schedules of natural species are used in design, architecture in theories/simulations in developing artificial systems. However, this sage does not involve the entire imitation of nature at the moment. But, a deep level understanding, implementation and modification cycle will result in 'design man-made-best from 'evolved-nature'

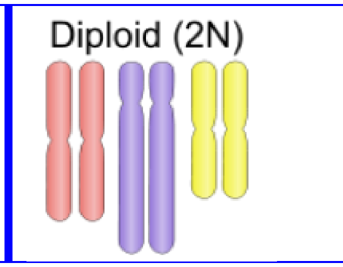
Vocabulary of Genetics	Definition
Stem cells	In any organism, stem cells are the first cells formed. On asymmetric division, one stem cell and one progeny cell are formed. The long lived stem/progeny cells are primarily responsible for growth.
Progeny cell	They divide into normal cells each time
Normal cells	The mitotic cell division produce two daughter cells in each step, unlike worker bees which do not produce offspring. The normal cells undergo less cell division cycles due to their relatively shorter lives
Gamete	Sperm or egg. It carries a full set of chromosomes which includes a single copy of each chromosome
Sexual reproduction	Sperm from male and egg from female combine in sexual act. They fuse into a single cell during fertilization
Fertilization phase	It is a sexual reproduction. Gametes fuse into a single cell.
Homologous chromosomes	Chromosome of the same type (pairs)
Triat	Characteristic (color of eye) inherited, but varies from one individual to another
Altruistic behavior	It is to increase its (species) own fitness It is exhibited in bees, ants, chimpanzees, lions, monkeys, and so on
Genetics	Study of heredity through genes
Gene	Piece of DNA (chemical factors) that codes for a polypeptide (specifying a certain trait)
Locus	Specific location of a gene on chromosome
Allele	Different forms of a genes those combined; determines a trait

Vocabulary of Genetics	Definition	Figure
Ploidy	Number of sets of chromosomes in a cell	
Haploid or gametic number (n)	Number of chromosomes in a gamete	
Haploid	One copy of each chromosome = 1* n \$\$-Ploid Set(s) Monoploid 1	

Diploid

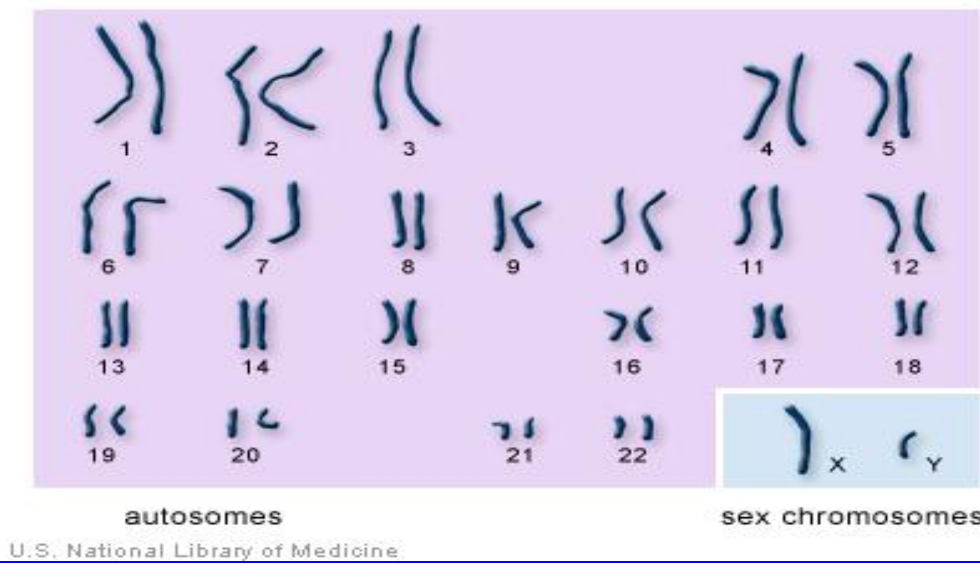
Two Copies of each chromosome = 2* n
Two gametes form a diploid zygote. Here, 2n number of chromosomes are involved.

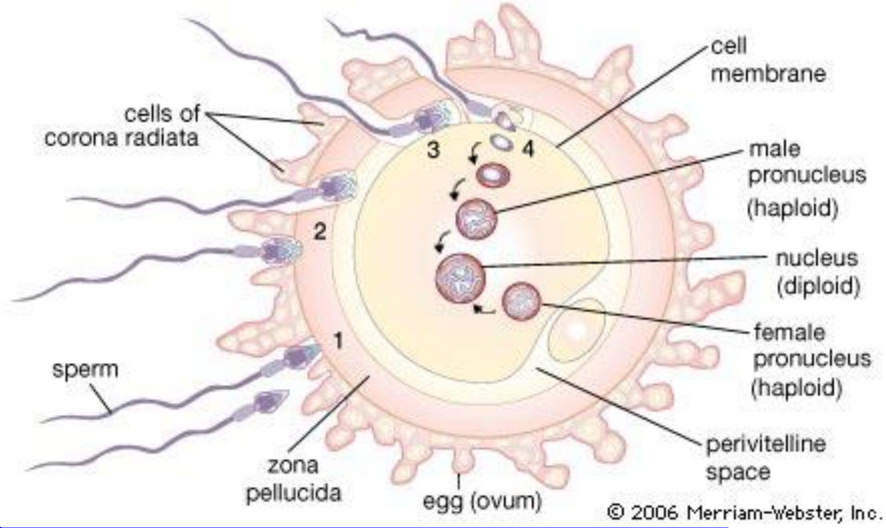
$$-Ploid	Set(s)
Diploid	2



Cross-over	
One-point	queen's genotype has been put in the left side of the generated brood's genotype
One-point	queen's genotype has been put in the right side of the generated brood's genotype;
Two-point	queen's genotype has been put in the middle of the generated brood's genotype
Two-point	queen's genotype has been put in both ends of the generated brood's genotype

Example: Humans are diploid species with n =23; there are 22 pairs of autosomal chromosomes and a pair of sex chromosomes. A typical human somatic cell contains 46 chromosomes: 2 complete haploid sets, which make up 23 homologous chromosome pairs.





Human egg cell fertilization	
1	ॐ The sperm release enzymes → ॐ Dispersion of corona radiata helped & ॐ Bind to zona pellucida.
2	ॐ Outer sperm head layer is sloughed off ॐ Exposing enzymes that digest a path through the zona pellucida.
3	ॐ Sperm fuses with the egg cell membrane → ॐ Zona pellucida becomes impenetrable to other sperm
4	ॐ Tail separates from the sperm head, ॐ Male pronucleus enlarges ॐ Travels to the female pronucleus in the center of the cell ॐ Chromosomes merge to form a fertilized egg

