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Implementation of Ant Colony Algorithm Review

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Abstract: *Due to its strong randomness and robustness for finding optimized solutions, Ant Colony Algorithm has been the focus for many optimization applications. In this review, we present a collection of previous works implemented using Ant Colony Algorithm. Each of these implementations developed the algorithm in a way suiting the application and improving the algorithms behavior in order to reach satisfactory results.*
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I. Introduction

The Ant Colony Algorithm is an optimization method that is used in a variety of applications to find the optimal solutions to difficult non-deterministic problems. The idea behind this method comes from the pathfinding behavior of ants that relies on indirect communication between ants. This is done by leaving Pheromone tracings by each ant as they move on their different random paths. Pheromones evaporate with time. However, shorter paths tend to have a stronger scent of pheromone than of the longer paths. This allows ants to follow the shortest of all paths towards any certain destination. Using this inspiration, many research applications have been developed to find optimal solutions for difficult random non-deterministic problems.

Since the ant colony algorithm suffers from two main weaknesses, many researchers developed some improved version of it. The first weakness is the slow convergence time in some involving problems. The second issue is getting stuck within the local optimal solution instead of reaching the global solution for the problem. Many of the suggested solutions introduced changes to the algorithm or even combined it with some previous method in order to reach desired results.

This review paper will be divided as follows. Part II will introduce 20 different implementations of the ant colony algorithm along with their changes made upon the algorithm. Part III is a short discussion while Part IV concludes the review paper. Part V makes some suggestions for future works on the topic.

II. Various Implementations of Ant Colony Algorithm

A. Database Query Optimization Based on Parallel Ant Colony Algorithm

The implementation of database management systems requires an optimized multi-join query (Zheng, et al. 2018) [20]. This optimization is vital for increasing the efficiency of the database. Nowadays, applications regarding relational database management systems are having more than a 100 joins in some cases. With this increasing number, the query execution plan corresponding to these joins increases exponentially. Ant colony optimization has been a great method for optimizing such a problem. However, traditional ant colony optimization does not solve the issue of local convergence. That is why, the idea of parallel ant colony optimization (PACO) algorithm is introduced.

1) Parallel Ant Colony Optimization:

In this method, the serial algorithm of ants is changed into a parallel algorithm. This method updates the pheromone based on a probability transition formula that calculates the pheromones on edges, heuristics information regarding movement in-between nodes and the set of accessible nodes for each ant. After all ants complete their paths. The optimal path is chosen from all paths. Also, pheromones are updated on edges. Next, ants choose their next node and move towards it. Then those reached nodes are added to the excluded nodes list. Pheromones on these paths are updated.

2) Proposed Query Optimization Algorithm:

After receiving the query submitted by a user, it gets a syntax check, relation verification and then gets translated into an internal form. This internal form is an expression in terms of relational algebra denoted in terms: query syntax tree. The query optimizer decides on which physical method to use in implementing those relational algebra expressions and then generates the query execution plans for them. These plans include the order of operations that the process will be according to and it includes the method by which the operation will be processed. This optimizer is supposed to choose the execution plan with the lowest cost and push it to the query execution engine. Then the user will be provided the answer to his query.

B. Study on Submarine Path Planning Based on Modified Ant Colony Optimization Algorithm

In this application, we try to optimize the path finding of submarines using the ant colony algorithm (Shan, 2018) [11]. This method includes in its cost function important factors such as the distance to the center from a waypoint to the threat and the total length of the track. To update the pheromone combining differential evolution algorithm, we solve the ant colony optimization problem in local optimization and enhance the global search performance. We use an intelligent strategy that includes the actual navigation status and navigation environment of the submarine in its state transition calculation of probability. Finally, important factors such as safety of sailing, hiding from enemies and endurance of submarine are all taken into consideration within the algorithm.

1) Submarine Path Planning Cost Model:

Due to the deficiency and slowness of grid method in calculating the path for the submarine, it is important to develop a superior method that is faster, more efficient and adaptive to complex underwater environment. In this method, the planning of the path for the submarine takes into consideration time and voyage route. It avoids obstacles, follows mission requirements, etc. The amount of pheromone for deciding on the important short paths gets priority. However, our cost function does not include an effect for fuel consumption minimization. It assumes that varying the speed of the submarine does not affect fuel consumption. Moreover, the path planned for the submarine also accounts for safety measures such as navigation depth, spring layers, detection of enemies, inner waves, the ocean front, etc. This method's cost function has both positive factors as well as negative factors in order to find the best path.

2) Improved Ant Colony Algorithm Implementation:

We introduced a method that combines a model of differential evolution to ant colony algorithm. The amount of pheromone will vary depending on the global optimization path. When all ants complete one cycle, the pheromone of other paths gets updated. Since the submarine has to follow certain strategies and tactics when moving in difficult environment, it has to take into account the following heuristic information factors. First circumvention factor: due to complexity of environment, some areas will be inaccessible. Therefore, depth will be variable and dependent. Second, maintenance factor: since the submarine cannot stay floating, the course of navigation will also be variant accordingly. Third, Distance factor: simply, distance of travel must be shortest.

3) Simulation and Implementation

At first, the terrain of the under waters is obtained and simulated. Then regions of threat and regions of concealment are set up between starting and ending points. Then, after determining voyage and safety factors, we adjust the coefficients of voyage cost, threat cost and concealment cost to obtain three different paths. The shortest, the safest and the integrated paths. We can adjust the weights on these different factors in order to arrange for the different possible tactics that are more appropriate for the situation.

C. Ant Colony Optimization with Improved Potential Field Heuristic for Robot Path Planning

For this application, the ant colony algorithm combined with an improved potential field algorithm is used for robot path optimization (Wang, Wang, Yu, Wang, & Liu 2018) [15]. The potential field is introduced as heuristic information into the algorithm. It shows good searching features for finding optimal paths. It also can find optimal and sub-optimal paths in all environments.

In robot path finding, a feasible path should be accurate to the goal point, avoiding all obstacles and well optimized. The ant colony algorithm is developed fixing many issues related to path finding for robots. This method is strong in its global search ability and reliability. However, it has some weaknesses such as sticking in local minima or having low search efficiency. Thus, we develop an algorithm that makes use of potential field algorithm along some other parts of previous works related to robot path finding.

1) Improved Potential Field and Ant Colony Optimization:

Our algorithm calculates the pheromone updates in a manner more suitable for robot path optimization that is called ant-cycle model. Thus, we will take into our algorithm some ideas from MAX-MIN Ant System to fix the issue of getting stuck within local minima. The idea imposed here is assigning certain limits to the pheromone trails.

2) **Improved Artificial Potential Field:**

The robot moves through an artificial force field. There are two kinds of forces acting on the robot within this force field. Attractive forces which represent the goal for the robot to reach. Repulsive forces which represent obstacles that the robot will avoid. This method is well-known since it has simple calculation formulas. However, it has many issues. One issue is that at large distances the force of attraction will be too great and will cause the reaction from the robot to run through obstacles and ignore their repulsive forces. The other issue happens when the robot gets in a position where the repulsive and attractive forces are equal and opposite, the algorithm gets stuck in local minima. Moreover, if obstacles are near the goal, the robot fails to reach it. Close obstacle and narrow passages cause oscillation problems.

In our improved method we modified the attractive potential field function to avoid the over attraction that causes collision with obstacles. This was done by adding a maximum threshold. If the distance between the goal and the robot is greater than the threshold a conic potential function is used. Otherwise, a quadratic potential function is used. To solve the oscillation issue near the obstacles, we changed the repulsive potential function. This is done by adding scaling factors. The new algorithm proved to have an enhanced performance solving those issues. However, one issue remains when the robot gets trapped in the local minima. We proposed incorporating the ant colony algorithm in with our method.

