OPTIMIZING THE CONTROL OF SPATIAL MECHANISMS USING GENETIC ALGORITHMS AND ANT COLONY

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Abstract - *This paper prosposes a new hybrid method for optimisation of the control of spatial mechanisms using genetic algorithms and ant colony. The new method is a combination of ant colony and genetic algorithm with very meanfull results. It can be apllied on a big variety of spatial control systems. Robotic systems, CNC machining systems, Coordinate measuring machines, e.t.c. In order to evaluate the proposed methodology genetic algorithm and a combination of genetic algorithm and ant colony are compared. The results of the comparison shows that the hybrid algorithm can optimize the value of the fitness function up to 95% and the execution time is optimizing up to 81%.*

Key words - Optimisation, ACO, GA, System Integration

I. INTRODUCTION

There are many techniques for optimizing spatial mechanisms and continuously are developing new, using the appropriate technology. In this work we use a hybrid algorithm combining ant colony with genetic algorithm techniques. The ant colony technique is designed to give an initial population for the genetic algorithm in order to avoid the genetic algorithm to start with a random combination of chromosomes. Thus achieved a big reduction in the time of the algorithm implementation and finding a good solution of the used objective function.

This technique can be used in many cases where are using spatial mechanisms for specified tasks. This is used in the control of robotic systems, machine tools, CMM, etc. The research shows that the proposed hybrid algorithm has better result when many points are used and, for example, exceed the value of 1000. It is a comparative study on the results by applying different combinations of algorithm parameters.

Genetic algorithms belong to the computer science area and constitute a search method of best solutions to systems that can be described as mathematical problems. They are useful to problems containing many parameters or dimensions and they is no analytical method that can find the optimal combination of the variable to make the system to react in the desired possible way. The Genetic Algorithm is inspired by biology. It uses the idea of evolution through genetic mutation, natural selection, and crossover. The Genetic Algorithms are very simple to implement. The values for the system parameters must be encoded so as to be represented by a variable that contains a number of characters or bits (0/1). This variable mimics the genetic code that exists in living organisms. Initially, the Genetic Algorithm produces a number of the variables for the begin, generating a population of solutions. That is calling initial population. Each solution (values for system parameters) is tested for how close brings the system to the desired reaction by a function that gives the capacity of the solution and measure called fitness function (F.F.).

The solutions that are closer to the desired, relative to the other, according to the measure gining by F.F., reproduce the next generation of solutions and by using a random mutation. By repeating this process for several generations, random mutations in combination with the survival and reproduction of the best approaching genes - solutions the desired effect will produce a gene - solution that contains the values for the parameters that meet best possible fitness function. The terms, often used by genetic algorithm, are Chromosomes and Genes, Initial population, Crossover, Fitness function, Reproduction and are discussed below.

Chromosomes and Genes indicate possible solutions. There could be N solutions for a problem (N chromosomes) in the solution space from which the best solution is sought. Each chromosome is formed by genes, which are the basic characteristics of the intended solution. Initial population is the set of randomly selected chromosomes (solution pool). Depending on the type of the problem, there could be certain number of initial solutions required. Crossover is a genetic operator making it possible to create new solutions using two existing ones. Crossover rate defines how many solutions to be parented. Similarly, mutation is another operator, which is used to direct the searching process to different paths. This prevents going back to the solutions which were encountered before. Mutation rate defines how many chromosomes to be mutated. Fitness function indicates how good the solution is for the given problem. There is a need to identify this function for every problem. This could be, for example, the total completion time in job-shop scheduling. In this case, each time new solutions are generated, completion time is calculated and new solutions are generated until the total completion time can no more be reduced. Reproduction is to keep the solution space size fixed for computational efficiency. Whenever new solutions are generated the solution space is updated and some of the newly generated solutions go into the solution pool and some old ones are removed. Generally, the famous Russian-roulette methodology is implemented to reproduce the solution pool. However, there is no limitation in this respect and the designer may develop his own strategy and method for reproduction. Detailed descriptions of genetic algorithms can be found in [1].