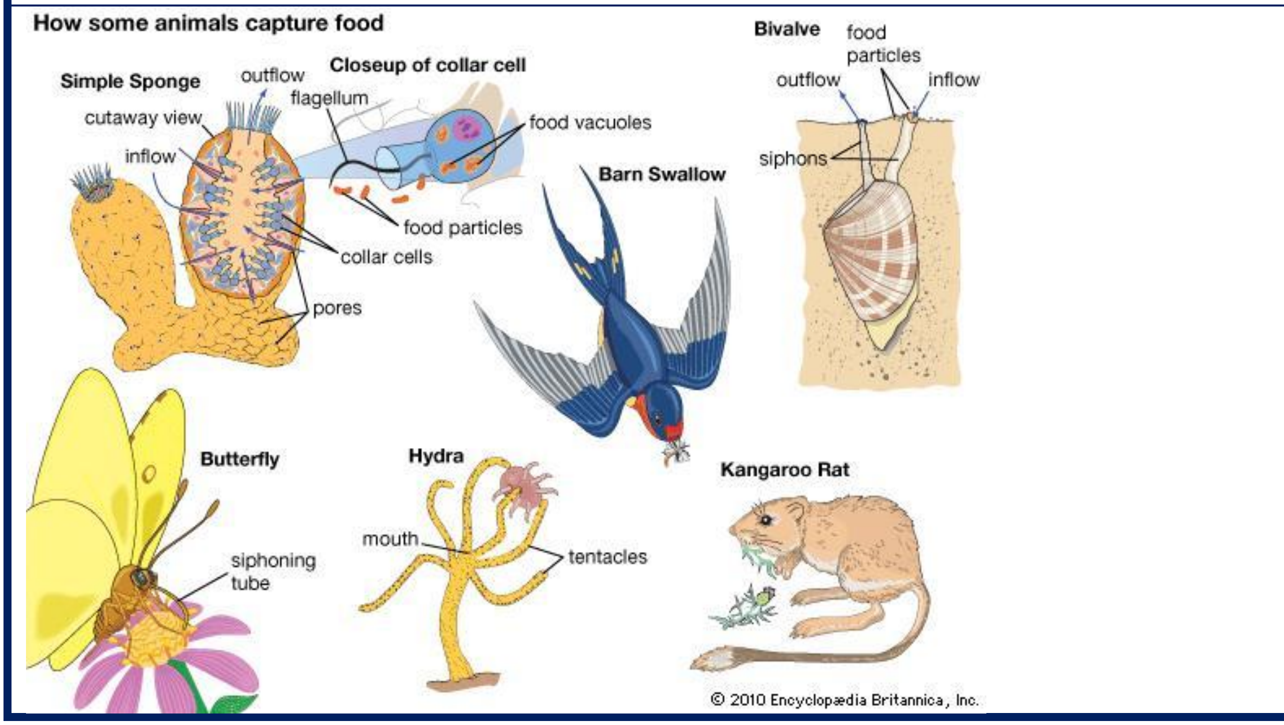
. Credit: © Merriam-Webster Inc.

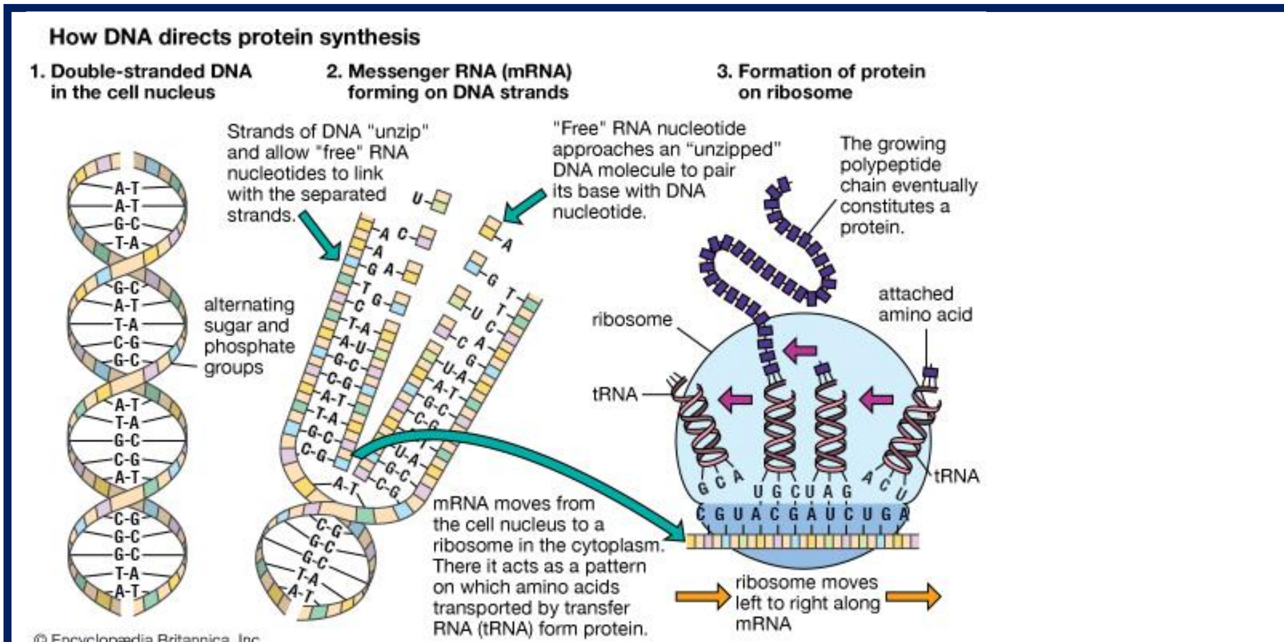
Polyploid	Cells with three or more sets of chromosomes (triploid or higher ploidy).	see table below
Aneuploidy	Leads to severe genetic disease in the offspring	

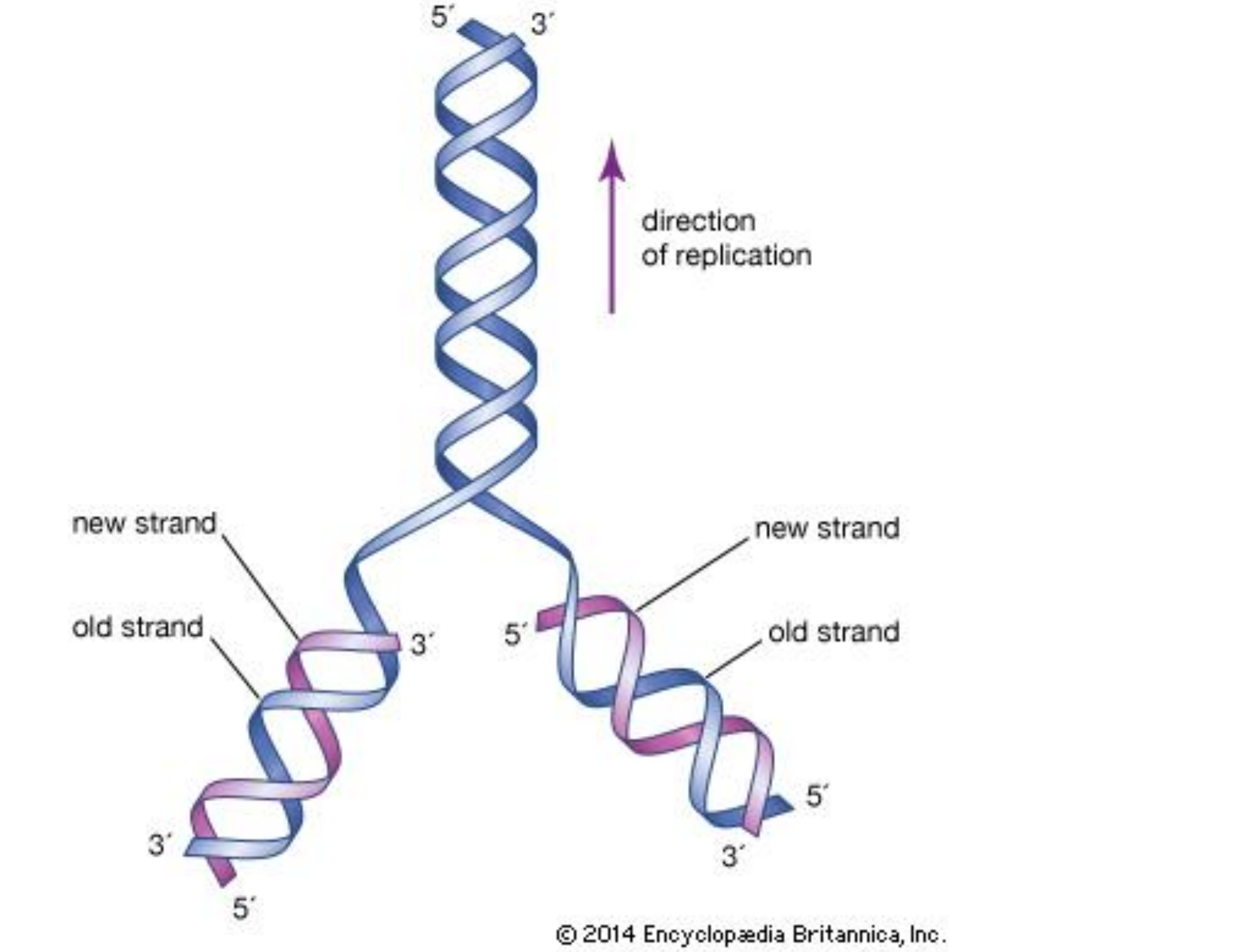
poly-Ploid	Set(s)
Monoploid	1
Diploid	2
Triploid	3
Tetraploid	4
Pentaploid	5
Hexaploid	6
Heptaploid or Septaploid	7

