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The Integration of Genetic and Ant Colony Algorithm in a Hybrid Approach

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Abstract: The genetic algorithm has many difficulties in solving path plan optimization. Problems like the lack of appropriate setting and settings for different applications. This research work proposes an improved genetic algorithm that combines ant colony algorithm for path optimization. The goal is to eliminate the parameterization uncertainty of the traditional genetic algorithm by introducing the ant colony optimizer. Through the hybrid algorithm, optimization is achieved in moving from point to point, reducing the total distance and improving the travel time. With the help of the global search features of the ant colony optimizer and the stepwise search features, the optimal parameters of the genetic are improved, and the finding of the optimal solution in the global application of the hybrid algorithm is accelerated. The experimental results show that the proposed algorithm can automatically obtain better parameters, especially in its initial values, having good solution accuracy, robustness and significantly better efficiency. The hybrid algorithm was tested on a TSP problem but has applications in spatial mechanics systems such as CNC machining, robotic systems and Coordinate Measuring Machines (CMM). A CMM application is also presented in the results of this paper. Experimental measurements show that up to 40% path planning optimization can be achieved compared to a simple genetic algorithm.

Keywords: *genetic algorithm, ant colony algorithm, hybrid approach, optimization*

1. Introduction

In recent years, many scientists have carried out research works on the problem of finding an optimal route. The problem of finding an optimal route is difficult to be solved due to the characteristics of many constraints and non-linearity. Various intel-ligent algorithms are used in path planning problems, such as the standard ant colony algorithm [1], particle swarm algorithm, genetic algorithm [2], and many others. The basic model of the Ant Colony System (ACO) was first proposed by the Italian scholar Dorigo M. in 1991 and was first used to solve the traveling salesman problem (TSP), but it did not immediately lead other researchers to deal with the same subject [1]. Just five years later, Dorigo published an article and described the working principle and mathematical model of the ant colony algorithm in more detail, which attracted the attention of more scholars, and then more related research gradually emerged.

During the rapid development of the ant colony algorithm, a number of achieve-ments have strongly promoted its development, such as the elitist strategy ant system and the Ant-Q ant system proposed by Dorigo et al. Research [3] proposes a mul-ti-optimization algorithm based on long short memory network and adaptive commu-nication strategy, which speeds up the convergence, as well as improves its accuracy, and helps the algorithm to escape from the local optimal solution. The extended ant colony algorithm can cover some specific fields. An automatic ant colony algorithm (AU-ACO) was proposed [4] in order to solve the constraint satisfaction problem (CSP). This reduces the assignment degree of the algorithm to some extent, improves the convergence speed, and has more opportunities to approach the optimal solution, which greatly improves the performance of the algorithm. In [4], some defects of the ant colony algorithm are discussed and applied to ship route planning after some im-provement. An ant colony algorithm is essentially a genetic one, which has certain characteristics of nature, such as the law of nature that the strong eat the weak and the weak are eliminated. The search factor of the algorithm species often has a certain randomness, and with this property, it can solve some problems that are difficult to solve by traditional algorithms, such as TSP problem, production scheduling and clus-tering problems. If direct search or dynamic programming is used, the computational complexity of the problem will be very high. The ant colony algorithm can skip many search paths and get an adequate result. However, the optimal parameters of the ant colony algorithm in applied models are often different and users spend a lot of time to find the right parameters for their own process. At present, the selection of ant colony algorithm parameters in the multi-task path planning system lacks a clear standard in the industry [4].

Various researches have also been conducted in search of hybrid algorithms for trajectory optimization [5- 3]. Among other characteristics, methods are presented to find the best way to measure various objects with a coordinate measuring machine (CMM) where a combination from genetic algorithm and a greedy selection crossover GSX is used. This hybrid approach with the optimization reduces the total

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path of the end effector and thus reduces the total measurement time [6- 4]. Automated pro-grammable devices operated remotely from a coordinate measuring machine (CMM) reduce operating costs and programming time [7- 5]. Thus, a strategy is proposed to automate measurement and planning processes by properly combining measurement and monitoring points in a logical order. Algorithms are considered based on how checkpoints are managed at a particular level, such as insertion, editing and deletion processes. A collision control program is created from the algorithm, which selects and processes control points during the path of measurement.