The optimization algorithms based on the operation of colonies of ants are studied by the Computer Science and Operational Research area. It is the first algorithm that aims at finding an optimal path in a graph based on the behavior of ants seeking a path from the colony to the food. If we compare the different characteristics of natural ants in relation to digital ants we see that the path that connects the nest with the food in natural ants, is a graph Nodes and Connections in the digital ants. Also pheromone left by ants naturally when they go to find food and evaporates as we know, in the digital ants, corresponding to different positions with numerical information, is giving us all the possible paths. The paths which does not satisfy the system are negative reactions (evaporation). The ACO algorithm finds the best solutions built from previous iterations. Each composition of the graph corresponds to a variable (artificial pheromone) and depending on how much better the solution is, the artificial pheromone is more. At the end from all possible solutions, the amount of artificial pheromone will give the optimal.

The combination of genetic algorithms ant colony methodology will give a new hybrid methodology for the optimization of the control of spatial mechanisms. Typicall example for the use of spatial mecanicm are Cordinate measuring machines (CMM). Coordinate Measuring Machines are usually controlled by computer and, whilst they can be utilized intelligently as a measurement device, in most cases they are programmed in order to inspect parts. The program can be setup to run automatically or manually. CMM programming projects are close to the robot or CNC programming philosophy. Graphical user interface is used for the control of the machine and the offline programming. The three-dimensional measuring machines and coordinate measuring machines (Coordinate Measuring Machines, CMM) are machines with which precision measurements are made and support quality control operations and design. They are extremely useful as they have the ability to record accurately the shape and dimensions of a mechanical piece whilst reducing the human error factor, in carrying out and reading the evidence, to a minimum. In addition, another important advantage of using machines CMM is the ability to perform curves and surfaces in general, and form fragments that can not otherwise be recorded, such as the blades of a turbine. The measurement accuracy of a complex mechanical part reaches today even the rank of 0.001mm (in special cases 0,5mm).

The aim of this research is to find a hybridid algorithm to optimize the control of spatial mechanisms. Mechanisms like Coordinate Measurement Machines (CMM), Computerised numerical controllers (CNC), robotic systems e.t.c. To build a methodology that can optimize the measure, requires a very sophisticated cognitive ability. It is a combination of different optimization methods which are integrated into a new one. The reliability and capabilities of the system have been tested by measuring the actual work of many objects. Experiments show the effectiveness of the proposed system.

II. STATE OF THE ART

Modern optimization approach have frequently applied by researchers in optimizing the turning process. D'Addona and Teti, had studied the possible minimum cost that can be achieved for their turning process using Genetic Algorithm (GA). The optimization results indicated that the GA was able to achieve minimum production cost, while considering technological and material constraint. However, the standard GA approach had a problem with premature convergence, where the output result mostly is the local optimum [2]. In turning process optimisation was using also Particle Swarm Optimization (PSO) approach [3] for the measure surface roughness and tool life. Satishkumar, Asokan, and Kumanan compared performance of GA, Simulated Annealing (SA) and Ant Colony Optimization (ACO) in optimizing multi-pass turning process. Their results were better for the ACO which gave out better solution compared with GA and SA [4]

The optimisation of spatial mechanism is a topic that continuously evolves in every field of applications. CNC machining systems is a part of these applications. The main aim is to reduce the cutting and the moving time of the tool during the cutting process. Researchers use a range of different technologies and algorithms, to solve this problem, such as simulated annealing algorithm [5], genetic algorithm [6], neural network algorithm [7] and ant-colony algorithm [8-9]. Tandon et all [10] are using an artificial neural networks (ANN) predictive model to optimize the cutting conditions subject to a comprehensive set of constraints. In an expert CNC system proposed by Mansour et al., the machining path process will be optimized by deciding the best path. Graphic features and geometric parameters are extracted from CAD part drawing and performed to control the machine motion to cut the part. For the optimization, genetic algorithms are used to find the best path and the shortest time giving at the same time the intelligence in the system. The cutting time is reduced and the efficiency of