Vocabulary of Honeybee foraging	Definition
Nectar	Nectar is the liquid in a flower
Pollen	It is a powdery substance transferred from one flower to another to make more flowers
Haplometrosis	A single queen independently starts a new colony. The first brood is reared alone until they emerge and take over the work of the colony. Subsequently, division of labor starts to take place. The queen specializes in egg laying and the workers in brood care.
Pleometrosis	A number of (i.e. multiple) queens associate and cooperate in starting a new colony. It exists

	in halictine bees , termites, paper wasps and in several species of ants






5´
3´
direction
of replication
new strand
old strand
3´
5´
new strand
old strand
3´
5´
5´
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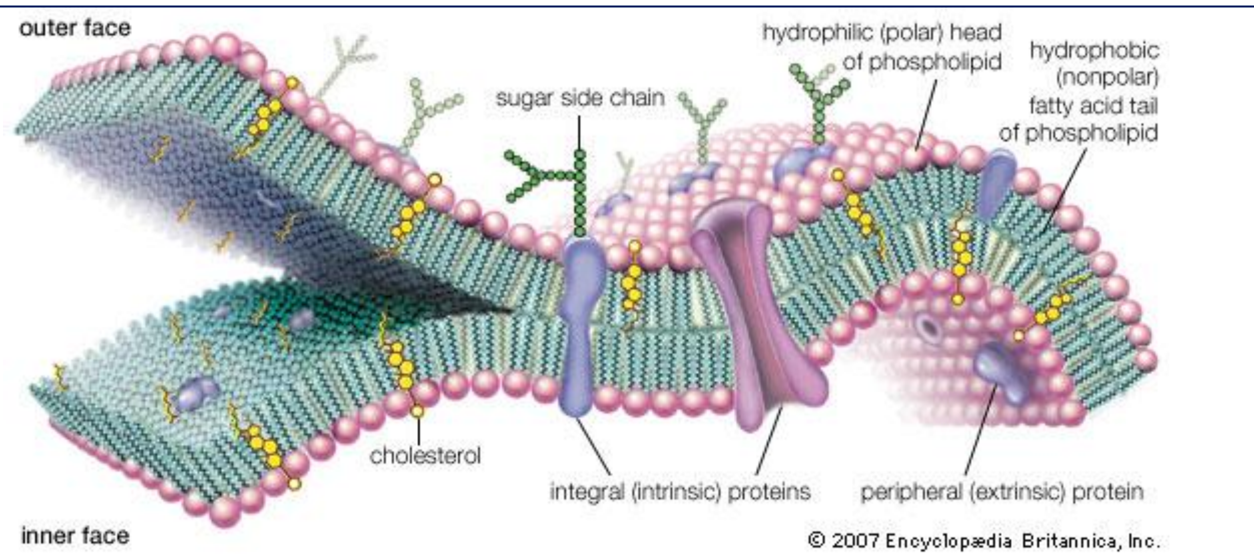
outer face
hydrophilic (polar) head
of phospholipid
hydrophobic
(nonpolar)
fatty acid tail
of phospholipid
sugar side chain
cholesterol
integral (intrinsic) proteins
peripheral (extrinsic) protein
inner face
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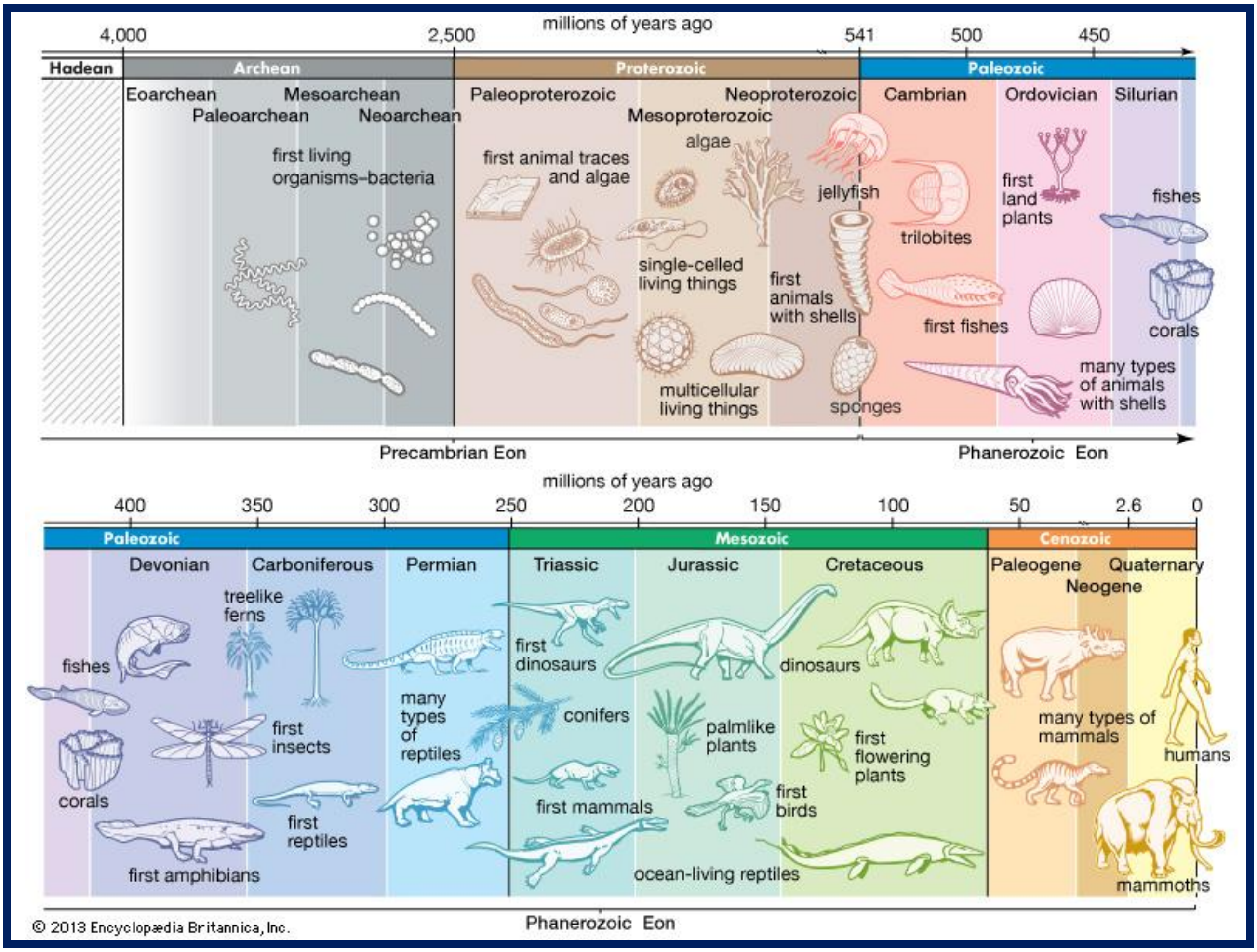
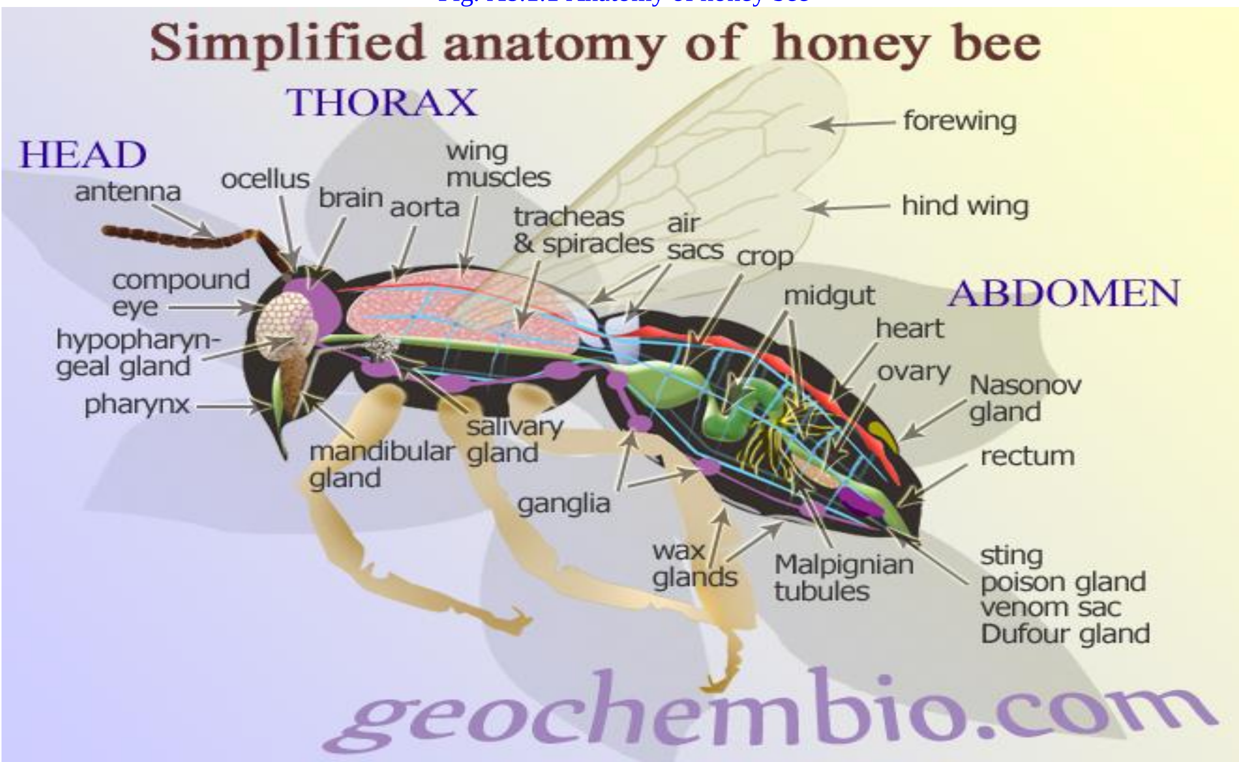
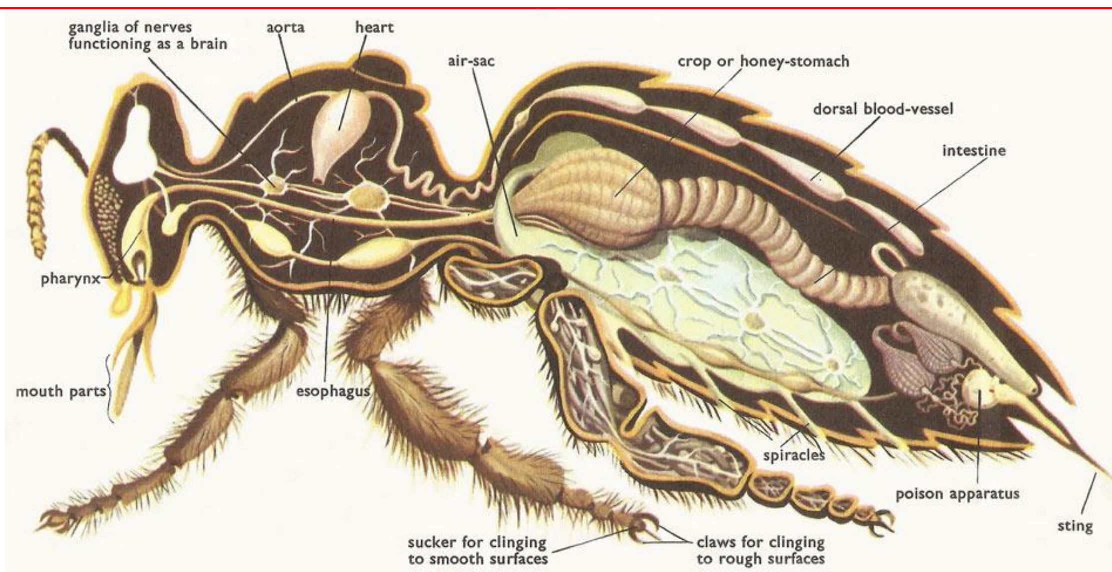

