# Application of Evolutionary Algorithms for Holding Force Optimization Using Dynamic Models for a Climbing Robot

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## Abstract

This paper presents unsupervised holding rule generation for a climbing robot Bernoulli holding pad, based on Evolutionary Algorithms. Dynamic variations in frictional coefficient of surface and robot state require adaptability on holding force, when combined with internal pad dynamics. A hybrid Evolutionary Algorithm (hEA) combining operators from Differential Evolution, Memetic Algorithm and Multi Objective aNd open-Ended Evolution (MONEE) Implementation was developed, tested and validated for augmenting robot pad dynamics in a dynamic environment, with the aim of reduction in pressure energy usage. Different variable combinations established in literature were permuted and results observed in terms of solution standard and speed. Comparative results showed the hEA method produced better results than other algorithms in terms of solution quality and processing time. Hence the work exhibited that hEA can improve holding force adaptability by providing quickly a set of near optimum conditions for the climbing robot.

## Keywords
Adaptive Holding Force, Dynamic Variations, Bernoulli Pad, Evolutionary Algorithms, Variable Optimization, Climbing Robot

# 1. Introduction

A sufficient adhesion mechanism is a challenge in climbing robots design to ascertain that the robot sticks to the vertical surface with maximum mobility, payload capacity and minimum energy consumption. The energy requirements of such a system can be more than 60% of the entire weight of the robot, hence optimization of the holding force for pneumatic holding devices can result in reduced energy requirements. According to Volodymyr Savkiv et al. (2017), robots and in particular climbing robots are extremely complicated dynamical systems for which the generation of behavior's is no easy task, since the number of parameters to tune for a behavior is very high. The challenges waiting for climbing robots require them to automatically generate and control a wide range of holding forces in order to be more flexible and adaptive to changing environments. Optimal control of holding force offers an interesting way to generate behaviors automatically based on elementary principles (cost functions, constraints). The optimization of the holding force for a Bernoulli pad entails selecting the correct pressure and height parameters for a set of commercially available pneumatic pads to achieve the optimal force. The optimal force is constrained by frictional coefficient of the surface and robot state. A number of studies have been proposed for the optimal design of holding force by applying deterministic optimization techniques: linear programming, nonlinear programming, and dynamic programming (Qingfang Zhang et al. (2022), Guisheng Fang, Jinfeng Cheng, (2023), Tianfu Ai1 et al. (2020). More recently, Evolutionary Algorithms (EAs) have been introduced for optimizing the design of holding techniques (Türkler L. Akkan T., Akkan L.Ö. (2020).

Evolutionary robotics is task oriented, but for successful learning in task performance, the robot must survive and be relevant (minimizing energy expenditure, increasing payload and traversing different wall materials). Hence the challenge is combining internal driven adaptability with external task driven optimization as shown by Evert Haasdijk et al. (2014). The internal environment consists of the Bernoulli pad variable parameters which we can vary to have different holding forces hence internal driven adaptability. The external environment consists of tasks due to the roughness of the surface and the robot state which cannot be varied, hence external task driven optimisation. Evolutionary algorithms have the advantage that they have two operator mechanisms i.e. survivor selection and parent selection Evert Haasdijk et al. (2014), therefore they can tackle the two way challenge presented here. The Bernoulli pad used for holding function in the robot has limited capacity due to the variation in environment dynamics caused by different coefficient of friction, different robot state and nonlinear actuators. The two sets of rules which need to be satisfied by the holding pad i.e. the internal driven optimisation and external task driven adaptability led to combining the particular operators of different EAs which are pertinent to solving the double edged problem. Hence the proposal for a hybrid Evolutionary Algorithm (hEA).

Evolutionary algorithms enable robotic systems that are self-adjusting to unknown or dynamic conditions (Radhakrishna Prabhu et al. (2018), they are random search methods that imitate natural biological evolution and/or the social behavior of species, whose behavior is guided by learning, adaptation and evolution. Computational systems have been developed to mimic these but the downside is that each technique is able to surpass others for certain type of optimization problem, however it drastically slows down or even fails for another one (Lucas da Silva Assis et al (2016). Hence the need for a hybrid algorithm which takes care of all facets of the problem by combining different operators.