Inspired by the hunting behavior of wolves, Mirjalili et al [8] proposed a Grey Wolf Optimization (GWO) algorithm in 2014. The social organization and hunting behavior patterns of wolves make the algorithm have strong searching ability. At pre-sent, the algorithm has been widely used in many engineering fields, including labora-tory scheduling, numerical optimization, image fusion, and power system configura-tion. In [9], a method of using Hybrid Grey Wolf Optimization (HGWO) for automatic adaptation to Variational Modal Decomposition (VMD) was proposed, which im-proved the accuracy of the original model. Reference [10] is based on the traditional algorithm proposed Augmented Grey Wolf Optimization (AGWO) algorithm, which introduces elastic mechanism, loop mechanism and attack mechanism The improved algorithm is obviously due to other heuristic algorithms in terms of local optimal avoidance and calculation accuracy. Regarding software, the literature [11] proposes the GWO-based, which prioritizes risks and uses built-in indicators and usability indi-cators, so that software development reduces more cost and offers higher product quality at a short period.

Since the end of the 20th century more innovative algorithms have been created. Some of them are bio-inspired neural networks, Artificial Immune Algorithm and Membrane Computing. What genetic algorithms and ant colony algorithms have in common is that their biological mechanisms are more similar to real life than other types of algorithms.

There is no unified classification or strict definition of Bio-inspired intelligence algorithms, since they are still in development. According to Binitha and Sathya [12], bio-inspired computational algorithms (BCAs) have a number of advantages over bio-inspired intelligent algorithms (BIAs). Bio-inspired intelligent algorithms (BIA) have some heuristic method that mimics nature's strategy, this could be a simple and non-figurative definition of bio-inspired intelligent algorithms (BIA). An analysis of the relationship between biologically inspired algorithms and traditional intelligent computing methods was presented by Bongard [13]. In the context of intelligent com-puting, bio-inspired computing algorithm refers to a kind of intelligent computing method that mimics the functions and structure of organisms, their individual and herd behaviors, and society's evolution by using a biological operating mechanism slightly similar to our own.

The integration of some related algorithms into a common theoretical framework is one of the future projects of bio-inspired intelligent algorithms. In addition, there should be a specific evaluation parameter for each task, such as computation speed or solution accuracy, when evaluating bio-inspired intelligent algorithms. This is due to the difficulty of finding an intelligent bio-inspired algorithm that fits all problems. When designing an algorithm, a practical principle should be followed and an algo-rithm with unnecessary complexity should not be chosen. Other research branches of bio-inspired algorithms include the initial parameter selection problem and the con-vergence speed problem. As biological research deepens, more and more bio-inspired algorithms will be developed [14].

Hybrid algorithms are also used in other routing optimization applications such as maritime transport. There scientific route planning is important to improve the effi-ciency and reduce the cost of the sea route. The most frequently used algorithms are genetic and ant colony, but their separate use gives premature and local optimal solu-tions, leading to stagnation of the search. In order to solve these problems and save the cost of marine survey, GA and ANT colony techniques are combined to propose a hy-brid algorithm to further improve the quality of the solutions. Through the experi-ments and software application, the proposed hybrid algorithm is proven to be highly efficient and robust, which could ensure the optimal route for single or multiple re-search vessels, thereby saving the time and cost of marine research route planning [15, 16].

According Luan et al. a hybrid genetic algorithm (GA) and ant colony optimiza-tion (ACO) approach is created to address a multi-criteria supplier selection problem. It combines the benefits of ACO with parallelism and efficient feedback with GA's ex-cellent global convergent rate. To evaluate and examine the performance of the origi-nal and hybrid algorithms as well as to improve the parameters, a numerical experi-ment was carried out. Results show how the new integrated algorithm improves qual-ity and efficiency, proving its viability and efficacy. It is a creative pilot study to use a hybrid AI-based GA and ACO algorithm to solve the supplier selection problem [17, 18].

Aiming at the problem that the ant colony algorithm alone is difficult to optimize parameters in the path finding optimization, in order to improve the convergence speed of the path planning problem, combined with the global or local search ability of different meta-heuristic algorithms, this work proposes an enhancement based on the genetic algorithm with ant colony optimizer. This algorithm obtains a set of optimal parameters using the ant colony optimizer, performs the genetic algorithm to get rid of parameter dependence in the path planning problem, and performs automatic param-eter selection.

The hybrid algorithm is relatively new but there are some applications that pre-sent problems in the application. In most cases the hybrid model starts with the genetic algorithm and then the ant algorithm is incorporated. The proposed methodology tries to improve this application by starting with the ants' algorithm which feeds with ini-tial conditions the genetic algorithm.