3) **Potential Field Ant Colony Algorithm:**

Since ant colony algorithm usually is slow at initial stage and take long to converge, in our algorithm, the ant colony is primed using information given from results of the potential field function. Moreover, choosing the direction of the next step within the ant colony method is decided using potential field. We, as a result, reached to a piecewise function that is adaptive depending on the environment. In the beginning of the search, pheromone is distributed uniformly and the initial path is found using ant colony algorithm. After a certain predetermined number of iterations is calculated, the potential field ant colony is used in order to avoid getting trapped in the local minima.

D. **Optimal Digital IIR Filter Design Using Ant Colony Optimization**

The infinite impulse response filters are a crucial part in the advancement of digital signal processing applications (Loubna, Bachir, & Izeddine 2018) [9]. They are superior to finite impulse response filters and have more desired performance. However, they do have an error surface that is nonlinear and multimodal. This brings up the necessity of optimization algorithm in order to resolve this issue. Ant colony algorithms are excellent in solving such problems. In our research, we propose two versions of ant colony algorithm to find the optimal filter infinite impulse response design. Then the two methods are compared in terms of performance and results.
However, the design of this type of filter faces two challenges. First, it has unstable regions of operation which is dealt with by limiting the parameter space region. Moreover, the error surface of such designs is multi modal. Previous methods of conventional gradients fail to find a global minimum and usually converges locally. That is why we develop the ant colony algorithm to optimize the multimodal problem and find the filter design.

1) **Ant Colony System:**

The ant colony system has the same algorithm of the traditional ant algorithm but with three additional changes: A Transition rule is introduced depending on a certain parameter. This way we include a balancing mechanism between intensification and diversification. The update rule for the global pheromone is only implemented on the best solutions' edges. Rules of updating local pheromones are applied while ants are constructing solutions.

2) **Infinite Impulse Response Filter Design:**

The advantage of having a proper infinite impulse response filter design is its ability to have certain desired characteristics and performance. Our aim is to optimize the coefficient of the filter in a way such that the output approximates the desired response of the unknown system. The error of between the unknown system and the output will be calculated as a mean square error and then minimized subsequently.

E. **Resource Scheduling for HF Reception based on Improved Ant Colony Optimization Algorithm**

High frequency reception is not quite efficient due to the complexity of the electromagnetic environment, the dense HF signals and the limited resources in the HF systems (Liu & Wang 2017) [7]. For those reasons, it is important to improve the resource scheduling algorithms of HF reception. In this application, we develop an improved algorithm based on Ant Colony algorithm and combining it with particle swarm optimization. The update of pheromone method is adapted and has the addition of elitist strategy and global asynchronous feature. This will avoid issues related to optimization like falling into local optimum or slow convergence.

There are issues related to receiving intense high frequency band. Devices used in reception are not configurable enough and can cause repeated reception or leakage of intelligence. For those reasons, improving the scheduling method of high frequency reception will improve the efficiency of reception. The ant colony optimization algorithm has the advantage of good learning ability. It is also robust and can easily be combined with other algorithms.

Particle swarm optimization is an algorithm that depends on the best solution for a looming and updating the settlement size. This is due to the changing the step length and utilization of information of population combined with the individual experience. In this application, the parameters of the ant colony are calculated adaptively using particle swarm optimization. Selection of parameters is not dependent on human experience or repeated experiments anymore. Parameter selection is continuous, random and accurate. This improved the performance significantly and made the ant colony more stable and faster to converge. This algorithm proved effective and feasible for this application.

1) **Recourse Scheduling for HF Reception:**

The resource scheduling function includes the following parameters: set of signals, set of devices, size of the cooperative system, location of devices, effective bandwidth, coverage area of units and of signals and the decision variables of resource scheduling. A probability function can be described as when the electric field intensity within the reception area is at least of the same value as the minimum electric field intensity is required by the reception device.

In order to have a rational scheduling algorithm and an effective task assignment, some constraints must be assigned. Those constraints are set considering task requirements and device performance. The task requirements are decision variables, devices only performing a single task at most, maximum number of received signals, the coverage of signals and band of frequency for signals and receivers.

2) **Resource Scheduling Based on Improved Ant Colony Optimization Algorithm:**

Signals are represented as nodes. Paths before nodes are considered as received signals. Any signals that don't conform to the constraints of the algorithm are removed along with their nodes in order to reduce the range of signals. Ants search for better solutions following previous pheromones left by other ants until conditions are reached. The pheromone algorithm is altered in order to avoid excessive amounts of it on some paths. This was done by adding the heuristic value of the efficiency between a path and a node according to a limiting function.

Ant colony algorithm is improved using a few parameters calculated using particle swarm algorithm. The particles' spatial location and space velocity are included in the calculation. We include the optimum position for single particles while for the whole swarm the optimum spatial position is found.

The steps of optimizing the parameters are as follows:

a. Initialization of particles.
b. Calculation of parameters and initializing the pheromone.
c. Updating the position and velocity of particles.
d. Check for conditions and repeat if necessary.

F. An improved Ant Colony algorithm for MapReduce-based Fleet Assignment Problem

Fleet assignment on large scale may harness the power of cloud computing especially when it gets optimized well (Yang, Yu, Zhang, Kuang, & Wang 2017) [17]. In this application, we propose an ant colony algorithm based on MapReduce framework. This algorithm has an improved way of updating and selecting pheromones, then evolved using two different modes of MapReduce for processing in order to enhance it further.

As civil aviation is growing and developing, it is becoming more complex and the used algorithms for scheduling are of low efficiency. This is why it is important to develop an efficient algorithm to enhance the assignment of fleets on a large scale. Parallel computing technologies proved useful solving many complex problems. In this application, we use cloud computing to implement the fleet assignment algorithm. We have MapReduce as the core framework of our hadhoob cloud computing. Furthermore, tasks are split into a Mapper and Reducer stages. This way, we simplify the distributed programming process and provide a reliable functional interface. The ant colony algorithm is the parallel algorithm combined with the cloud computing. We develop two algorithms of the ant colony relying on two modes of MapReduce of processing.

1) **Technical Constraints:**

In our model, a flight string connects arriving flights to departing flights on any certain day making a flight connection for one aircraft. If all combinations of flight strings are optimized in accordance with some technical constraints, we have the essence of flight assignment solution. The technical constraints are:

a) **Time of Connection and Over Station:**
In any flight string, the airport of arrival for the former flight should be the departure airport for the upcoming flight while the time over station have to be satisfied.

b) **Uniqueness Principle:**
Any certain flight must only be occupied by one plane while one plane has only a single unique flight string.

2) **Mathematical Model:**

Our mathematical model includes the following factors. The set of planes, the maximum number of planes, the set of flights and flight strings, decisions in regard to maintenance bases, decision in regard to flight string assignment, decision in regard to flight string inclusion of plane, flight numbering, arrival and departure of flights, arrival and departure airports and finally the minimum time of passing a station.

The objective of our model is to minimize the number of planes and maximize the opportunities for maintenance. We introduce a function that constricts each plane to one flight string. It also ensures that each flight only has one flight string. Number of planes constraint, time over stations constraint and airport matching of destination and departure constraint are also constrained to certain limits according to information within the function.

3) **Fleet Assignment Ant Colony Algorithm:**

In our research, we developed an improved method of ant colony for the fleet assignment problem. The enhanced update rule for pheromones relies on added factors that are dynamic and volatile. The initial value of pheromones, set of optional flights available, chosen flights and the initial flight are all determined using a roulette selection method. Pheromone updates determine the optimal schedule for each iteration. Initial flight's pheromone gets updated from the flight string.