millions of years ago
4,000
2,500
541
500
450
Hadean
Archean
Proterozoic
Paleozoic
Eoarchean
Paleoarchean
Mesoarchean
Neoarchean
Paleoproterozoic
Mesoproterozoic
Neoproterozoic
Cambrian
Ordovician
Silurian
first living organisms–bacteria
first animal traces and algae
algae
jellyfish
trilobites
first land plants
fishes
single-celled living things
first animals with shells
first fishes
corals
multicellular living things
sponges
many types of animals with shells
Precambrian Eon
Phanerozoic Eon
millions of years ago
400
350
300
250
200
150
100
50
2.6
0
Paleozoic
Mesozoic
Cenozoic
Devonian
Carboniferous
Permian
Triassic
Jurassic
Cretaceous
Paleogene
Neogene
Quaternary
treelike ferns
fishes
first dinosaurs
dinosaurs
many types of reptiles
conifers
palmlike plants
first flowering plants
many types of mammals
first insects
humans
corals
first mammals
first birds
first reptiles
first amphibians
ocean-living reptiles
mammoths
Phanerozoic Eon

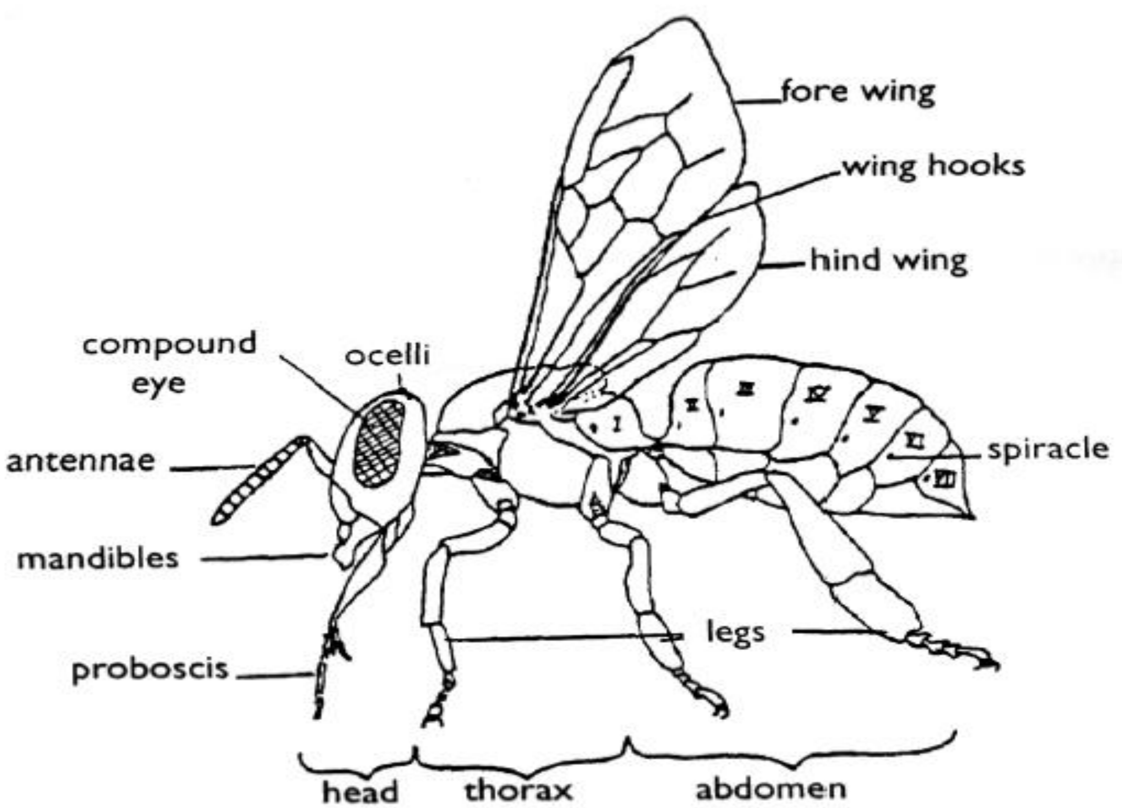
Appendix 8.1:

Anatomy of honey bees: The anatomy of honey bee with different details is in Fig. 8.1.1.