2. Related Algorithms

2.1. Ant colony algorithm

The ant colony algorithm is derived from the pathfinding behavior of ants in the process of finding food in nature. It adopts a distributed parallel computing mechanism, which has the advantages of easy combination with other methods and strong robustness. The foraging process of ants has many similarities with the robot path planning problem, so it has become a hot research topic in the field of robot path planning.

The ant colony is assumed to be the starting location when determining the best path, and the food supply is assumed to be the target point in order to imitate the behavior of ants in nature. The whole path planning process can be considered as the process of ant colonies foraging on the map, because ants can release a pheromone on the path they travel, and within a certain time, other ants can perceive the effect of this pheromone. It stands to reason that the ant tends to walk in the direction of the high concentration of this substance. Through this positive feedback, the ants show the shortest path and gather more ants and gradually guide the next ants to choose that path. Ants communicate and coordinate with each other in this way and eventually find an optimal or suboptimal path to avoid obstacles.

Each ant begins its journey in a randomly selected city, and as it moves forward, it adds the list of cities it has visited up to that point to its memory. In the application of this procedure, the concept of pheromone is also related and included with the trajectory formed between node i and j, and shows the attractiveness of the trajectory to ants, with the term τij. The initial pheromone for all ants can be calculated as:

$$\tau_{ij} = \frac{m}{TC} \qquad (1)$$

where TC is the cost of a initial cycle, which can be generated by a heuristic solution, and m represents the number of ants.

This attraction is combined with heuristics that represent prior information about the problem, provided by sources independent of the ants. This information is denoted by nij and is generated as:

$$n_{ij} = \frac{1}{C_{ij}} \qquad (2)$$

cij denotes the cost of the route from node i to j. In the traveling salesman example, we assign an ant to a random city (the total number of ants cannot exceed the number of cities) and complete a cycle. To decide to move from one city to another, each ant uses the rules of a probability roulette.

The probability of moving from a city i to a city j comes from the formula:

$$p_{ij} = \frac{\tau_{ij}^{\alpha} * n_{ij}^{\beta}}{\sum_{i=1}^{M} \tau_{ij}^{\alpha} * n_{ij}^{\beta}} \qquad (3)$$

where M is the number of cities and α, β the degree to which the pheromone and the heuristic information affect the solution.

After each ant completes its cycle, an amount evaporates. The pheromone evaporates through the formula:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} \qquad (4)$$

with ρ ranging between 0 and 1.

In this way, possible wrong decisions gradually disappear during the iteration process. Evaporation is followed by an increase in pheromones in the used trajectory. New amounts of substances are added to the trajectories chosen by the ants. The pheromone is added through the following formula:

$$\tau_{ij} = \tau_{ij} \sum_{i=1}^{M} \Delta\tau_{ij}^{k} \qquad (5)$$

With $\Delta\tau_{ij}^{k}$ the amount of pheromone left by k ant, with type

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{1}{C^k} \; if\ the\ path\ is\ selected\ by\ the\ ant\ k \\ 0\ else \end{cases} \qquad (6)$$

where C^k is the cost of the cycle the ant made. When the cost of the cycle is low, then more pheromone is released, thus increasing the probability of its selection in the next iteration.

The flow chart of the above process can be described as follows (Fig. 1):

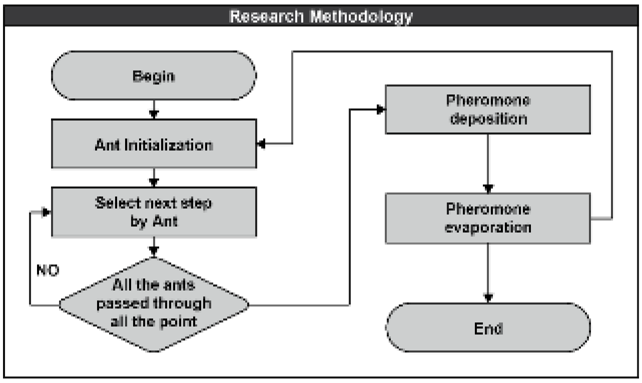

Fig. 1. Ant colony methodology.

Initially, each ant starts from a randomly selected point. The probability of going from one point to another is related to a coefficient α representing the relative weight of the pheromone trajectories and a visibility coefficient β representing the distance between the points. As the ant moves forward, it stores in memory a list of the points it has passed so far. The criteria are then checked for successful access to points. If the answer is no, then the ants keep looking for new spots where they fail. If the answer is yes, the ant has completed its cycle and the number of pheromones on the chosen path increases. When the cost (distance length) of the loop is low, more pheromones are re-leased, increasing the probability of being selected in the next iteration. After a phero-mone is placed, a percentage of the pheromone will evaporate into non-preferred pathways. The ants then repeat the process again based on the number of iterations, but with new pheromone tracking data.