As the current flight gets processed, next flight is chosen according to a transition probability. The function includes concentration of pheromones between flights, time between departure and arrival, as well as some weighting factors. Pheromone concentrations are limited by an upper and lower bounds. The volatile factor is used to adjust the speed of convergence. It relies on the calculation regarding bases of maintenance.

4) **MapReduce-based Ant Colony Algorithm:**
For this application, we developed two modes of processing. One is the MapReduced-based improved ant colony optimization algorithm (MRIACO-I) and the other one is (MRIACO-II).

5) **MRIACO-I:**
Using Map function to transfer intermediate data while we use Reduce function in building the ant colony, searching for the optimal solution and updating the pheromone values.

6) **MRIACO-II:**
We use Map for building the ant colony algorithm while we use Reduce for finding optimal solutions and updating pheromones.

7) **Map Function:**
a) All related parameters get initialized such as number of ants, flights, flight strings, etc.
b) An initial flight gets picked according to a roulette function.
c) According to a transition probability, the next flight is chosen.
d) The flight string gets updated.
e) According to heuristic conditions, fitness of solution is calculated. Then the algorithm repeats.

8) Reduce function:
a. All relevant parameters get initialized.
b. According to optimal solution criteria, update transition probability.
c. Check for validity of constraints.
d. Output the optimal fleet assignment schedule.

G. **Implementation of the Protein Sequence Model Based on Ant Colony Optimization Algorithm**
In this application, an algorithm is developed for optimizing the process of building protein sequences, (Aimoerfu, Shi, Li, Wang, & Hairihan 2017) [1]. We develop ant colony algorithm in order to construct the protein model known as two dimensional hydrophobic hydrophilic (2DHP).

1) **2DHP Grid Model**:
Two dimensional hydrophobic hydrophilic grid models are used in order to simplify our work instead of dealing with the 3D protein models. Then, twenty types of amino acids were classified in regard to hydrophobic hydrophilic property. Thus, amino acid protein sequences are represented using sequences of H and P.
To make the 2D model transformation, proteins are folded on the grid points in 2D. Protein sequences are expressed using binary character strings. As a result, folding proteins in our model is regarded as inserting a sequence in the 2D grid according to two conditions: First, within the grid, pairs of characters that are adjacent in the sequence must border each other in the grid. Second, any character must occupy a single grid point only.

2) **2DHP model based on ant colony algor**ithm:
One of the more difficult problems in computational biology, biochemistry and physical thermodynamics is the protein folding problem. However, it can be split into three problems:
a) The design of a model for proper protein folding.
b) The Definition of an energy describing function for calculations between protein residues.
c) The design of an algorithm searching for configurations achieving lowest energy in an optimized way.
Based on the ant colony algorithm, we construct the protein sequence model of 2DHP on two stages: construction of the initial solution then updating of the partial search.

3) **Initial Solution Construction:**

We construct a direction selection function that uses the heuristic information to the sequencing of the protein and develops it towards the candidate of the best solution. The updates of the heuristic function are changed using heuristic parameters. Ants follow the random walk process while avoiding previous walks in order to construct a conformation candidate. However, in tight and long sequencing conformations, it is inevitable that an ant will take a walk through a blind alley which will invalidate the construction of the path. Moreover, 2DHP amino acids do not allow for overlapping. Thus, it is set up in a way to judge the initial solution beforehand checking whether it is possible to insert the current solution or not and adapt accordingly.

To sum up, to construct an optimal path, topological paths of sequences are found as many as possible. Second, to diversify solutions and avoid partial convergence, we develop some strategies that are randomized within the step of inserting the protein chain. Finally, the path will be constructed using the directional sequence found from previous work. According to the direction sequence, the initial solution is drawn. Then, search update is modified subsequently according to the candidate solutions.

4) **Partial Search Updating:**

The initial solution gets judge using the partial search updating in order to get a more optimal solution. It first uses a function that detects the number of possible H-H bonds on the initial solution, making it an updating reference. Then, the pheromone updating procedure takes place as previous ants build up a new sequence and add it to the bonds of H-H topologies. Thus, the sequence gets modified directly. New ants rely on previous ants to have better modifications opening the road towards the optimal solution. Updating takes two types: the point mutation with regard to place and the point mutation with regard to direction.

H. **An Improved Routing Algorithm Based on Ant Colony Optimization in Wireless Sensor Networks**

Within wireless sensor networks, energy is limited and routing data in the most efficient way is very crucial (Sun, Dong, & Chen 2017) [12]. Optimizing paths for data transmission is an essential requirement. We develop a better variant of the ant colony algorithm using improved heuristic information function and taking into consideration the direction of data transmission and residual energy. In this manner, we reduce energy consumption and increase the life time of the network.

The wireless sensor network is a standalone system that can collect, process and transmit data to the user terminal. Usually, these networks are run on batteries in each sensor. The network is interdependent on the battery life of the sensors as a network. It is important to distribute the tasks among the network and optimize energy consumption to prevent the network from dying early. Doing so requires optimization of the data routing through the network. In our research, we develop an improved algorithm that harnesses the information regarding positioning and search directions. It also computes the distance and transmission direction taking into consideration the participation scale of each ant with regard to the whole search process. The new algorithm improves the pheromone updating process through introducing the route evaluation index. Those additions reduce the consumption of energy in the network, extend the life cycle of it and optimize the routing algorithm in the communication process effectively.

1) **The Network Model:**

In this application, the objective is to find the most optimal path from a starting node to a destination node. Assumptions of our model are: sensor nodes and based stations do not change positions. Also, Nodes are assumed isomorphic. Third, we assume symmetrical links, meaning we can calculate the approximate distance from the senders given the transmitted power and following the received signal strength indication. Last, given the recipient's distance, each node changes the power transmitted accordingly.

The energy consumption model is dependent on the distance from the sending to the receiving node. It is much more expensive to send data to nodes that exceed a certain optimal distance depending on each network configuration. Energy consumption is made up of two components: losses regarding power amplification and losses of the electric circuitry.

2) **Algorithm Improvement:**

In ant colony optimization algorithm, ants follow a probability decision rule to select their next route. The function takes into account the pheromones and information regarding heuristics on the edges. The importance of those to factors is weighted by two impact factors. Pheromone proportions vary according to the impact factor used. We develop a modification to the impact factor function. This modification improves the behavior of the algorithm allowing it to converge faster at early stages and preventing it from falling into local convergence. Also, the pheromone proportions decrease as time passes by which is a desired behavior. As a result, the speed of convergence is faster at the start and slows gradually as the algorithm progresses further.

3) **Improvement of Pheromone Update Strategy:**

Fast local convergence can be caused by too large concentrations of pheromones on some routes. This is why it is important to introduce a pheromone threshold in our algorithm. In addition, the energy currently available in each node is not considered in the traditional algorithm. Reaching the shortest path leads to early death of some nodes in the network which in turn reduces the life time of the network as whole. Thus, we optimize both the energy of each node and route finding at the same time.

When all the ants arrive at their destination nodes, each ant represents its optimal route. Then, we produce a fitness function to select the most optimal route. It takes into account the average residual energy as well as the minimum energy of passing ants through the path. Pheromones are updated accordingly. Through this method, only the path of best fit will be chosen after going through all iterations. Finally, the energy balance through the network is improved greatly.

4) **Improvement of Heuristic Information:**

Previous versions of ant colony algorithms only take the transfer distance to the next node into consideration. However, it does not include the distance from nodes to sinks throughout the network. This parameter affects the consumption of energy throughout the network. In communication, the closer a sink to the node, the better energy conservation of the network will be. Thus, distance from nodes to sinks are included in the heuristic information calculations.