## 1.1 Objectives

This is an on going project whose main aim is to improve low weight and energy conservation in a climbing robot holding pad, so as to make the robot useful in dam wall inspection. The research objectives of the project are:

1.1.0 Modelling of aerodynamic wall climbing robot for dam wall inspection based on Bernoulli Principle using MATLAB environment.

1.1.1 Identifying & optimizing various variables to improve the efficiency and effectiveness of the wall climbing robot adhesion using evolutionary algorithm techniques.

1.1.2 Development of an adaptive control based wall climbing robot with a mechanical framework exhibiting optimum holding force for dam wall inspection.

1.1.3 Evaluating the effects of adhering characteristics of the wall climbing robot and comparison of various design parameters with the experimental data, obtained through developed prototype model.

This paper is looking at objective three and developing an algorithm which will aid in designing the control system for the holding pad.

## 2. Literature Review

Adhesion mechanisms vary according to the applications and working conditions and along the years various types of climbing robot adhesion models have been developed. These range from electric adhesion methods, Magneto Rheological Fluid adhesion method, Hot Melt Adhesive, suction based adhesion, Vortex Regenerative Air Movement adhesion, Bio inspired adhesion, and Gripping based Adhesion (Guangzhao Cui et al. (2012), M. Watanabe et al. (2013), Marc Osswald, Fumiya Iida (2013), Andreas Papadimitrou et al., Pongsiri Borijindakul et al. (2021), Ozgur Unver et al. (2006). The selection of adhesion mechanism is complex due to the requirements for different surfaces, elevations, fluid media and working conditions. The Bernoulli based adhesion technique, which falls under Aerodynamic Adhesion, has advantages over different models in terms of high force/weight ratio and accurate adaptability to a range of surface conditions (XiaoQi Chen et al. (2008). Holding force optimization has been used as a technique to obtain light weight robots (Kaige Shi, Li Xin (2016), V.G. Chashchukhin (2020), Mikhail Polishchuk, Volodymyr Oliinyk (2018), William R. Provancher et al. (2011), Dong Zhang et al. (2023), and in this paper Evolutionary Algorithms were used for the optimisation architecture.

A variety of operations found in literature review utilise aerodynamic based adhesion design, whose major research thrust concentrated on force generation. This related work shows that experimental analysis has been limited to mechanical effect on the adhesion efficiency. Kaige Shi and Xin Li (2020), used the Zero Pressure Difference technique for advancement of suction units which are energy efficient, smaller and lighter than traditional suction units. However, water consumption of the suction cups is very high, which if reduced will allow the robot prolonged work, carrying its own water so that it is not connected to a supply. Andreas Papadimitrou et al. (2019), used the vortex generation technique enabled via electric ducted fan. This enabled lightweight, high payload and faster robot. However the robot had high power consumption to run the fan. Daniel Schimdt and Karsten Berns (2013), used negative pressure adhesion based on extra entries and an all-directional system with adaptive seals. The robot suffered from variance in suction force due to irregularities on the surface. Ruixiang Zhang and Jean Claude Latombe (2013), used the lazy force control strategy which can be adopted on the Bernoulli pad to switch on pressure as and when needed to increase navigation speed and payload.

Consequently there is a distinguished gap on the examination of important design specifications such as height/pressure trade-off relationship with dynamic environment. Therefore the major benefit of this work is experimental verification of the use of a commercially available Bernoulli adhesion mechanism, while providing a novel insight on the adhesion nature against a target surface and robot state.

The aim of this paper was to improve low weight and energy conservation in a climbing robot holding pad, so as to make the robot useful in dam wall inspection. Hence an adaptive holding force architecture was designed. Optimal holding force for any given dynamic scenario was developed by utility model based optimization techniques in creation and regulation of dynamic behaviour of a robot aerodynamics-based holding pad. The model was designed to minimise a given criterion such as energy consumption subjected to the surface friction or robot state constraints. The equation for calculating adhesion force under different conditions was derived from the dynamic model (established in previous work by Haitao Qi et al. (2019), using the Derivative rule.