2.2. Genetic algorithm

The genetic algorithm mainly uses the law of "survival of the fittest" from biologi-cal evolution. In this logic a law is revealed in the process of biological evolution in nature where the group that is best suited to the natural environment often produces a larger group of offspring. An elitist logic is therefore followed in the reproduction pro-cess.

Taking the initial population as a starting point, after running a cycle, some groups are eliminated and can no longer enter the cycle, while the other part partici-pates in reproduction. Survival of the fittest plays a very important role in this process. Due to bad weather and the encroachment of natural enemies, the survival rate of many animals in the wild is very low. Even in groups that survive, populations are created through competition. In the process of evolution, new individuals may be cre-ated due to mutation. The effect of total mutation creates a new group and replaces the old group.

The genetic algorithm includes the following main processing steps: The first is to make the encoding of the solution for the problem to be optimized. The encoding of a solution is called a chromosome and the elements that make up the encoding are called genes. The purpose of coding is mainly to solve optimization problems. The develop-ment and application of the fitness function comes second. The objective function of the optimization problem essentially determines how the fitness function works. The value of the fitness function is used to define how the law of natural selection will op-erate. Which chromosomes are suited to survive, and which are deleted are deter-mined by the probability distribution based on size. The chromosomes that are still ac-tive collectively make up a population, which is capable of procreating new individuals. The structure of chromosomes is the third factor. Coding is used to combine the parents' genetic makeup. Crossover facilitates next generation, which results in a novel approach. Lastly, there is mutation. Gene mutation can happen while creating new solutions, changing the coding of some solutions to increase the efficiency of the solution (Fig. 2).

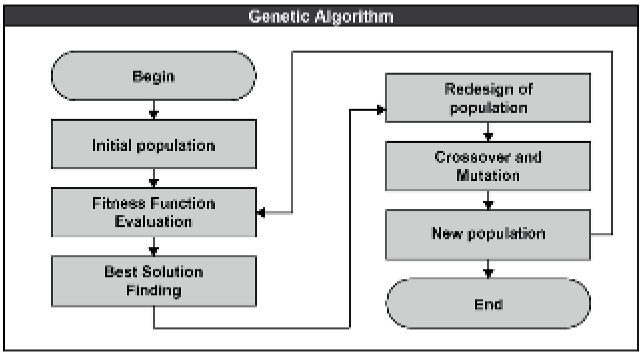

Fig. 2. Genetic Algorithm.

3. Hybrid Genetic algorithm based on Ant Colony Algorithm

The method combines the advantages that derive from the aforementioned algorithms. The genetic algorithm is fed by the initial population produced by the ant colony algorithm, allowing GA enrichment to produce the best results. The genetic algorithm is strengthened by the ant colony algorithm, which also optimizes the path-finding process.

The Genetic Algorithm serves as the hybrid method's basis. In contrast to conventional search methods, GA uses a collection of points called individuals rather than a single point search. Each one stands for a potential fix for the issue. Through the use of methods like selection, crossover, and mutation, the population in these algorithms gradually evolves into the most advantageous area of the search space.

The ACO algorithm is based on the finding of Hamiltonian path of the graph G = (C, L), where C is a number of points, L is a set of links that completely connect point C, and Jcicj is the cost (distance) between ci and cj, that is, the distance between points I and j.

Each ant starts at a randomly selected place, and as it moves forward, it adds the list of points it has passed to its memory, which initially saves the starting point.

In iteration t, each ant k goes from node I to node j, with probability given by the following function, and each choice moves to a point it hasn't previously visited:

$$p_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} * [n_{ij}]^{\beta}}{\sum_{ieN_i^k} [\tau_{ij}(t)]^{\alpha} * [n_{ij}]^{\beta}} \qquad j \in N_i^k \quad (7)$$

where nij = 1/dij is the heuristic information that can be used to describe the ant's preference to travel to the following stop in city j when the ant is in city, defined as the inverse of the distance between two points.

τij (t) is the quantity of pheromone that connects two points' edges. The colonial experience is explained. The value of the deposited pheromone is set to a starting value t0 in the first iteration of the procedure that is too low.

A and β are two parameters that determine the relative influence of the phero-mone trajectory and the heuristic information, and Nik is the set of neighboring points that Ant k has not yet visited.