CNC machining is highly improved. The results shows a reducing of the overall processing time by 18.63% with the proposed method which is tested to a piece with 8 indentations [11]. A methodology, based on genetic algorithms that assure evolutionary generation and optimization of NC programs on the philosophy of C.A.D. models of manufacturing environment, is proposed by Kovacic and Brenzocnik [12]. This philosophy can be adopted also to other machines, for example coordinate measuring machines (C.M.M.) [13], laser and plasma cutting machines, welding machines, [14], robots and manipulators [15]. Balic and Korosec [16] have shown how with the help of artificial intelligent techniques (Neural Network), the prediction of milling tool-path strategy might be made in order to determine which milling path strategy or their sequence can show the most effective results for free surface machining.

Another field of applications of spatial mechanisms is the robotic systems. Sagris et al. present a methodology for the geometric design of Cartesian spatial robotic arms [17], where a hybrid algorithm is used. In this algorithm a combination of a genetic algorithm, a quasi-Newton algorithm and a constraints handling method is applied to an open loop spatial robot with three revolute joints. The design variables include the base position, the geometry of the links and the joint angles of the robot. The calculated solution places the end-effector at prescribed poses, avoiding simultaneously singular configurations. The same optimization algorithm is used in [18] for a point cloud alignment, without user involvement. A collision avoidance algorithm using backtracking was proposed by Yogita Gigras, Kusum Gupta [19]. In this research ant colony algorithm was also used for finding the optimum shortest path to reach to the destination. Buniyamin N., Sariff N., Wan Ngah W.A.J., Mohamad Z. [20] proposed the accurate representation of heuristic and visibility equations of state transition rules to solve the Robot Path Planning (RPP) problem. Michael Brand, Michael Masuda, Nicole Wehner, Xiao-Hua Yu [21] compared two different pheromone re-initialization schemes and described the best of them based on the simulation result. To optimize the robot path planning in a dynamic environment they used an application of ACO.

III. PROPOSED METHODOLOGY

This methodology is based on a combination of intelligent techniques. The algorithm of ant colony extract an initial population that is entering in the genetic algorithm to allow the GA to rich the optimum solution. In other words the ant colony algorithm gives a boost to the GA, thus achieved optimization in finding the opimum path.

The basis of the hybrid methodology is the GA. In contrast to conventional search techniques, the GA does not use single search point (single-point search), but a population of points called individuals (individuals). Each individual represent one possible solution to the problem. In these algorithms, the population evolves continuously to best areas of the search space, using techniques such as selection, crossing and mutation.

According the ACO, C is the number of points, L is the set of interconnections that fully connect the points of C and J_{cicj} is the cost (distance) between c_i and c_j which is the distance between points I and j.

The optimization of this problem is in fact the problem of finding the Hamiltonian path of the graph G = (C, L), where the path is a closed loop ψ which is crossing once the nc nodes of the graph G and its length is given by the sum of J_{cicj} of the arcs from which it is composed.

Distances don' t need to be symmetrical and the graph does not need to be fully connected. Initially, each of the ants starts from a point randomly selected and has a memory that initially stores the starting point, and as the ant proceeds, it adds to that memory the list of points that has passed to that point.
Each ant k is transferred during iteration t from node i to node j, selecting each time to move to a point that has not yet been visited with a probability given by the following function:

$$p_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} * [n_{ij}]^{\beta}}{\sum_{ieN_i^k} [\tau_{ij}(t)]^{\alpha} * [n_{ij}]^{\beta}} \qquad j \in N_i^k \qquad (1)$$

Where $n_{ij} = 1 / d_{ij}$ is the available heuristic information and is defined as the inverse of the distance between the two points, and expresses the preference as the next station of the movement of the ant the city j when the ant is in the city i.
τ_{ij} (t) is the amount of pheromone found on the edge joining the two points. It explains the experience gained from the colony. In the first iteration of the algorithm, the value of the deposited pheromone is set to an initial value t_0 that is very small.
A and β are two parameters that determine the relative effect of the trace of pheromone and heuristic information, and Nik is the set of adjacent points of the ant k that has not yet been visited.