5) **Improvement of Ant Searching Range:**

The complexity and convergence of the algorithm are largely affected by the search scope and group size during the search process. The search scope is restricted in order to reduce the complexity of the algorithm and the energy consumption, consequently. First, we restrict the search to be within a certain optimal distance as a priority. If the range does not include any suitable node, then the search distance is extended. Moreover, during the search, shorter paths are considered in combination with finding a proper orientation towards sinks.

I. **Implementation of Robotic Path Planning Using Ant Colony Optimization Algorithm**

Recently, robot pathfinding has become a crucial task for several applications (Joshy & Supriya 2016) [5]. Robots are excellent in situations that humans might be endangered at such as mining, dealing with heavy machinery, high temperature works, etc. In this application, we develop an optimization algorithm that finds an optimized path for robots using ant colony optimization algorithm. The robot path finding achieved is enhanced and implemented with good tracing skills avoiding most obstacles.

1) **Algorithm and Approach:**

The environment around the robot is set up as a grid of cells. Cells can be either empty or occupying an obstacle. The robot chooses a movement from six directions. Forward horizontally, vertically or diagonally and backward horizontally, vertically or diagonally. The priority is always for the diagonal forward choice. If at a certain cell the robot finds it impossible to continue towards the destination, it traces steps back until it finds different choices to achieve a different path. If diagonal movement is blocked, the robot chooses to move vertically forward or horizontally forward according to obstacles in the way and a particular priority of action. The distance is calculated as the path gets constructed. In this manner, the robot reaches its destination along the most optimal path avoiding all obstacles.

The pheromone in the algorithm helps the robot identify the shortest path. There are two pheromone values in the algorithm. Obstacles occupying any cell are assigned a value of one in the pheromone grid. Path pheromone values are set to zero. The pheromone gets updated due to existence of obstacles and path finding, subsequently. When the robot detects an obstacle, the pheromone assigns that cell a zero and all cells around it become two. Once the destination is reached, the path pheromone values are set to three. Finally, the values of pheromone due to path and obstacles are added together as the final pheromone level.

J. Research of Neighborhood Searching Fractal Image Coding Algorithm based on Ant Colony Optimization

In this application, an improved fractal coding algorithm developed from ant colony optimization combined with neighborhood search matching is proposed (Lou & Li 2015) [8]. Utilizing the complexity of the image itself and applying fractal geometry in image compression is the method of fractal image compression. Collage theorem and iterated function systems are the basis theories in the method of fractal image compression. In the traditional method, the original images gets subdivided into regions called R blocks. Each R block has a corresponding matching region that is searched for throughout the image. Those matching regions, called D blocks, are of double the size of R regions. The fractal encoding of the image is made up of the coordinates within the upper left corner and parameters of affine transformation of the D blocks. This method has a slow matching speed and a long time of coding since it applies full range search for block matching. Therefore, we introduce the addition of neighborhood search which considers that most of the domain blocks have the matching near the range blocks. This way the search is narrowed and the algorithm is improved, greatly reducing the calculation required.

The ant colony algorithm can be implemented in order to improve the search process of D block and R blocks, shortening the time of fractal encoding and enhancing the image compression overall quality. The idea of neighborhood search in fractal image coding is as follows: first, the division of image into sub blocks to determine the range blocks. Second, defining the domain set of blocks by searching for the matching domain blocks in all neighborhoods related to range blocks. Moreover, using ant colony algorithm, we make the R blocks and D blocks within the same classification going through the clustering algorithm and thus we decrease the total matching processes, reducing encoding time required.

1) Fractal Block Coding:

Consists of three major parts:

a. Segmentation of range blocks: dividing the original image into non overlapping blocks called R.
b. Selection of domain blocks: making the search pool of domain blocks from the original image.
c. Mapping: making an affine transformation relating the domain blocks to the range blocks.

The mathematic principle behind fractal image compression uses iterated function theory. They key lies in constructing a compression transformation. Then, attaining a small error between the original and transformed image. The main task within this process is to search for the domain blocks' best matches in each range block. In previous works, this was done through full search algorithms to achieve the image transformation. Although that method gave results of good quality, it had a very long time of encoding.

2) Fractal Image Coding Based on Ant Colony:

Jacquin, through his analysis, found that most matching of range blocks to domain blocks are found in close proximity to range blocks. Subsequently, we use the eight neighborhoods in our searching algorithm. This restricts the search scope. After searching for the best matching domain blocks in those regions, we make the fractal image approximation for each of those blocks. We record the coefficient of matching for those blocks and their addresses. Then, we apply ant colony algorithm clustering in order to form the sample space for our data. Thus, we carry out the search of matching probability for the domain and range block classes.

We quantify the fractal parameter of our approximation. Usually, majority of time is spent on the calculation of matching R blocks and D blocks. We eliminated unnecessary matchings in order to reduce the encoding time significantly. From the sample space of data acquired from the ant colony clustering algorithm, and depending on the distance between range blocks and domain blocks, image regions are classified. Moreover, by applying a threshold value, at some small distances between the domain and range block, we can approximately say that two blocks are the same. In this way, we reduce the matching calculations even more.

Another classification scheme by Barnsley suggests segmenting the image into four, then calculating the mean and variance of the gray level sub blocks. Those get sorted and classified by size then divided into smooth, edge and texture pieces. Depending on the gray variance of those 4 sub blocks, the image block is divided into 16 more blocks. As a result, we adopt large image blocks to process fractal image approximation for region with slow changes and we adopt small image blocks to process fractal image approximation for region with dramatic changes. In this manner, we improve image compression ratio and enhance the encoding speed.

K. Coke Oven Pushing Plan Optimization Scheduling Research Based on Improved Ant Colony Algorithm

In coke production, oven pushing schedule optimization is a crucial process, especially when dealing with abnormal conditions where disordered sequences often come up (Tao, Gao, & Sun 2015) [14]. To resolve such conditions, we must establish an optimized pushing schedule model that achieves the least losses regarding costs, distance, time and coefficient of pushing in order to restore the proper conditions in normal process. Moreover, it is also necessary within our algorithm to improve an adaptive optimization to resolve the schedule model.

Coke oven pushing is a complex process that requires exhaustive scheduling. The process may face several issues such as sequence disorder, unexpected accidents and other irregular operating conditions. The sequence disorder issue come up often and can cause losses in costs, time, maintenance, etc. Also, for abnormal conditions most companies rely on manual systems of arrangement. However, using an optimization scheduling algorithm that works in abnormal conditions will allow for minimizing costs and improving the dealing with condition process effectively. Previous works on optimizing such conditions were not accurate enough and did not meet conditions well enough. Other works on the same problem focused only on costs but did not turn the sequence back to normal.

In this application, we will consider distance, time and the pushing coefficient factors into our scheduling model. This way we establish an improved optimization algorithm reliant on the ant colony optimization to solve the issue.

1) Problem Analysis:

During the production of coke in oven sequences, sequence disorders happening often times. Adjustments of operation sequences are needed to be performed to move from this pushing state to another pushing state. Going through several pushing sequences, it is possible to go back to normal sequencing. The process usually can be costly in terms of distance, time and other factors. The goal of our algorithm is to minimize those costs during the recovery process.

The main plan of the coke oven follows the principles:

a. The pushing sequence is conformed to proper conditions.
b. Stoves are working according to regular schedules.
c. Enough time for overhaul is ensured.
d. Pushing coefficient is set to 1 ensuring management of the coking process.

The main constraint conditions are:

- Minimizing the distance traveled by the car during disorder conditions.
- Minimizing overhaul time and coking time delay costs.
- Minimizing any additional costs of maintenance caused by coefficient of pushing.