**Differential Evolution (DE) Algorithm, Memetic Algorithm (MA) & MONEE Implementation (MI)**

Storn and Price(1995) coined a Differential Evolution (DE) algorithm which is a populace primarily based optimization method. It is comparable to genetic algorithms (Janez Brest et al. (2006).

MAs are also the same as GAs but chromosomes are generated by memes and not genes. Before being involved in the evolutionary process, in MA every chromosomes and offspring gain some experience first which makes MA distinctive. Therefore MAs is used to describe GAs that heavily use local search (Merz and Freisleben 2002). On the other hand, the local-search algorithm can be designed to suit the problem nature (Gagandeep Sharma et al. (2015.
MONEE Implementation is an open ended EA where $xij$ continuously broadcast their genome. When an optimal holding force is reached, it randomly selects one of the received genomes, modifies that using mutation and starts a new cycle with different external task driven optimisation $yjk$, according to the surface frictional coefficient and robot state. The credits for each genome received are compared by calculation of an exchange rate between tasks. A linear weighting scheme is used to calculate the exchange rate by matching credits to the different tasks (Olaf Hagendorf et al. (2013).

## 3. Methods

Evolutionary Algorithms (EAs) were used to formulate the heuristics which will later be incorporated for control of the sensors and motors in order to attain adaptive holding force in the robot Bernoulli pad. However, EAs do not require the actual variable values to be entered, but the number of variables. Therefore to link the EA search to the actual values, an objective function and fitness function are used. Priyank Jain et al. (2013), have used the Derivative rule successfully for adaptive mechanism in the design of a MRAC scheme. Hence the Derivative rule was also adopted in this paper for the adjusting mechanism (the objective function) of the Bernoulli pad to the external environment factors in conjunction with EA.

Construction of the dynamic model was done using a pressure (cost)-height trade off. The problem relates the holding force generated to the frictional coefficient, robot state, height and cost. These are presented in Table 1 along with three optional states the robot can achieve for a certain force. The deciding factors for the holding force are the frictional coefficient, robot state, height and pressure. The objective function is to minimize the total cost (in terms of air requirements), and the Derivative rule was used for formulation. Fig 1 shows the holding pad model used, and Figure 2 show the real life setup utilized to get these values and also for validation.

Table 1. Test problem for Bernoulli pad

| **Force/N** | **Dependency** | **Option 1** | | **Option 2** | | **Option 3** | |
|---|---|---|---|---|---|---|---|
| | | **h/mm** | **C/P** | **h/mm** | **C/P** | **h/mm** | **C/P** |
| 0.30 | $\mu, a$ | 0.10 | 0.85 | 0.20 | 0.87 | 0.30 | 0.90 |
| 1.20 | | 0.10 | 1.05 | 0.20 | 1.20 | 0.40 | 1.15 |
| 0.70 | | 0.70 | 0.90 | 0.70 | 1.10 | 1.00 | 1.02 |
| 0.60 | | 0.50 | 0.88 | 0.60 | 0.99 | 0.50 | 1.22 |
| 0.80 | | 1.03 | 0.93 | 1.50 | 0.97 | 0.80 | 1.20 |
| 0.85 | | 0.60 | 1.05 | 1.50 | 1.13 | 1.50 | 1.20 |
| 0.90 | | 0.70 | 0.97 | 1.50 | 1.10 | 1.40 | 1.12 |
| 0.40 | | 0.50 | 0.82 | 0.60 | 0.87 | 0.70 | 0.92 |
| 0.50 | | 0.70 | 0.85 | 1.00 | 0.94 | 1.10 | 1.20 |

The problem was modelled as a transportation problem to represent all four variables in the Bernoulli pad so that it is adaptive to its environment by presenting associations among data and reasoning processes used to solve the problem. As shown in Figure 1, the Bernoulli pad model consists of 2 sources (Pressure and Height), 2 intermediate points (Surface frictional coefficient and robot state) and an output (Optimal holding force).