Due to the quick response of the ant algorithm at the beginning, is used with its own parameters to give the first results. If the algorithm continues to run, it creates lasting changes in fitness function until they find the optimal number of repetitions. From other experiment tests it seems that after 5-6 iterations the algorithm returns a fairly good value in fitness function. Thus, the ant-colony method is using as the first stage of the hybrid methodology.

The results of the ant-colony feed the genetic algorithm with initial population. This initial population is already optimized and helps its to reach best value for the fitness function much more quickly and efficiently. Applying mutation and crossover techniques are creating generations that the algorithm needs to work better and to reach a satisfactory value for the fitness function.

Thus, the genetic algorithm starts with the initial configuration. The Random initialization of members of the original population is replaced with the result of the ant algorithm. Then each member is rating on the basis of the given qualification function. After that follows the procedure of choice for each member (chromosome) of the current population. Chromosomes with great value in the fitness function are more likely to be selected. Next comes the process of crossover and mutation for some members of the population based on a specified probability. Completing the genetic processes and returning to the fitness function the termination criteria are checked. If they are not satisfied the process is repeated, otherwise, the system gets the optimum value of the hybrid algorithm.

The methodology overview is shown in the figure 1.

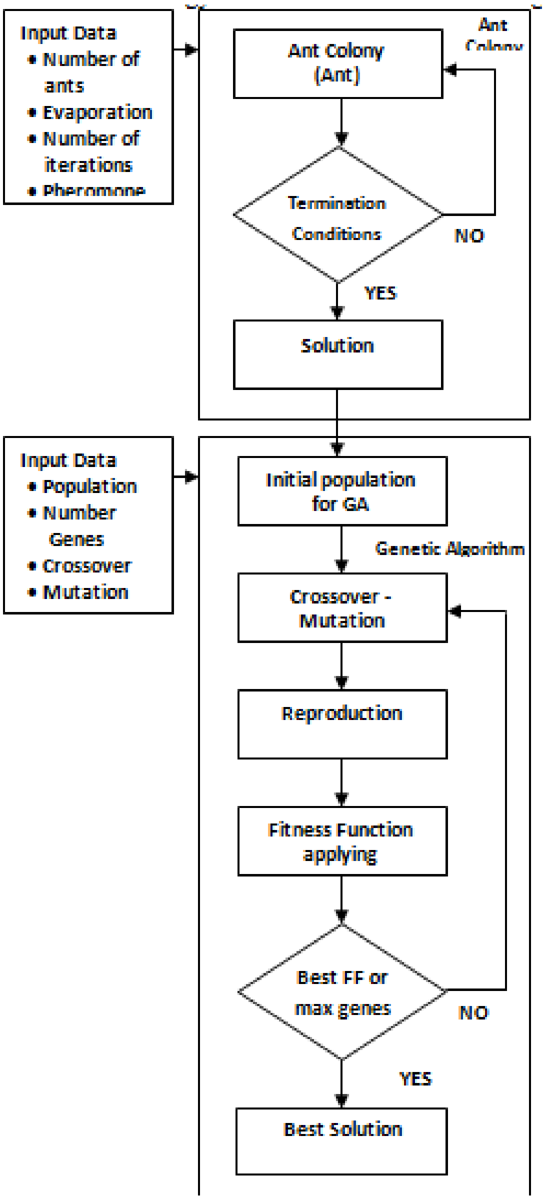

Fig. 1: Proposed methodology

IV. EXPERIMENTAL RESULTS

This paper is comparing the use of Genetic Algorithm with the use of a hybrid model combining ant colony and genetic algorithm. For the comparison is used the conventional problem of TSP (Travel Salesman Problem) to solve. The optimization problem of TSP fully corresponds to the optimization of spatial control mechanisms problem.