2) Scheduling Model:

All costs are represented as punishments. The following factors of costs are considered in our minimizing calculations. Any additional distance punishment within a single cycle is included in the cost function. The time delay regarding coking and overhauling is also included. Pushing coefficients within a cycle such as the stove amounts in difference to the plan. Those factors are weighted by calculated values. The function model provides a minimizing sequence during restoration of the normal conditions that include all related cost factors.

3) Adaptive Ant Colony Algorithm:

The model for punishment of scheduling optimization between any two pushing states is transformed into a shortest path model between two nodes. First, the ant starting position is settled at the start of disorder state. Next, an ant chooses the next state using heuristic probability function. This is reliant on the pheromone and the visibility between two states in the coke pushing plan. As an ant arrives at certain pushing state, the pheromone gets updated subsequently. Evaporation rate is also updated accordingly. The pushing plan is constructed as ants form their own paths and leave pheromones on them. The path with the most pheromone on it makes the optimal pushing plan. Due to the positive feedback mechanism in the traditional ant colony algorithm, the ants behavior keeps them within local optimal solutions. Setting up limits for the pheromone prevents falling into local optimal points.

4) **Initializing the Pheromone:**

The starting value for the pheromone has a great effect on the algorithm behavior. However, the size of the oven optimizing problem may vary. Thus, the initial value for the pheromone must also vary according to the proper size of the coke optimizing problem. We include in the function calculation the factors of number of stoves, number of disorders, and the probability of ants' selection. Those factors strengthen the algorithm's search ability.

During the iterative process, the pheromone range set causes the convergence speed to be slower and the efficiency of the algorithm goes down. However, we introduced an adaptive global rule for updating the pheromones. The pheromone increases as the size changes within an optimal path. As a result, the efficiency and convergence speed of the algorithm improve greatly.

L. **An Optimization Model for Evacuation Based on Cellular Automata and Ant Colony Algorithm**

As buildings become more complex and huge, it is more crucial to establish more dynamic evacuation plans in order to account for emergencies and optimize the evacuation process very well (Ye, Yin, Zong, & Wang 2014) [19]. Thus, we develop a proper simulation model of pedestrian evacuation behavior including heuristics representing real conditions in order to make a proper and effective scientific evacuation plan. Our algorithm is built upon cellular automata model combined with ant colony algorithm. Heuristic information model accounts for moving rules of neighbors from the cellular automata as well as the law of export selection. Those heuristics are harnessed within the ant colony algorithm to reflect the personnel behavior of pathfinding more realistically.
Due to the simplicity and effectiveness of cellular automata model it was easily realized as simulation model on computer even from complex situations. It can be used to describe the dynamics of pedestrians' evacuation process successfully. Public buildings vary in structure and function. Thus, the evacuation process can be more complex and need to be accounted for in the function calculation in order to reach better models. This application develops an improved cellular automata model reliant on the ant colony algorithm in order to simulate the evacuation process of pedestrians from a classroom with obstacles. It also gives analysis of the available exit options and possible movement routes on evacuation.

1) **Cellular Automata Model:**

The cellular automata model is made up of cells, cell spaces, neighborhoods and evolutionary rules. Each cell's value is determined depending on its neighboring cells in every step of the process. This model uses Moore's neighborhood that involves the eight surrounding cells. Thus, a pedestrian can move to any of the eight surrounding cells unless they get occupied. All cells' statuses are constantly changing at the same time.

If multiple ants are competing for a single cell at the same time, one is chosen at random while the others can stay on their spots. Next, they can choose their routes again until they find their destination. If ants are not able to choose an optimal route, they pick a sub optimal cell with no consideration to the export orientation.

2) **Improved ant Colony Algorithm for the Model:**

In our model, ants start from the evacuation starting nodes. Their destination is the exit nodes. The pedestrians are represented by the ants. Each ant starts from a randomly selected node. Depending on the environment parameters, ants move from one node to the next one. Their decisions are taken on a probability function that depends on the calculation of distances and inclusion of heuristic information from the environment. After a certain number of iterations, all ants complete their routes. Shorter routes have more pheromone left on them than the longer ones. In addition, pheromones have a function of evaporation over time. Through this feedback mechanism, the optimal path is found and used by all the ants.

M. **School Bus Routing Problem Based on Ant Colony Optimization Algorithm**

School bus transportation is an important part of the education experience in students' lives (Huo, Yan, Fan, Wang, & Gao 2014) [4]. The scheduling and routing problem of school buses is crucial in dense regions and big schools. The proper optimization of but pathfinding can minimize the costs, time of bus services and make the transportation experience more convenient. For this application, an algorithm is developed to solve the school bus optimization problem. A mathematical model for a single center and a single bus is implemented. In our case, we collected data related to a secondary school in Beijing and analyzed it completely. Data included questionnaire analysis, distribution of addresses, bus stop selection and generation of routes. The problem was then solved and optimized using ant colony algorithm.

There are two concerns when it comes to the students' every day travel from and to the school. First, students' convenience and time during traffic congestion is a big problem when it comes to bus transportation. Second, safety of students is also a concern in public transportation. Optimizing the traveling route of school buses can reduce the problem significantly. This process is implemented through few stages. It starts by preparing the data, selecting appropriate bus stops, adjusting the time of school bells then scheduling the optimized routes. Through the use of ant colony algorithm, we will account for optimizing all aspects of the problem and generate the shortest path for the buses.

1) **Data Preparation:**

Due to the wide spread concern for the safety and convenience of students in Beijing, and due to the high traffic congestion surrounding schools, we started collecting data through analysis and distributed questionnaires. Most primary and middle school students of Beijing have to go to schools nearby their homes. According to the surveys, majority of students live no more than 5 km away from their schools. About 50% of student in Beijing use motor vehicles to go to and from schools every day.

Students' choice of travel method is dependent on few factors such as economic conditions, age, travel distance, available bus service and distance to bus stop. Time of travel, distance of travel, safety and other costs are also important factors. According to the survey, people consider a 10 min walk an acceptable time. In our work, we introduce the following constraints in order to develop the bus routing problem:

- All bus stops must not be farther than 0.5 km from any home.
- Students within the range of 1 km will not be included in the bus route.
- The main objective of the function is to optimize travel time.

2) **The Distribution of Students' Homes:**

At first, we address and label all the students houses on the map. We make a series of operations on the map like information extraction of roads, ignoring of certain areas, etc. Most of the homes are distributed around the school which is more practical for the bus routing. As a first step, we must generate the bus stops depending on the clustering of addresses according to the distribution. Only homes that are farther than the set maximum distance are included in the clustering and bus stop generation. The clustering algorithm is reliant on Euclidean distance metric. Next, we use the location allocation routing method for route generation. This method suggests that each student is assigned to some selected sites and then gets a path. This way, bus stops get generated, students get assigned and routes are implemented. Each stop is represented by a circle of 500 meter radius with the center coordinate set where the stop is located. The student count within the circle are the students who will use that stop. This is to be accounted for since they must not exceed the number of seats on the bus.

3) **Mathematical Model:**

The following assumptions are used to develop our mathematical model:

- One center.
- One vehicle model.
- Schools and students locations are given.
- Every student uses one stop.

The bus routing is then represented as a cost minimization problem where the function is aiming to optimize the travel time of students.

The function will include the following constraints:

- A bus stop has one bus.
- Students must not exceed the number of seats on the bus.
- A stop has only one route.
- Buses leaving a stop must equal to the buses returning to that bus stop.