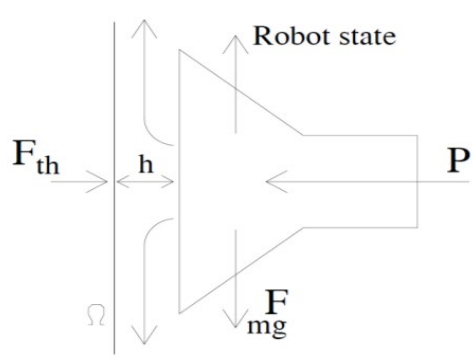


Figure 1. Climbing Robot Holding System

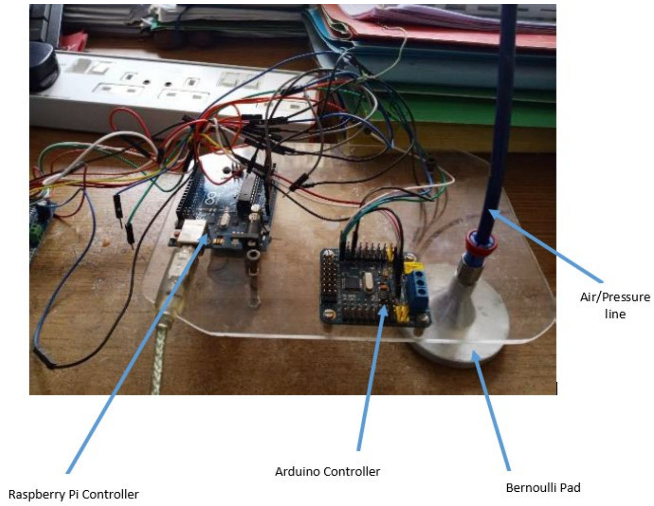


Figure 2. Experimental and validation setup

## Objective Function

Using the Derivative rule, the objective is to minimise the overall pressure transportation cost, while satisfying source (x,y), process ($\mu$,$a$,$v$), output (F) and flow constraints ($\rho$). The source has limited supply (as shown in the experiments [7]) and the inbetween processes have limited capacity to handle the supplies (i.e the holding pad has a limit to the optimum force it can generate). The output $F$ has known demand. The air pressure movement is transported to the destinations through the processes. This scenario can be formulated as follows:
Notations

| | |
|---|---|
| $x_{ij}$ | -The quantity of air and height transported from supply $i$ to process point $j$ – Pressure and height (x,y) |
| $y_{jk}$ | -The quantity of air and height transported from process point $j$ to process $k$ – due to frictional coefficient, robot state ($\mu$,) requirements |
| $C_{ij}$ | -Unit energy cost from supply $i$ to process $j$ |
| $C_{jk}$ | -Unit energy cost from initiation $j$ to process $k$ |
| $S_i$ | -Total supply from supply $i$ |
| $CP_j$ | -Capacity due to process/initiation $j$ |
| $D_k$ | -Demand to pad in view of environment $k$ - demand to pad in view of environment |
| $Z$ | - Energy expenditure / cost (measured in terms of air supply) |

The constraints ensure the supply limitation, process capacity and output requirements respectively. The problem definition can be represented mathematically as follows:
Minimise

$$Z = \sum_i \sum_j C_{ij} x_{ij} + \sum_j \sum_k C_{jk} y_{jk}$$

$$\sum_j x_{ij} \le S_i$$

$$\sum_i x_{ij} \le CP_j$$

$$\sum_j y_{jk} \ge D_k$$

$$\sum_i x_{ij} - \sum_j y_{jk} \ge 0$$

$$x_{ij}, y_{jk} \ge 0$$

[2]

## Fitness Function

Each solution generated by the algorithms needs to be scored to designate closeness to the objective function. This score is brought about by applying the fitness function to the test. In our case the fitness function was formulated for finding values for a set of variables which satisfy given constraints:

- Considering the four variables $x$,$y$,$\mu$ $and$ $a$ the problem is to find the best set of values for $x$,$y$,$\mu$ $and$ $a$ so that their total energy value is equal to a value $C_{ij} + C_{jk}$
- We have to reduce the energy sum of $x + y + \mu + a$ from deviating from $C_{ij} + C_{jk}$ i.e. $|x+y+\mu+a-(C_{ij} + C_{jk})|$ should be zero. Hence the fitness function can be considered as the inverse
- Fitness function =1$|x+y+\mu+a-(C_{ij} + C_{jk})|$/ (3) [13].

The performance of the four EAs was compared using the Bernoulli pad design optimisation problem in MATLAB. The goal is to find the least pressure usage of the holding pad subject to constraints on surface friction and robot state. Comparison among the four EAs with respect to their ability to solve the holding force problem was done using a height-pressure trade off construction of the dynamic model. The four algorithms were intergrated into a simulation environment in MATLAB. Coding was done in C++ for the Objective Function, Fitness Value and Local search definitions as shown in Fig 3. This enabled inclusion of the actual variable values and the local search in terms of surface and robot states in view of the adaptive holding force.

The attainable force, dependency, along with 3 optional combinations that vary from cheap and weak (option 1) to expensive and strong (option 3) are presented in Table 1. Activation of any of the EAs makes the evolutionary process select one of the three options that meet optimum holding force at minimum cost. Accordingly the objective function and time to completion changes. Objective function optimisation by the EA still continues. The number of generation cycles was not used as compared to the processing time to measure the speed of each EA due to the fact the number of generations in each evolutionary cycle is different from one algorithm to another. In all experiments, the solution truncated when one of two following standards was achieved: objective functions reached the least value (since it is a minimisation problem) or fitness value closest to one.

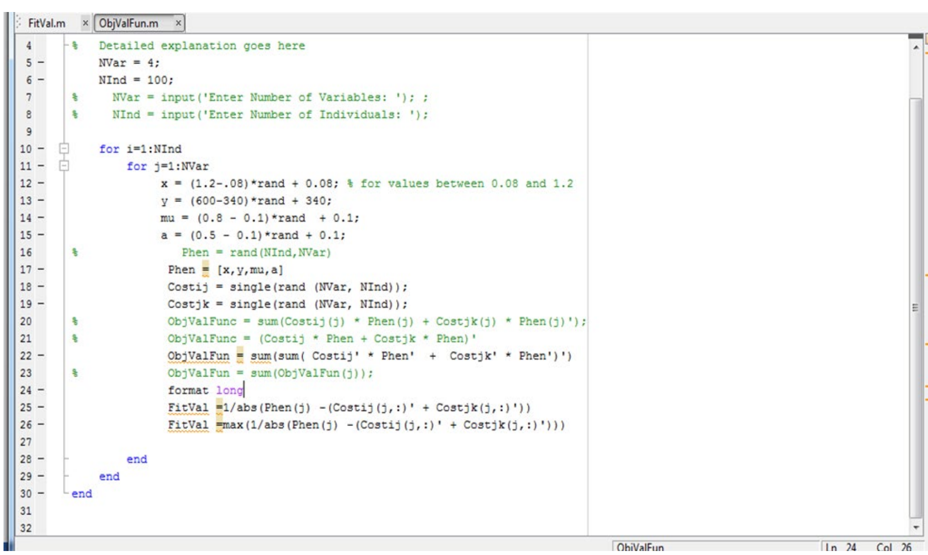


Figure 3. Objective Function and Fitness Value and Local Search representation in Matlab

From the comparison of the configuration and results of the three EAs, a framework was provided for adoption in climbing robots holding pads for adaptivity, through a hybrid algorithm.