Using a simulation program, developed under matlab, an algorithm compares the results between a genetic algorithm and a hybrid model. Measurements were made with the help of various parameters. The first parameter has to do with the number of points to be used. Corresponds perfectly to the number of points that can use a system to move. For example, in a robotic system the movement of the system will be the points to pass, in a CMM the points that will scan, in a CNC the points that will make the cuttings etc.

For the genetic algorithm were used as parameters the population of chromosomes, the number of generations and the rate crossing and mutation. For the ant colony were used as parameters the number of ants, the number of repetitions as well as data on the pheromone. The number of points used in the simulation model was 100, 200, 300, 500, 700 and 1000, which werer sufficient numbers for testing spatial mechanisms, since in most cases the control of such systems does not exceed this number of points.

For chromoses population were selected the values 100, 150 and 200, while the reputations were 1000, 5000 and 10000. For crossover and mutation rate consistently used the values of 0,8 and 0,3 respectively. For the ant-colony parameters the used population was 100, 200 και 500 ants and the reputations 5. The number of reputations was selected after tests in which one good value of the ant-colony result was included in the first 5 trials. The increasing of this value (5) shows a very big delay in the execution time of the algorithm. This makes the hybrid methodology lags significantly in terms of the simple algorithm execution time. The above combination of parameters gives 162 different cases. Table 1 shows the used parameters.

Table 1: Methodology Parameter

Points	100	200	300	500	700	1000
GA population	100	150	200			
GA iterations	1000	5000	10000			
Ant population	100	200	500			
Ant iterations	5					
Crossover Prop.	0,8					
Mutation Prop.	0,3					
Evaporation Coef.	0,1					

In the following figure the algorithm is executed for 700 number of points, 200 ants and 100 iterations (Fig. 2)

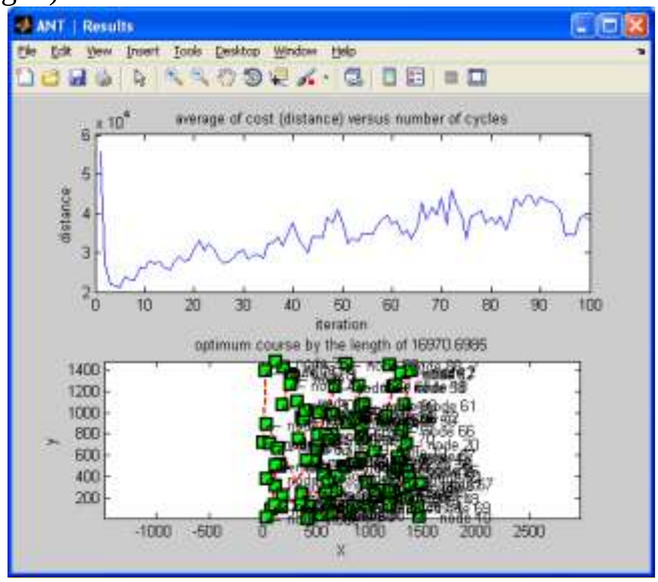

Fig. 2. Ant-colony with points - 700, ants - 200, iterations - 100

In fig. 2 is used only the ant-colony method with 700 points, 200 ants population and 100 iterations. It is clear that in the ant-colony method the value is going up and down in each iteration. From this variation of the value the system is keeping the best in the first 5 iterations. This optimum value from the first 5 iterations is fed into the genetic algorithm to start with the best price in the initial population.

In figure 3 is used only the genetic algorithm. With population size 200 and 5000 genes, the optimisation of the fitness function is shown.