The ant method is applied with its own parameters to produce the initial results because it is efficient to begin with. The fitness function is permanently altered as the algorithm continues to run until it determines the ideal number of iterations. The ap-proach gives quite good fitness function values after 5–6 iterations, according to vari-ous experimental studies. As a result, the hybrid technique's first phase uses the ant colony approach.

The results of the ant colony provide an initial population of starting points for the genetic algorithm. This initial population has been optimized to help achieve the optimal value of the fitness function faster and more efficiently. By applying mutation and crossover techniques, the generation algorithm should perform better and achieve a generation of satisfactory values for the fitness function.

Therefore, Genetic Algorithms start with an initial configuration. The outcomes of the Ant algorithm take the place of the initial population members being randomly ini-tialized. Then, each individual receives a score based on a certain fitness function. The selection procedure is thereafter carried out on each chromosome in the present popu-lation. Larger fitness function values increase the likelihood that chromosomes will be chosen. Then, based on a certain probability, there is the process of population mem-bers crossing across and evolving. Finish the genetic process, then switch back to adap-tive mode to verify the termination requirements. If not, restart the process; otherwise, the hybrid algorithm's best value is used by the system.

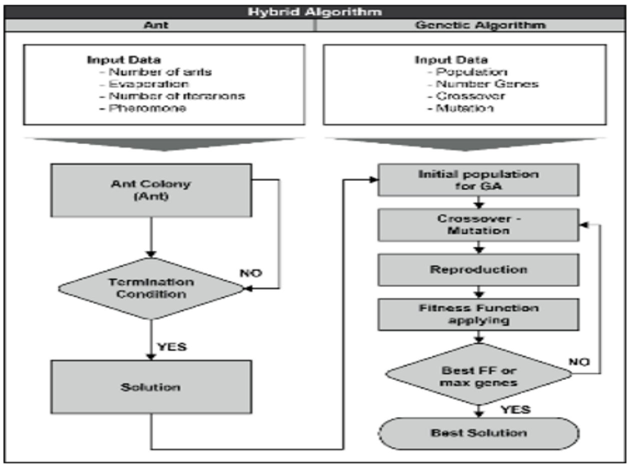

Fig. 3. Hybrid Algorithm.

The methodology overview is shown in the figure 3. This section may be divided by subheadings. It should provide a concise and precise description of the experi-mental results, their interpretation, as well as the experimental conclusions that can be drawn.

4. Experimental results

To perform the experimental measurements, a TSP (Traveler Salesman Problem) algorithm was used to determine the best path between a number of sites. The TSP al-gorithm was initially developed just using GA, but later it was built using the above-mentioned hybrid method. The optimization produced by the hybrid algorithm was determined in this manner. The total distance traveled is calculated depending on the choice of access points, using the Euclidean distance formula. The experimental data were run in two different situations, with the first referring to a simulation model developed in Matlab™ programming environment and the second applying to CMM. Using different parameter sets the hybrid algorithm was compared with simple GA. Different datasets included different number of points, population for genetic algo-rithm and different number of generations. Thus, a vector of form elements is parame-terized:

BS = {Points, Population, GA_Iteration, Ant_Population}

The results of the simulation model are analyzed next. When the number of points is relatively small (100) the optimization in the combination BS = {100, 100, 1000, 100} is 19.81% of the hybrid methodology (ANT-GA) in relation to the simple genetic algo-rithm (GA), while the processing time increases to about 12%. When the number of points increases to 200 with parameter vector BS = {200, 100, 1000, 100} the optimiza-tion of the hybrid methodology (ANT-GA) compared to the simple genetic algorithm (GA) is 37%, while the processing time increases to about 18%. With a number of points of 500 the optimization on the trajectory is 64%, with and it reaches 75% when 1000 points are used (table 1). It should be noted that as the number of points used in-creases, so does the time to calculate the result. But given the fact that the technology of computing systems evolves very quickly one can overcome the delay created in the calculation of the optimal solution (Figure 4). Table 1 below shows the total distances of the trajectories calculated with a combination of parameters GA_Population = 100, GA_Iterations = 1000, ANT_population = 100, ANT_Iterations = 5, ANT_coefficiency = 0.2, ANT_a = 1, ANT_b = 5.

Table 1. Distance optimization with BS1.