## hEA Formulation

The operators for the above algorithms were then combined according to the needs of the problem at hand which is an adaptive Bernoulli holding pad. Design variables are $x, y, \mu, a, F$ $and$ $C_{ij}$ $and$ $C_{jk}$ are optimisation parameters. These are encoded in the objective function and fitness function as follows.

• Using MA inspiration, memes/parents are selected randomly and are allowed to obtain some knowledge, through a vicinity search (mutation)
• Using DE, for the chromosome for each offspring, possible substitution is created using the differential operator (crossover)
• Lastly using the MONEE ranking criteria, the credits for each genome received are compared by calculation of an exchange rate between tasks. The chromosome with the best credit is then selected.

## hEA Pseudocode

```
BEGIN
Step 1: MA
        Begin;
        Create stochastic populace of P solutions (memes)
        Calculate the fitness (k): For each member k∈ ;
        Do local search (k): For each member k∈ ;
                For j=1 to length of chromosome k; (number of variables)
                Value (j)= value (j)+e;
        If there is no improvement in chromosome fitness then value (j)= value (j)−e;
        If there is no improvement in chromosome fitness then retain the original value (j);
        Next (j);
        End;
Step 2: DE
        Begin;
        Define crossover ratio(CR) and mutation ratio(F)
                k=1 to iterations count;
        Chose an iteration randomly (mutation or crossover);
        If crossover;
        Chose two parents stochastically ka and kb;
        Create a child kc=crossover (kaand kb);
                kc=local-search (kc);
        Else If mutation;
        Chose one chromosome k stochastically;
        Create a child kc=mutate (k);
                kc= local-search (kc);
        End if;
Step 3: MI
        Define genome g, set of defined tasks T, and credits for task CT and exchange rate RT
        Calculate objective function value end;
        Select fitting exchange rate
                For i=ic do begin
        Calculate credits end;
        Populate the ANOVA table for objective function with the use of credits
        Decide optimum ranges and intervals using the ANOVA table End; END
```

From values in Table 1, a stochastic populace P was created using the values for x, y, μ, a and F, using the objective function. Crossover and Mutation ratios were created from values in literature and trial and error. Performance of each algorithm is governed by its operators that affect its performance in terms of solution quality and processing time. A large number of experiments were conducted to acquire the optimum operator values that suit the test problem. For each algorithm, an initial setting of the operators was established using values reported in literature [14, 15, 16, 17, 18, 19, 20, 21]. Then the parameter values were changed one by one and the results were monitored in terms of the solution quality and speed. Hence the three operators combined in hEA, enable parent selection (external task driven optimization), survivor selection (internal driven adaptability) and the ranking criteria.

The performance of the four EAs was compared using the Bernoulli pad design optimisation problem in MATLAB. The goal is to find the least pressure usage of the holding pad subject to constraints on surface friction and robot state. Comparison among the four EAs with respect to their ability to solve the holding force problem was done using a height-pressure trade off construction of the dynamic model.

The attainable force, dependency, along with 3 optional combinations that vary from cheap and weak (option 1) to expensive and strong (option 3) are presented in Table 1. Activation of any of the EAs makes the evolutionary process select one of the three options that meet optimum holding force at minimum cost. Accordingly the objective function and time to completion changes. Objective function optimisation by the EA still continues. The number of generation cycles was not used as compared to the processing time to measure the speed of each EA due to the fact the number of generations in each evolutionary cycle is different from one algorithm to another. In all experiments, the solution truncated when one of two following standards was achieved: objective functions reached the least value (since it is a minimization problem) or fitness value closest to one.

## 4. Results and Discussion

Using the four EAs, results obtained from solving the case problem are summarized in Table 2 and Figs 4, 5 and 6. Comparison of the performance of each algorithm was done using using two criteria: (1) the quality of the solution as represented by the objective function iterations needed to reach a good target value; (2) the time taken to reach the optimum target holding force value.