Fig. A8.1.1 Anatomy of honey bee







Nervous system: The nervous system comprises a small “brain” and 7 ganglia right down the body. The 7th is near the end of the abdomen. Wings, hemolymph, legs, etc. are under the control of ganglia.

Head: The head of the honey bee consists of eyes, antennae and feeding structures. The simple eye called ocelli, determines the amount of light present in the surroundings. The compound eye, on the other hand, understands color, light, directional information from the Sun's UV-rays. The role of antennas is to smell and detect odors and in measuring their flight speed. The bee's jaw is called mandible. It is useful to eat pollen, feeding larvae/ queen, cleaning hive, grooming, fighting, cut and shape wax.

Thorax:The wings, legs and muscles controlling the movement of bees are in thorax. The larger forewing has a role in flight and a means of cooling mechanism. With the hind wing, comparatively smaller, the honey bees fan away heat in the hive.

Abdomen

Digestive system: The stomach is a storage area holding freshly collected nectar or water for transport to/from the nest. Honey bees have reversible movement of foods from mouthparts to/from a honey stomach.

Reproductive organs: Queen bee has spermatheca and female reproductive organs. The drones have male reproductive system.

Stinger system: The worker bees have stinger system for defense from invaders. The queen also has a stringer to kill the competing ones. But, drones do not have stinger system, as their sole role is to participate in mating flight with queen.

Physiology

String:The stinger is located at the end the abdomen and it is barbed. The poison gland produces venom and it is tied to the digestive tract of the bee. A honey bee stings predators, human beings with its stinger mostly as a defense operation of hive. Since the stinger is barbed, it often becomes lodged in the tissue of victim. It further releases an alarm pheromone alerting the workers of hive to continue combat. The bee dies as the stinger, the venom sac and other parts are pulled out of the honey bee's body. Yet, the seventh ganglion attached to stringer system continues to pump venom into the wound from venom sac. If the stinger is not removed quickly, the symptoms gradually increase to unbearable pain and sometimes to emergency.

Appendix 8.2: Honey bee foraging in nature

The foraging activity of honey bee is briefed in chart A8.2.1.

Chart A8.2.1: Foraging bee activity: Nectar collection and conversion to honey in real honey bees in nature

Alg. Nat. Xxx: Bird's eye view of honey production in nature
Scout bees exploration of flower patches
Forager collecting nectar
Onlookers analyzing resources

Desirable characteristics for selection of a flower patch for nectar collection
- ⊙ Min(Distance from the hive)
- ⊙ Higher(Quantity of nectar and sugar content)
- ⊙ Less(Amount of energy needed to harvest to patch

KB. A8.2.1: New vs established hive

if	New honey hive
then	A few of first born bees will go for exploration of flower patches
if	Established hive
then	Scouts (past employed foragers) will do exploration for new flower patches

KB. A8.2.2: Quality/profitability of a flower patch

If	If flower patches have plentiful amount of nectar/ pollen & nearer (less distance) to hive & collection needs less effort &
Then	Preferred patches
If	Preferred patches
Then	More bees visit that food source
Else	Few bees are deployed

Waggle and round dances of worker honey bees

KB. A8.2.3: Honey bee choice of round and waggle dances

If	Distance between source and hive < 100 meters
Then	Round dance
	– Round dance does not give direction information
If	Source is far away
Then	Waggle dance
Conseq	Tremble dance is performed
if	foraging bee perceives a long delay in unloading its nectar
	o Longer distances cause quicker dances (Hamdan 2008; Mackean 2008).

KB. 8.2.4: Honey bee choice of waggle dance in repeated foraging flights

If	nectar amount present in the food source > threshold
Then	Employed foraging honey bee (EFHB) performs waggle dance informing nest mates & goes to food source or No waggle dance & continues to forage [probability values for these options are highly related to the quality of the food source]
If	Nectar amount < threshold
Then	EFHB comes back to hive, & performs waggle dance & it becomes unemployed bee/scout bee

Chart A08-2.1b: Forager (worker) honey bees in honey production

Scout bees exploration of flower patches

- Scout bees explore (search for) promising flower patches
- Waggle dance by scout bees at the dance floor
  - communicate to onlookers – waggle dance
- Follower bees waiting inside the hive accompany in commensurate with overall quality
- Scout bee accompany to flower patch

Onlooker(s)

- → Analyses information from waggle dance of scouts, foragers, other onlookers
- → Search nearby sources around
- → Checks for the nectar.
- → Onlookers decide Prospecting flower patches/number of bees to be recruited per patch
- → Old position forgotten
- → New position remembered.
- → Takes a decision to abandon flower patch
- → Onlookers determine the best forager bee based on fitness function
- → Other bees follow the best forager based on probability to sources with high nectar content

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Employed bee
[former scout -- discovered flower patch]

- \+ Has prior experience in neighborhood search
- Follows to locations of flower patches indicated by scouts and onlookers

Scout bees exploration of flower patches

- − No prior knowledge of location flower patches
- \+ Past experience as employed forager

Stopping criteria

If	Surrounding food sources exhausted
Then	New hive
If	Winter
Then	Stored food used

If	Past scout
Then	HB has experience in foraging
If	nectar exhausted
Then	Employed forager becomes un-employed

Onlookers +scouts

- Abandoning a flower patch

Role transitions of foraging bees between employed, scouts , onlookers

	Forager→ Unemployed
If	Source is exhausted
Then	employed bee becomes unemployed scout
Else	Forager continues
If	nectar amount decreased to a low level or exhausted
Then	Foraging bee abandons the food source Unemployed bee ← foraging bee

	Scout → Forager
If	The solution is better than the abounded one
Then	The scout will become an employed bee.
If	Source discovered by scout
Then	Exhausted is replaced (Eqn.1

Pseudocode A8.1: Honey bee exploration for flower patches

Continue Foraging exploration

- → Scout bees search
- → Employed bee introduces modification to location of source
- → Position of source with higher nectar is remembered
- → Information transmitted to onlookers
- → Generates modification to location of source
- → Later rechecks for quantity of nectar
- → Old position is forgotten and new one remembered

Foraging activity

- → Sources for abandonment determined
- → New sources are found randomly
- → The new search sources replace the abandoned

End if winter

If	Food source searched by bee (i) > threshold
Then	It is a leading bee & Goes for exploration & Deploys more bees
If	Food source searched bee (i) is relatively low
Then	Gives up that source & Explores for another source
If	Food source searched bee (i) < threshold
Then	It follows leading bees and continues to explore
If	Searching times around a hive >> upper_limit & no patch worth for exploration found
Then	It abandons that source & explores for a new one

Foraging activity

While Food source is profitable | not exhausted

- Going to food source
- Nectar collection from flower patch
- Conversion nectar to honey in the gut (of bee)
- Estimation of nectar still available
- Unloading honey at the pool in hive
- Waggle dance/no waggle dance