Distances			
Points	**GA**	**Ant-GA**	**Optimization**
100	17136	13742	19.81%
200	37777	23821	36.94%
300	68440	36496	46.67%
500	137202	48740	64.48%
700	232099	59783	74.24%
1000	378394	93612	75.26%

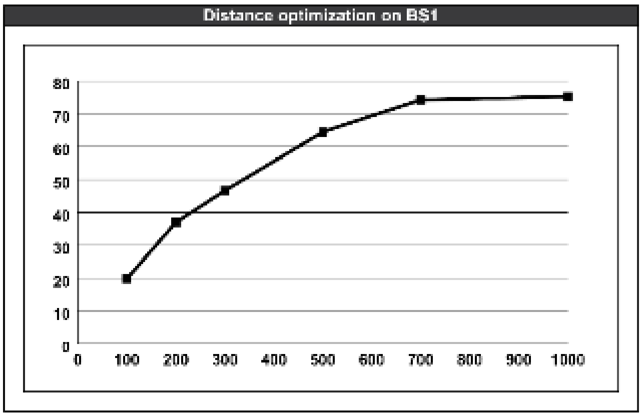

Fig. 4. Optimization with BS1 parameters

By changing the vector of the BS parameters, the optimization times are modified, with the typical case of BS = {Points, 200, 10000, 500} where, in contrast to the previous case, there is little optimization in the few points, while as the points increase, a great improvement of the hybrid is observed algorithm compared to the simple GA (Figure 5). Thus, Table 1 below shows the total distances of the trajectories calculated with a combination of parameters GA_Population = 200, GA_Iterations = 10000, ANT_population = 500, ANT_Iterations = 5, ANT_coefficiency =0.2, ANT_a = 1, ANT_b = 5. (Table 2).

Table 2. Distance optimization with BS2

Distances			
Points	**GA**	**Ant-GA**	**Optimization**
100	12234	12099	1.10%
200	18377	17708	3.64%
300	27758	26443	4.74%
500	52254	40656	22.20%
700	76235	49765	34.72%
1000	128973	76512	40.68%

A CMM machine was used to make an application in a second phase under actual conditions. The algorithm was evaluated on a SCIROCCO-RECORD by Brown & Sharpe DEA CMM machine with three sliding joints and two rotating joints in order to assess the method in real-time circumstances (Figure 6). The results showed that for GA_Population = 100, GA_Iterations = 1000, ANT_population = 100 the trajectory improves to about 18%, compared to 19.81% of the simulation model. In the case of 500 points with GA_Population = 200, GA_Iterations = 10000, ANT_population = 500 an optimization of 21% is observed, compared to 22.2% of the simulation model, while using 1000 points with GA_Population = 200, GA_Iterations = 10000, ANT_population = 500 an optimization of 37% is observed, compared to 40.68% of the simulation model.

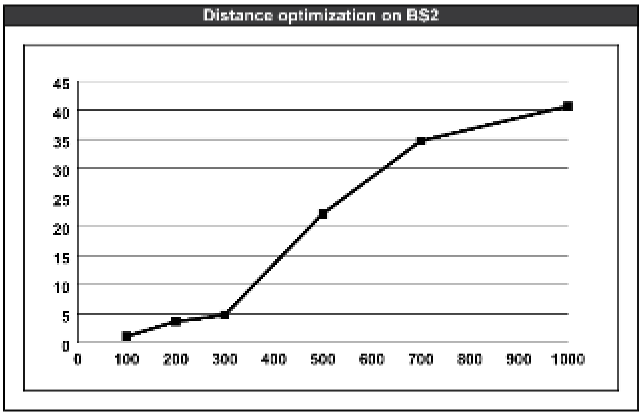

Fig. 5. Optimization with BS2 parameters.

Fig. 6. Brown& Sharpe DEASCIROCCO-RECORD.

5. Conclusions

An ant colony and genetic algorithm-based hybrid design route optimization al-gorithm is presented out in this study. The GA starts at an optimal level thanks to the ant colony's preparation and subsequent reproduction of the initial GA population. The final run of the model with proper parameterization yields the best results in route planning. The algorithms are tested on solving classical TSP problems. The percentage of specialized optimizations grows as the number of registration points rises and the number of GA iterations falls, as demonstrated by measurements carried out in a sim-ulated scenario. Therefore, hybrid algorithms are the best choice when there are many of points and we need to acquire the best results quickly. Experimental measurements show that up to 40% path planning optimization can be achieved compared to a sim-ple genetic algorithm. These measurements were also verified by the application to a real orbital guidance machine, a CMM, where a small deviation of 3% from the simu-lation values is observed, which may also be due to an error in calculations and meas-urements.

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