N. **The Tracking Framework for Lobe Fissure Based on the Modified Ant Colony Optimization Algorithm**

One of the most commonly used imaging technologies in medical applications is the computed tomography. Lung lesions are inspected using this technology (Chen, Wang, Shen, Chen, & Fang 2014) [3]. However, it requires some computer aided diagnostic software to be more useful and informative. In this work, through an improved tracking framework, we extract lobe fissures in lung images using a modified ant colony optimization algorithm. The segmentation procedure's accuracy is improved through increasing the pheromones consistency on lobe fissure.

Lobe fissures in CT image scans are difficult to detect and extract. This usually causes faults in the lobe separation process. Unlike previous works on this topic, we found that the sagittal view of lungs can be more informative and better to work with for our case than dealing with the axial view or coronal view. Both the axial and coronal views cannot display all of the information relevant to the lobe fissure.

Thus, our focus is mostly for the unobvious lobe fissures. We try to find a tracking framework that is fast and efficient in order to extract the lobe fissure. To have good accuracy in our results, we modified the ant colony algorithm by adding several calculation rules in order to increase the walking ants' numbers on lobe fissures. In this manner we have more pheromone produced on the contours allowing for the ants to better follow the paths. At the end, the optimal with highest amount of pheromone will be the optimized solution.

1) **Robinson Filter and Kirsch Filter:**

In the beginning, we implement two filters to improve the edges of the region under study. Points of the image are put in a convolution algorithm of eight parts. The maximum responses for each of these parts correspond to only the certain edge direction relevant. The maximum of those eight directions represents the image edge amplitude. Codes of the edge direction are the serial numbers of the maximum response.

Before entering the ant colony algorithm, two filters are applied in order to enhance the performance of the algorithm and make it more efficient. Those two filters are Kirsch filter and Robinson filter. In this experiment, Robinson filter's amplitude on lobe fissures is less than other regions of the lung. However, Kirsch filter's amplitude on lobe fissure is higher. Since all pixels on lobe fissures have the same direction, the resultant path from this algorithm might not be the most optimal. Thus, we define a function to avoid this issue and find the optimal path.

2) **Design of Modified Ant Colony Algorithm:**

The lobe fissures are tracked using the modified algorithm of ant colony optimization. The algorithm is simulated as ants investigating the paths from starting points to ending points. From the sagittal view of the lung CT image, we could observe that the lobe fissure's intensity is lower than the lung tubes' intensity but higher than the lung region's intensity. Therefore, using the Otsu method of location map to obtain the lung tubes. Adopting an intensity function to initialize the pheromone in our algorithm is done to create the pheromone tables and so the location map.

3) **The Updating Tule of Pheromone:**

In our modified ant colony algorithm, according to two rules we update the pheromones. A local rule and a global rule. Local rule is used when each ant completes its own track. Next, the ending nodes of every round is updated using the global rule. Within the local rules there is a function of evaporation update as well. In creating the new direction for any ant within the algorithm, we implement two ant methods of movement. In the random step, an ant can go in any of the eight possible random directions. It can also be assigned a controlled direction using a certain variable. Finally, when ants complete their paths, we can obtain the most optimal path.

O. **Study on Cloud Resource Allocation Strategy Based on Particle Swarm Ant Colony Optimization Algortihm**

Allocating resources efficiently in cloud computing environments is a crucial task (Yang, Liu, Xiu, & Liu 2012) [18]. Cloud computing resources are distributed and diverse. Dynamic real time user demands are not easy to predict. Using ant colony algorithm combined with particle swarm algorithm, we develop an optimization function for the resource allocation problem. We also modify the ant algorithm in order to resolve the issues of slow convergence and the parameter selection problem.

Using the internet, a large scale computing model can be used to provide the virtualization, abstraction, dynamically scalable management, storage and computing platform for outside users depending on their needs. The ant colony algorithm can be used to optimize the cloud computing resources through the heuristic optimization algorithm. It has the ability to solve the issue of real time change in user demand.

1) **Cloud Computing Resource Allocation Model:**

Cloud computing can be thought of as a computing machine that is virtual. It has special software to simulate the implementation of hardware. When a task is run by the virtual machine, the task agent requests the resources from the proxy algorithm in the virtual environment. Improving the resource utilization of the proxy mode will increase the efficiency of the network and provide a better service to the users.

2) **Ant Colony Optimization Algorithm Based on Particle Swarm Algorithm:**

From the characteristics of the cloud resources, we measure each node's CPU power, capacity of memory, external capacity of memory and bandwidth. These resources are taken in as the node's pheromone values and used in the calculation of pheromone initialization. Ant colony algorithm has two issues when it comes to cloud resource allocation problems. First, depending on the provided characteristics, the colony might get mislead into a local optimal point starting from a certain pheromone. Moreover, since cloud resources usually are implemented on very large scale and have strong randomness, those disorganized resources might cause the colony to take too long in order to reach the optimal path to resources. As for the first issue, we resolve it by updating the pheromone timing as a new task gets assigned to nodes computing. This way nodes of decreased performance are included in the pheromone updates. As for the second issue, relying on the strategy of rewarding and punishing, the better solutions get rewarded while the worse solutions get punished. This is done via updating the pheromones accordingly. As a result, we increase the difference between the optimal solution and the rest of solutions. This makes the solution converge faster.

3) **Prediction of Execution Speed of Resource Nodes:**

Due to differences between each node in terms of hardware, software and structure environment, it is quite hard to predict the speed of executing any number of tasks. However, instead, we assign different tasks to certain nodes in order to optimize the usage of the cloud resources. This way the overall performance of the cloud environment is increased. Also, the execution speed and the prediction model of the cloud is improved through accumulation of implementation and experience.

4) **Combinatorial Optimization of Initial Pheromones Weight Parameters Based on Particle Swarm Algorithm:**

Since different tasks require different resources and higher performance in one regard or another, it is important to develop our method to account for that kind of requirement. Introducing weight factors in the calculation of pheromones in a way that combines the parameters of particle swarm algorithm in order to improve the performance of ant colony optimization. As a result we evaluate how much of a good fit is our solution by finding the global optimal solution starting from the current optimal value. This algorithm has robustness, good global capacity, fast convergence and does not require much parameter adjustment.

The algorithm produces a group of K particles randomly in our solution space. Those particle are updated using the track of locations according to two values: the optimal solution found for each particle and the global optimal solution found by all particles.

The steps to execute the algorithm are as follows:

a) The Task Agent receives tasks submitted by the user.
b) A particle, represented as different weighted factors, goes through 20 iterations in the modified ant algorithm and arrives at an optimum solution. This determines the starting pheromone amount in the algorithm.
c) A timer is set by the task agent as ants are sent onto deciding the relationships between different tasks. They will determine the next step direction according to the algorithm.
d) As each ant arrives at a virtual node, the node gets sorted into either as effective node or not an effective node. This is done according to a formula. Pheromones are updated accordingly.
e) Ants coming from effective nodes bring feedback pheromone amounts as positive feedback.
f) Each node that feedback ants pass by are modified by pheromones.
g) If no feedback ant has come through some route, the task agent will assume that suitable resources do not exist on that route.

After completion of all routes, pheromones are updated according to the success or failure of the route set up by each ant. Failed tasks are assigned to other nodes as necessary.

P. SAR Image Ship Detection Based on Ant Colony Optimization

An important application in image extraction is the edge detection extraction. Ship detection in SAR images can be implemented using the ant colony algorithm in order to extract the edges of the ships (Li & Wang 2012) [6]. Using this method, we effectively extract ship targets with good accuracy and keeping the structure of the images intact. The results show the effectiveness of the algorithm in optimizing the solution of detecting the edges as well as showing the broad possibilities of applications for the future.