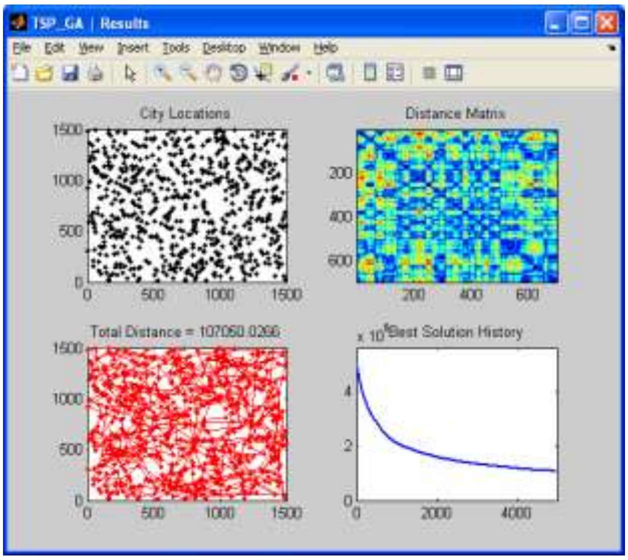

Fig. 3. Genetic algorithm with GA population size = 200, GA number of interations =5000

In Figure 4 is shown the hybrid algorithm with the combination of ant-colony and genetic algorithm. In the hybrid algorithm the GA is starting with optimal initial population (the output from the ant-colony) and the final result is the best value of the fitness function.
final result is the best value of the fitness function.

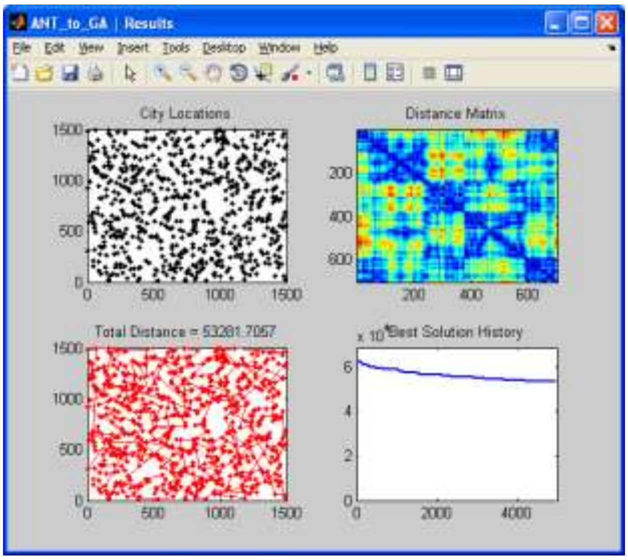

Fig. 4. The Hybrid Algorithm

The experimental results contain trial with a large combination of different parameter values. In table 1 are showing the values of the parameters. With the increase of the population size of the ant the execution time of the algorithm is increasing too much but the value of the fitness function is optimised.

The increase in time is due to the fact that the hybrid algorithm contains both the ant and in the other case they do not exist. Figure 4 shows the increase in time compared to improving the fitness function, using simulations with a different number of points.

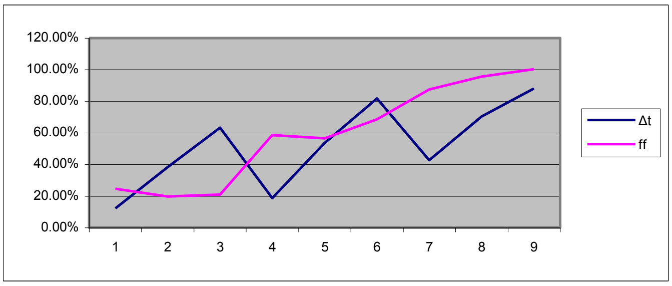

Fig. 4. Hybrid methods – time and fitness function optimisation

V. CONCLUSION

In this paper, a hybrid methodology for optimization of spatial mechanisms has been presented with a combination of ACO and GA. From the experimental results it appeared that there was an improvement of up to 95% in the evaluation of the fitness function and 82% in the processing time of the algorithm. This suggests that this hybrid methodology can provide important results of improvement in spatial mechanisms movements. It should be noted that the improvement is increasing as the number of points used is increased. This makes the methodology even more important in scanning applications (CMM) where a very large number of points are required for the process to be effective.

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