Continue

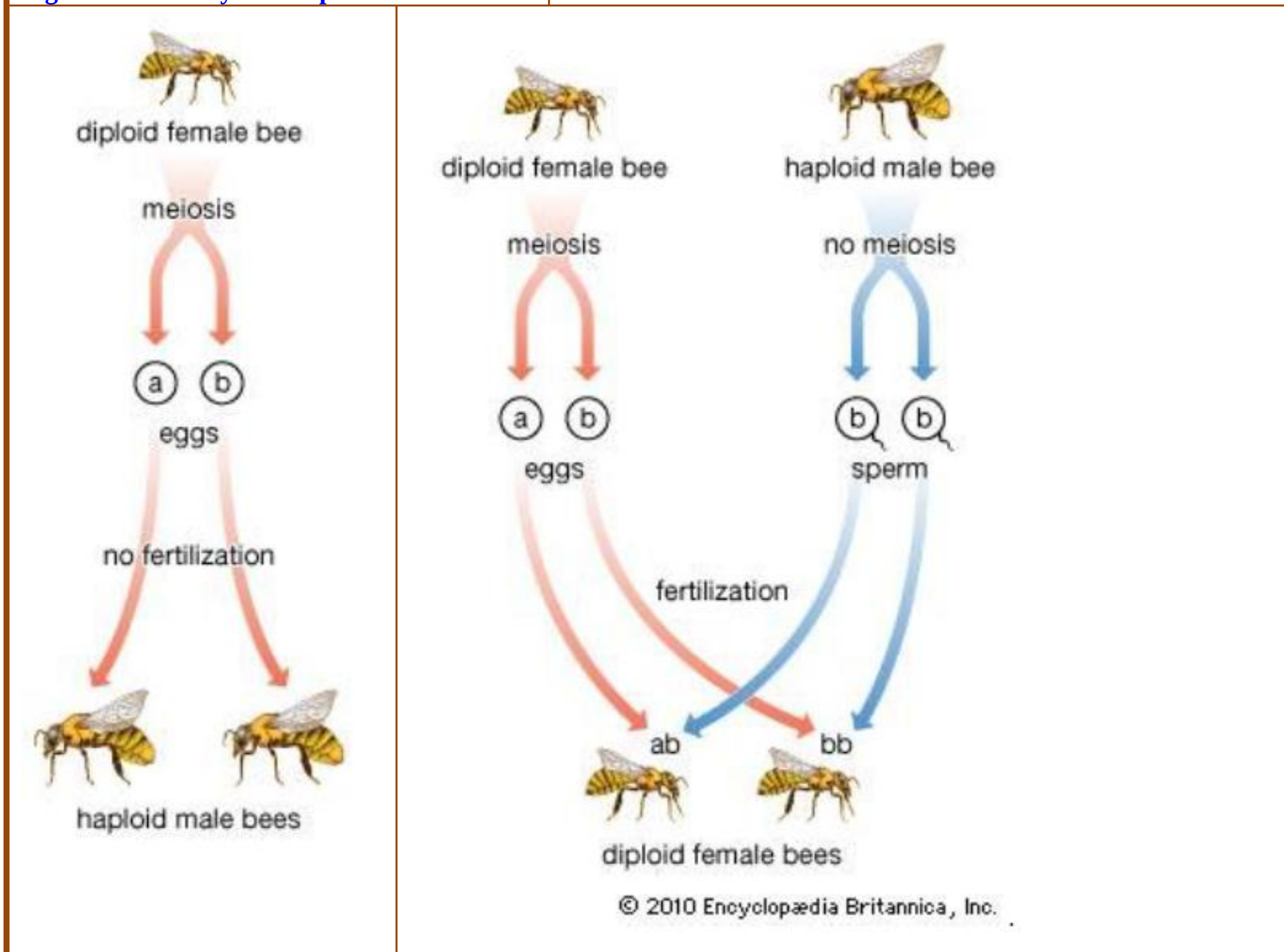
If	There is more nectar (fitness) in the solution compared to the previous one.
Then	Employed bee remembers new position & forgets the old position. counter is reset to 0
Else	Location of old position retained counter ← counter + 1 Ref: [22]

Appendix 8.3: Honey bee mating in nature

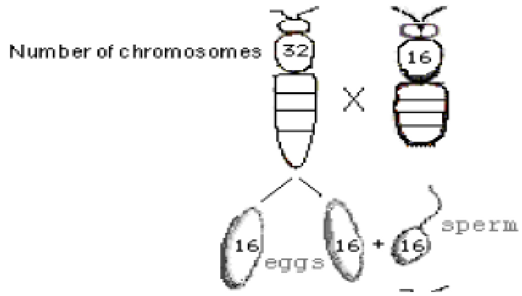
Reproduction

The queen honey bee participates in sexual activity with a series of drones in mating flights. Every drone successfully transfers sperm into spermatheca of queen dies and queen never participates in mating for the rest of her life. The reproduction (of progeny) starts then and continues for several years, daily laying hundreds of eggs of size of comma (",") in the bottom of wax cell in brood area of the hive. The brood care till they reach adult bee level is looked after by work bees and queen has no role in this process. But, queen, at will/need, produces fertilized (sperm + female gamete) or unfertilized (only female gamete) eggs in the diploid and haploid modes (fig. A8.3.1, chart A8.3.1).

Fig. A8.3.1: Honey bees reproduction



Queen Drone



→

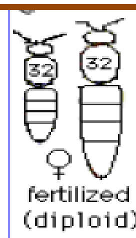


chart A8.3.1: Reproduction information of honeybees

	honey bee		
Drone	Male	Has only mother	No father
Queen/workers	Females	Has mother	Has father

#generations back	Members	#generations back	Members
6	13	11	144
7	21	12	233
8	34	13	377
9	55	14	610
10	89	15	987

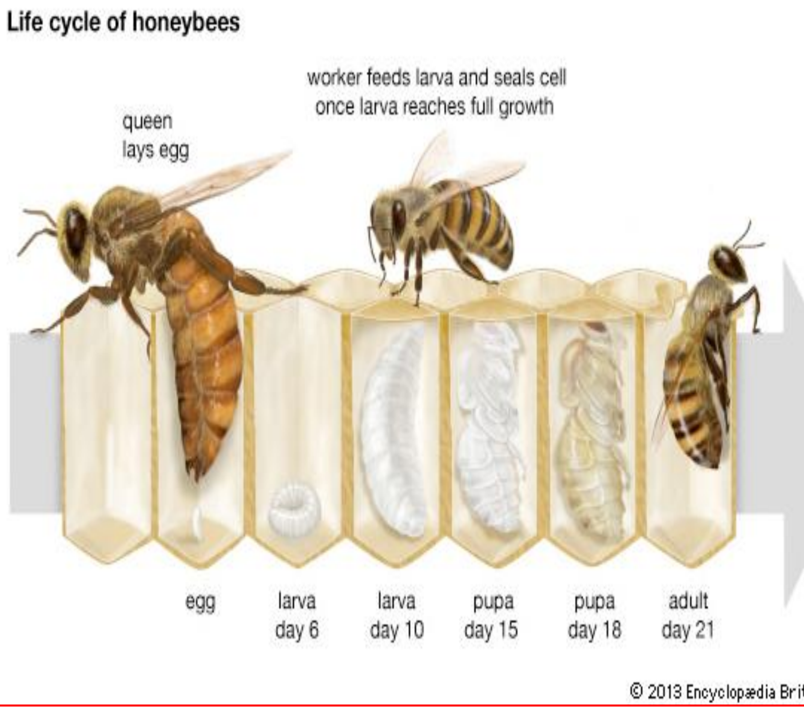
The queen is diploid in genetic makeup; that is to say, half of her genes are derived from her mother and half from her father.