1) **Edge Detection Based on Ant Colony Optimization Algorithm:**

Since ant colony algorithm has a few weaknesses such as the long search time or local convergence, we developed a method that updates the pheromones twice and allows for adjustment of the optimization threshold dynamically. Edges of objects contain the most important information when it comes to segmenting images. We use ant colony optimization to detect edges of images according to the following process:

a) Initialization process: ants are assigned to different nodes randomly. Those nodes are considered as starting points for ant paths and will have an initial pheromone value.
b) Construction process: each ant moves from one node to the next one according to a transition probability function. The function includes in the calculation pheromone values and heuristic information.
c) Updating process: the pheromone matrix is updated on two steps. The first comes after constructing the path of each ant. The second ensures constraining the pheromone to the threshold function.
d) Decision process: the pheromone gets compared to the threshold node by node. This is to check if the nodes are edges or not.

Q. Application of Ant Colony Algorithm on Automatic Testing Path Optimization in Complex Circuits

We develop an application of ant colony algorithm in establishing the shortest path for testing complex circuits automatically (Xinmei, Peng, Junling, & Wen 2012) [16]. Our research presents a system model, an implementation scheme, and realized experimental results on the automatic testing of complex circuits using a moving probe test on complex circuits. In complex circuit testing using moving probes, it is important to find the most efficient pathing in order to save time and resources of testing since the complex circuitry can consume a lot of time being tested. Many previous works were developed to find the most optimal path such as net algorithm, fuzzy logic, neural networks, artificial potential, etc. However, most of these methods had issues such as complexity and efficiency.

1) Realization of Ant Colony Algorithm on Online Testing Path Optimization of Complex Circuits:

The most common method for testing complex circuits automatically is the flying probe testing method. Automatic testing using this method requires an optimization algorithm in order to improve the efficiency of the test and conserve time and resources. A number of ants is assigned to each node within the circuit randomly. Ants move from one node to the next depending on a probability function and heuristic information in regard to the circuit. As paths are constructed, ants update their paths' pheromone values with regard to the time and distance taken.

2) Steps of the Algorithm:

a. Initializing parameters, time, cycles, size of largest cycle, number of ants, number of nodes, and heuristic information of paths.
b. Changing the time cycle.
c. Updating the tabu list.
d. Updating the number of ants.
e. Calculating the probability of movement towards the next node.
f. Updating the tabu list's pointer.
g. If some element within some cycle did not finish, increase the number of ants.
h. Update the pheromones of all paths.
i. Check for termination conditions.

3) Setting the Experiment:

The implementation of experiment to optimize the path finding of the flying robot probe has the following method. First, from a CAD software, we obtain the electric network for the circuit to be tested. Then, a net table is complied. Coordinates of specific circuit are calculated and distances in between them are found. Using the ant colony algorithm, we search for the optimal solution for the paths. If the circuit is more complex, the circuit is divided into virtual grids in order to have a set of sub circuits. Each part of the grid gets optimized locally. Then, the partitions are each considered a node and then the overall circuit is optimized between those nodes.

R. Study on Route Optimization of Logistics Distribution Based on Ant Colony and Genetic Algorithm

In vehicle route optimization, two of the most commonly used methods are the genetic algorithm and the ant colony algorithm (Qin, Qin, & Li 2012) [10]. Both of those methods has some drawbacks. The genetic algorithm has the disadvantage of iteration redundancy while the ant colony algorithm has the disadvantage of falling into local optima. We develop a hybrid algorithm that combines those two algorithm to solve the logistics routing optimization problem in a feasible, efficient way.

Logistics play a crucial part in the economy. Distribution costs are essential in the expenses list and reducing those is very important. Optimizing the distribution routes reduces costs, improves the delivery time and customer satisfaction and reduces mileage and emission of vehicles. Ant colony algorithm has been used for route optimization in previous research. However, it suffers from two drawbacks. First, it can get easily stuck in a local optimal solution. Second, it may take too long computing the solution. However, genetic algorithm has the advantage of converging fast to the solution. It also suffers from the lack of feedback data within the algorithm. It also has many redundant solutions. Thus, we develop a combined algorithm that improves both methods and provides a more effective algorithm without these drawbacks.

1) A Mathematical Model of Logistics Distribution Routes Optimization:

In logistics distribution, route optimization takes many factors into account. Customer demand, delivered amount, time, mileage, vehicle capacity, and delivery time are all part of the optimization problem. In our work, we have a few assumptions and conditions:

- Delivery vehicles must all start from one center of distribution. They also return to it.
- Each distribution point cannot require more than the capacity of one delivery vehicle.
- The length of route distribution should not be more than the maximum distance a delivery vehicle can take.
- Each client must get their needs with one delivery only.
- There are enough vehicles in the distribution center.

In this model, the cost of transportation can be time, distance or cost based on each case conditions. In our calculation, the operating costs and the number of vehicles can be added. Our model has an objective function, a capacity constraint function, a limit on the task vehicle number to only one and having a limit of one vehicle used by each need point.

2) **Design of Hybrid Optimization Algorithm:**

In route optimization of logistic distribution, ants represent the delivery vehicles. Those ants have the job of the travelling salesman. They all start from the point of departure. According to certain criteria, they move from one customer to another. Visited customer get deleted from the list of potential next customers. The ant does not finish its job until all customers have been visited. Then, the local pheromone gets updated along each path. According to a local update strategy, a cycle is constructed after all ants have completed a single tour. Then, optimal and sub optimal routes are selected from those cycles and then mated up using the genetic algorithm. As a result of operation of mutation and mating progeny, a best solution is selected from all optimal solutions. The pheromone gets updated and the next loop starts.

Since the genetic algorithm improves the solution's diversity, the use of it at the end of each cycle as a mutation algorithm prevents falling into local optima effectively. As the solution of the genetic algorithm is more optimal than the ant colony's, the number of cycles required to reach the optimal solution will be greatly reduced. In the design of the algorithm, the supply points are the customers, the supplies represent the demand by each customer, and the initial vehicle load is zero. Each vehicle is supposed to pass by each customer until the vehicle cannot take the next customer's load. It then returns to the distribution center. Empty vehicles move to the next loading round of actions.

3) **Steps of the Algorithm:**

The number of supply points is given, their coordinates found, distances in between calculated, ants randomly assigned to these points, rated loads, maximum iteration number and iteration counter initialized.
Ants move to the next city unless it has already been visited or the required load cannot delivered by the current ant. A path is found according to probability function for all cities depending on selection of roulette. As a vehicle gets unloaded, loads are subtracted from the vehicle and the visited location is added to the tabu list. If the load is not enough for any of the possible next destinations, the ant returns to distribution center. Paths traversed by vehicle is accumulated to the total length.

Pheromones get updated using the rules. From all the paths of the one particular city, the optimal solution and sub optimal solution is found. Through the mating process we get the new optimal solution using the rules of the genetic algorithm. The mutation algorithm is performed on the optimal and sub optimal solutions using rules of the genetic algorithm. The best solution is found from all of the optimal and suboptimal solutions. Pheromones get updated using the global rules of update.

S. **Route Optimization for Bus Dispatching Based on Genetic Algorithm-Ant Colony Algorithm**

For this implementation, we propose a new method for optimizing the dispatching of buses using a genetic ant algorithm (Tang, Ren, & Zhao 2009) [13]. The mathematical model we developed is a multi-objective route optimization algorithm taking into account some limiting conditions. The genetic algorithm is used in conjunction with the ant colony in order to resolve some issues and improve the performance of the overall results. The combined algorithm has better performance and faster convergence. It improves the randomness and determinability of the ant colony algorithm.