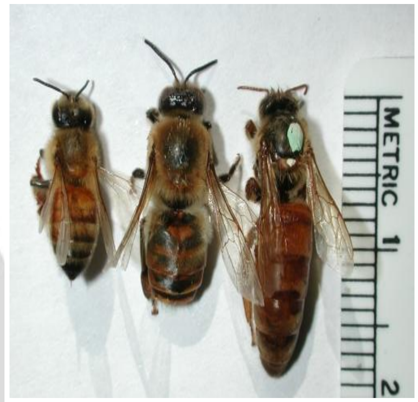
The males (drones) are haploid; that is, they have only half the genes possessed by the queen, all of them derived from the mother

Members of family tree before n generations

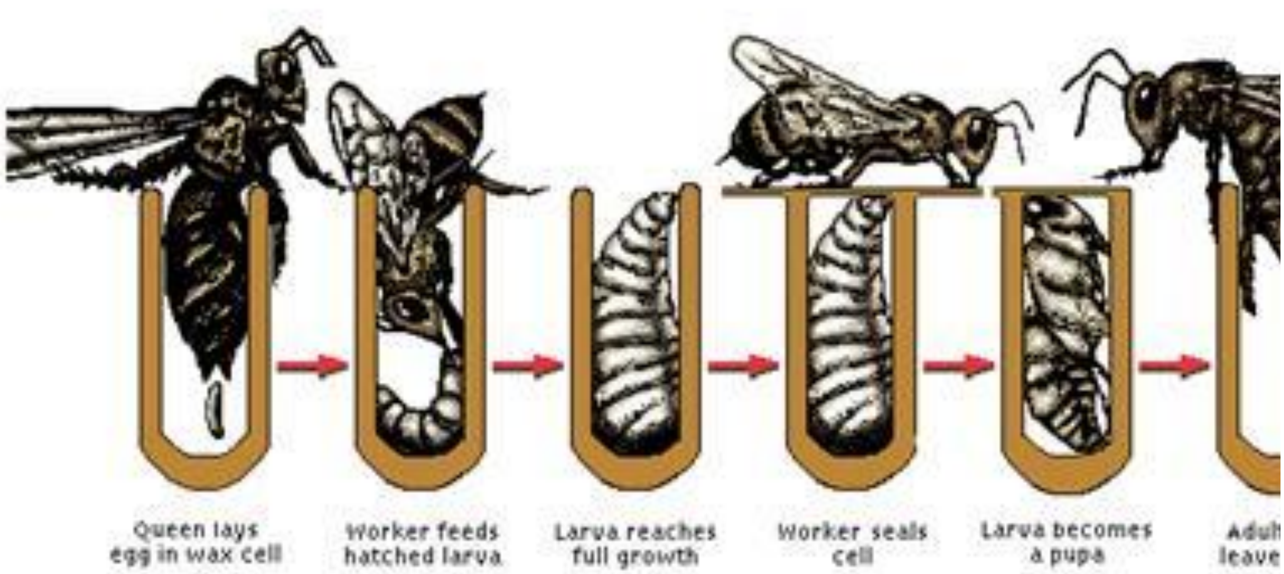
#generation back	Members	
0	0	
1	1	Father
1	1	Mother
2	2	Mother Father
3	3	Mother Father Mother
4	5	Mother Father Mother Mother Father
5	8	Mother Father Mother Mother Father Mother Father Mother

Fig.A8.3.1b:Egg laying → adult bee





Left to right : worker, Drone, Queen honey bee



Metamorphosis of Queen Bee - worker egg hatches after 3 days into a larva - Larva (several moltings) Day 3 to Day 8½ - Nurse bees feed it with royal jelly at first, then pollen & honey for 6 days. Queen cell capped~ Day 7½ - Pupa~ Day 8 until emergence - Emergence~Day 15½ - Day 17 - Nuptial Flight(s)~Day 20 – 24 - Egg Laying~Day 23 and up		
	Egg→ Larva → Pupa →Adult	

Chart A8.3.1b: Knowledge bits in honeybee reproduction

Drones (Fathers of honey bee colony) life cycle

Until	Winter	
	If	Drones mating flight &
		Successful mating
	Then	Dies mostly
	Else	Goes to hive
continue		
	Drone will be driven off the hive	
	They die in winter and starving for food	

	Queen Life cycle
While	No new queen | queen spermatheca is not empty
	Queen bee in hive
	Mating with drones in air
	Returns to Hive
	Reproduction
	If Fitness(brood) >fitness(queen) Then NewQueen ← Brood Queen existing discarded
Continue	

New queen selection

	Brood → Queen
If	Broods are better than queens
Then	Replacement of weaker queens by fitter broods
Else	Same queen(s) continue

Natural **Honey bee mating (HBM) Process** (NHB_MP)

One queen : Mating dance in the hive
Flying Kms high away from hive Kms far off
1000s of Drones flocking around with queen
similar speed

	Queen goes for mating flight
Until	Spermatheca is full
	Drones also fly
	Queen mates with eligible drones
	If speed < lowerLimit | spermatheca is full

While	speed of flying of Queen is above threshold i.e. speed of the queen reaches its minimum speed OR Spermtheca is not full
Continue	Mating flight
	Return to hive

	Returns to hive
Continue	Mating flight

Drone leaving sperm into spermatheca of queen

	HB-26
If	queen is with the high speed level, or fitness of drone = fitness queen
Then	Drone passes the probabilistic decision rule
If	Drone passes the probabilistic decision rule & queen passes the probabilistic decision rule
Then	probability of mating is high
If	probability of mating is high
Then	mating
If	mating is successful
Then	Drone passes sperm into Queen's organ Plugs Sperm stored in queen's spermatheca

Continue	
	Queen (best solution) selects sperm of drones probabilistically
	Creation of new broods (trial solutions) Cross over drones' genotype with the queens Use of workers (heuristics) to conduct local search on broods (trial solutions). Adaptation of workers fitness based on the amount of improvement achieved on broods
until	life span of queen/hive/new brood replaces existing queen

	Reproduction
While	new queen is chosen | gametes exhausted| 2 to 3 years |
	Daily 1500 to 2500 eggs
	Egg laying
Continue	

Egg laying
Fertilized egg → female honey bee
Picks up sperm of a drone from sphermatheca
Combines with gamete of her
Unfertilized egg → Drones(Haploid)
At will queen produces egg without drone's sperm
Breeding Eggs
Egg laying in the corner of honey comb
They stick to the wall
Care taker work bees in Egg → Adult honey bee

If	crossover of drone's and queen's genotypes
Then	new brood (trial solution) generated
If	Brood
Then	Worker bee care (local search)

If	Emergency
Then	Female work bees (which are sterile) also lay eggs (Haploid mechanism)

	% Need based population
If	Colony is lack of food sources

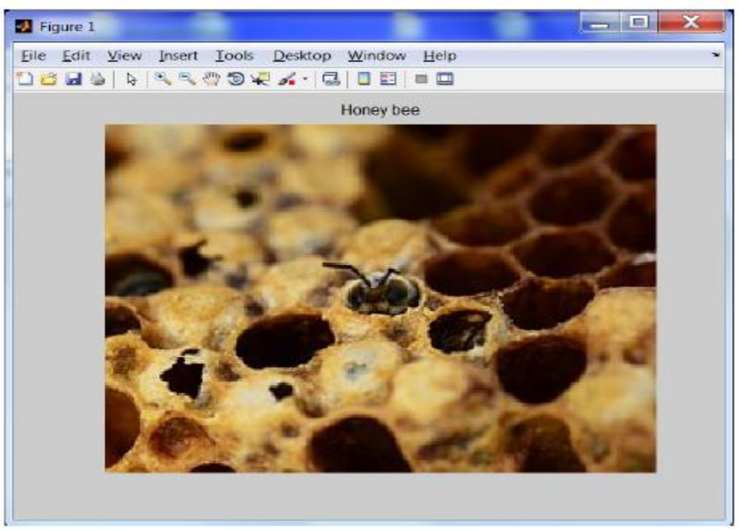
	% Unfertilized eggs
If	Sperm in the spermatheca of Queen is exhausted,
Then	It produces unfertilized eggs
	% New queen
If	Sperm in the spermtheca of Queen is exhausted,