In optimization problems for bus dispatching, the objective can be the interest of passengers or the bus enterprise's. Due to the randomness, indeterminacy and difficulty in data collection, practical operation in businesses deal with difficult factors to reach satisfactory results. In this work, we develop an algorithm that optimizes the dispatching process and delivers a solution for this problem.

1) **Genetic Ant Colony Algorithm:**

In order to take advantage of the strengths in both ant colony algorithm and genetic algorithm, we develop a combined method. The genetic algorithm has a searching ability that is extensive and simple. It is expandable and well randomized. However, it has a weakness in regard to good feedback system. It can have many redundant iterations. As a result, when we combined it with the ant colony algorithm, the pheromone update works as a guidance for genetics algorithm. And results found using genetic algorithm are useful for updating the pheromone. In this parallel system, high efficiency is obtained finding a more accurate solution.

2) **Algorithm Procedure:**

Introducing the general idea, the bus corporation will be the dispatching center. All buses start form the center and go to the bus stops making a full circle. There are a maximum number of buses and number of passengers per bus. Buses can only travel a maximum distance. Within the algorithm, ants search for the optimal route combining constraints set by the interest of the company in regard to route combinations for several iterations until the satisfactory solution is reached.

In public transit, minimizing bus mileage, travelling costs, runtime, number of buses are all important factors. Also maximizing the load factor for buses is good for the company. In our work, the objective within the algorithm is to optimize the number of passengers' direct arrival on a line. This affects the line coefficient of the route attracting passengers in one way, that is, when a bus takes long routes on the way, travel time and cost will be increased and less passengers will take that route. Which in turn will reduce the number of passengers' direct line of arrival.

3) Constraint Conditions:

- The maximum value for the nonlinear coefficient of attraction for each line.
- The load factor for each bus must lie between 50% and 120% as they pass each stop.
- The maximum distance allowed for each bus to travel which should not exceed half the maximum of a circle.
- The time between two consecutive buses. The company wishes to maximize it and passengers wish to minimize it. We decided to make a regular fixed value.

4) **Selection:**

According to a probability function, decision is made in regard to the most feasible solution. The function includes in its calculation a few factors. The fitness of the solution of the colony, the information left behind, the pheromone values, the heuristic information dropped for the clients, excluding all passed points, information collected during travels and some weighting factors. According to roulette selection, a parent set of solutions is selected. Then, excellent solutions get selected from that set randomly and the repeated solutions get deleted along with the solutions lying outside the boundaries. After that, the pheromones get updated accordingly and the process gets repeated.

5) **Crossover:**

To have a cross generation of solution, we generate individuals using a probability crossover in order to determine the global search ability. In this way, we get two parent individuals as well as a single random number. This number determines the criteria of stopping the cross generation. Upon completion a decision set is generated and the local pheromone gets updated.

6) **Mutation:**

The operation of mutation decides the capability of the local search of the algorithm. It also aids in the generation of new individuals. Each individual has equal chance of variation. An individual is selected and given a random generated number. This number determines the variation operation's stopping criteria.

7) **Pheromone Updating:**

The next step of the process is the global pheromone updating process. Using the aggregation principle for updating pheromones, we introduce the definitive pheromone sum update mechanism. To illustrate, the total pheromone amount is constant. The remaining pheromone in the pheromone matrix keeps the same proportions in regard to the volatilized pheromone after each process. This will incur a dynamic balance in the algorithm system.

T. **Application of the Hybrid Algorithm Combining Ant Colony Optimization Algorithm with Micro Genetic Algorithm to the Optimization of Multilayered Radar Absorbing Coating**

In this research, we present an optimization algorithm for designing multilayered materials used for radar absorption (Chao, Liu, & Yang 2008) [2]. This algorithm is based upon the combination of ant colony algorithm with the micro genetic algorithm. To meet practical requirements of radar absorption material design, we introduce specific constraints for optimization. Total thickness and types of materials used in the design are accounted for in the search process for the optimal solution.

The ant colony algorithm has a few good characteristics that makes it more perfect for this kind of application. First, it uses positive feedback which gives fast discovery of good solutions. Second, it has a distributed computation which prevents early convergence. Moreover, it uses a constructive heuristic information which help reach acceptable solutions in the early stages. Thus, the ant colony algorithm proves to be robust and easy to combine with other algorithms in various applications. Thus, we develop a combination of ant colony algorithm and micro genetic algorithm in order to find optimal designs of materials for radar absorption. The designs obtained aim for high performance, lightweight, broadband, thin, radar absorbent characteristics with real electromagnetic parameters.

1) **Construction of the Multilayered Radar Absorption Materials:**

The design of the radar absorbent materials is accounted for using a multilayered coating backed by a perfect conduction plane. The design includes calculation of the characteristic impedance for the input, the thickness of the layers, the permeability and permittivity of the layers and the last layer which is the conducting plane. Thus, we find the reflection coefficient of the design and minimize it.

2) **Process of the Hybrid Algorithm**:

At first, all parameters are set and initialized. Second, solutions of the ant colony algorithm are obtained and the pheromones are updated. Third, solutions obtained from ant colony are transferred to the micro genetic algorithm to optimize the thickness of each layer in regard to some constraints. Fourth, best solution of each iteration is picked and global pheromone gets updated. Finally, termination conditions are checked and the best solution gets outputted.

3) **Ant Colony Optimization Algorithm Design:**

For this application, ant colony algorithm is used to find the optimal solution of the coating layers combination. The objective is to make a sequence of material codes from different layer combinations of radar absorbent materials and multiple choices of usable materials. Each ant moves from the starting point picking a random material code in every step, then make a sequence after a certain number of steps. This sequence is a representation of one radar absorbent material construction. Pheromones get updated after every sequence construction by reducing the values using evaporation local update rule. This is done in order to diversify our searching process for all later ants to prevent premature convergence. After a certain number of steps, ants make a sequence and provide the radar absorbent material construction. This gets transferred to the micro genetic algorithm in order to optimize its thickness for every layer. Next, according to the best sequence construction and best thickness optimization, the pheromone global update rule is used to give more importance to the best ant solution.

4) **Micro Genetic Algorithm Design:**

The micro genetic algorithm begins with a given small, random population. In the traditional genetic algorithm fashion, this population gets evolved and converged for a few generations. Only the best individuals are kept from previous generations that converged. Then, a new population is randomly chosen again and the process restarts. The operator of crossover is a single point operator. No mutation operator is utilized in this micro genetic algorithm.

III. Discussion

Given a general look at all of those implementations we can deduce that the ant colony algorithm has a great capability to be integrated with many other algorithms in order to enhance its usefulness and reach better behavior. It can also be developed in a parallel behavior or a series behavior. Different methods improved on the initialization of pheromones while some other introduced limiting factors. Moreover, introducing enough heuristic functions of information will provide more desirable behavior of the algorithm. The algorithm proved useful for many real life problems regarding pathfinding, scheduling, combinatorial designs, sequence construction and optimization, cost reduction, time management, resource management, image segmentation, etc. This gives a brief insight on the strength and robustness of the ant colony algorithm.

IV. Summary

To conclude, the ant colony algorithm has been developed in many applications to suit the needs for optimizing a solution to a problem. Integrated with different mathods and adaptations, this algorithm is used to deliver an optimized objective function set by the developer in order to resolve the given non deterministic problem in an efficient and fast way. The algorithm proved to be robust and flexible as well as having well randomized behavior that allows to search for the minimum within most optimization problems.

V. Future Work

Given its flexibility to be implemented in various applications, it is useful to be developed even further for optimization problems related to code optimization, gene sequencing, encryption, image segmentation, automation, etc. This algorithm requires some setup of standardization in order to allow for easier integration with any application. Weaknesses need to be resolved for the standard method.

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