Then	Queen produces new eggs
	Worker bees also produce eggs
	% population control
If	Colony becomes too crowded
Then	Queen stops laying

Then	one of her daughters is selected as a queen to participate in mating flight for continuation of laying fertitilized eggs
	laid egg → hatches into larva→ pupate→ adult bee

	brood contesting against queen
If	New brood is better than the current queen
Then	Brood takes the place of the queen.
If	Brood fails to replace the queen
Then	Next mating flight of a queen this brood will be one of the drones

Supplementary information (SI)




```
Queen =
    Spermathecal_size: [3x1 double]

            Speed: 100
          genotype: 1
   Speed_decay_factor: 0.9000

Queen.Spermathecal_size

     7
    14
    21
Broods.perflight

    20
    40
    60
    80
   100
echo off
```

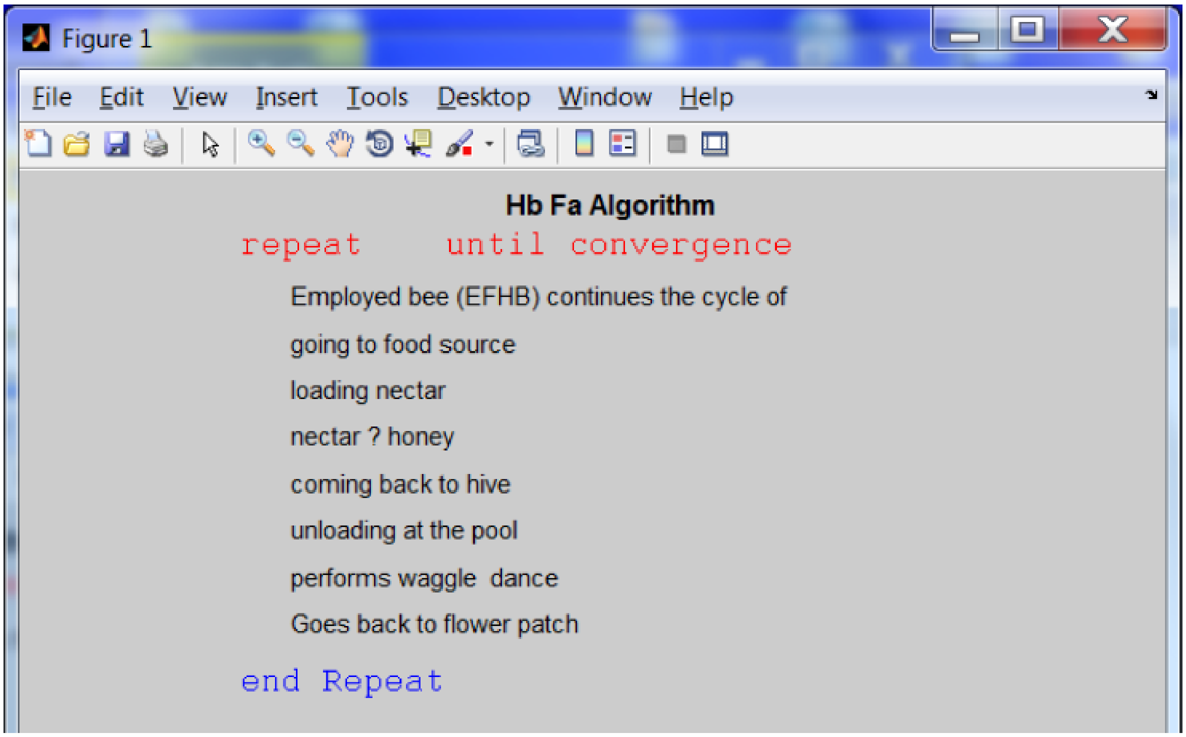
```
%    hb_jpeg.m
%
clean
Queen.Spermathecal_size =[ 7, 14, 21]' ;
Queen.Speed = [100];
Queen.genotype  =[1]';
Queen.Speed_decay_factor    = [0.9]';

Broods.perflight    = [20, 40, 60, 80, 100]';

Queen
echo on
Queen.Spermathecal_size
Broods.perflight
echo off
hb02jpg = imread('hb02.jpg');
image(hb02jpg)
axis off
title('Honey bee')
```

```
return
hb.fig02='hb02.jpg';
hb.def = 'honeyBeeAlgorithm';
hb.def,
figure,subplot(211)
image(imread(hb.fig02)),
%colormap(map)
axis off% Remove axis ticks and numbers
axis image
```

Output	OOP

foraging.food
 	
'Ant'
'Honey bee'
 	
foraging.hunting
 	
'Fire fly'
'Bat'
'Vulture'
'Lions'
'toothed Whales'
 	
Biology.HomeBuilding
 	
'Honeybee'
'Ant'
'Wasp'
 	
Biology.Mating
 	
'Honeybee'
echo off
 	
Bees.categoris
 	
'Queen'
'Drones'
'Onlookers'
'Scouts'
'Employed'WorkBees'
 	
Bees.Process_knowledge
 	
'Nector to honey conversion in gut'
'stringer activity'
 	
Bees.Skills
 	
'Fanning air'
'Water sprinkling'
'Biting invaders'
 	
Bees.tasks
 	
'Foraging'
	`%`
	`%HBFM.m`
	`%`
	`clean`
	
	`foraging = {'food'; 'Hunting'};`
	`food = {'Ant' ; 'Honey bee'};`
	`hunting = {'Fire fly';'Bat' ; 'Vulture' ;`
	`'Lions';'toothed Whales'};`
	`foraging.food = food;`
	`foraging.hunting = hunting;`
	
	`HomeBuilding = {'Honeybee'; 'Ant';'Wasp'};`
	`Mating = {'Honeybee'};`
	`Biology.foraging = foraging ;`
	`Biology.HomeBuilding = HomeBuilding;`
	`Biology.Mating = Mating;`
	`%display`
	`echo on`
	
	`foraging.food`
	`foraging.hunting`
	`Biology.HomeBuilding`
	`Biology.Mating`
	`echo off`
	`%`
	`categories = {'Queen';`
	`'Drones';'Onlookers';'Scouts';'Employed''WorkBees';`
	`};`
	`Bees.categoris = categories;`
	`tasks = {'Foraging'; 'Honey Preservation'; 'Brood`
	`caring';'Serving Queen'; 'Hive defence'; 'Emergency`
	`Fertilization'; 'Hive site exploration'};`
	`Bees.tasks = tasks;`
	`Process_knowledge = {'Nector to honey conversion in`
	`gut';'stringer activity'};`
	`Skills = {'Fanning air'; 'Water sprinkling';`
	`'Biting invaders'};`
	
	`Bees.Process_knowledge = Process_knowledge;`
	`Bees.Skills = Skills;`
	
	`echo on`
	`Bees.categoris`
	`Bees.Process_knowledge`
	`Bees.Skills`
	`Bees.tasks`

'Honey Preservation' 'Brood caring' 'Serving Queen' 'Hive defence' 'Emergency Fertilization' 'Hive site exploration' echo off	echo off




```
%
% OO_HbFa algorithm
%
clean
st2= {
'Employed bee (EFHB) continues the cycle of'
'going to food source'
'loading nectar'
'nectar ? honey'
'coming back to hive'
'unloading at the pool'
'performs waggle  dance'
'Goes back to flower patch'};
subplot(111)
title ('Hb Algorithm',  'FontWeight','bold')
text(.04,.99,['\fontsize{12} {\color{red} \fontname{courier} repeat    until
convergence} '])
%
for i = 1:8
    yy= 0.98-i/15;
     text(.14,yy,['\fontsize{9}',st2{i,:}])
end
text(.04,yy-0.08,['\fontsize{12} {\color{blue} \fontname{courier} end Repeat  }'])
axis off% Remove axis ticks and numbers
```

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