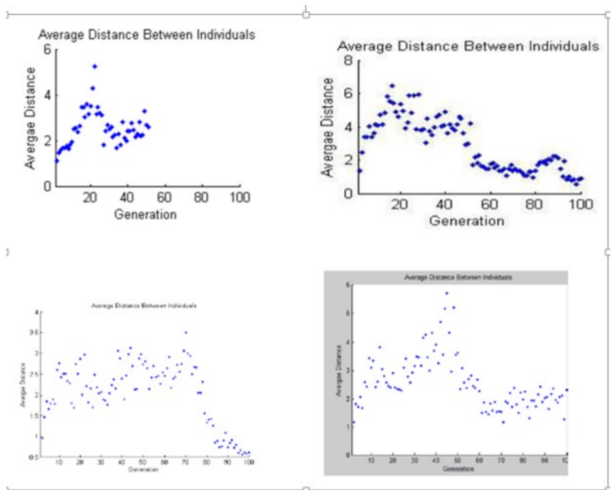


Figure 4. Average distance between individuals for Hea, DE,MA and MI respectively

Fig 4 shows the average distance between individuals for the different algorithms. Where average distance between individuals is an indication of diversity. Small average distance represents low deviation in the population and vice versa. It shows that for MA the graph has wide neutral areas containing similar optimal values between generations 10 to 70, unlike for hEA which lies within range 20 to 50 generations. DE has lean neutral areas but tends to digress with increasing number of generations and MI has wide areas which show deviation. 5. As can be seen in Fig 4, other algorithms required 100 tests to get conclusive results and others required 50.

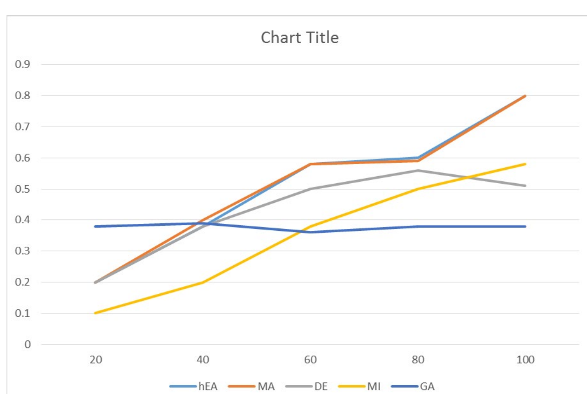

Figure 5. Actual Fitness vs Time/s for hEA, DE,MA and ME

Fig 5 shows the processing times for the different algorithms to solve the holding force problem by reaching a targeted objective value function. hEA and MA managed to achieve the best fitness within the given time. DE and MI have low fitness but are much better than the generic GA for the case problem.

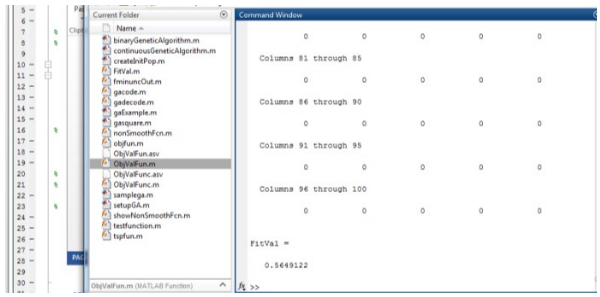


Figure. 6. Fitness value selection in MATLAB

Fig 6 shows that using the hEA code, it produces a number of different values for the variables but selects the one with the best fitness value. A small portion of the result was used.
Table 2 is a comparison of the flow velocity and air volume requirements when the different algorithms were simulated in MATLAB on the same surface area. MA had the least flow velocity but its air volume was high. This could be due to the diversity in its population values. hEA had a slightly higher flow velocity but low air volume and presented the best values. This could be because its diversity is low as well as a good time to reach desired fitness value.

Table 2. Flow Velocity and Volume Requirements per Algorithm

| **Algorithm** | **Area covered/m$^2$** | **Flow velocity l/s** | **Volume of air used/Nm$^3$/h** |
|---|---|---|---|
| hEA | 25 | 60-80 | 95 |
| DE | 25 | 80-100 | 120 |
| MA | 25 | 50-80 | 120 |
| MONEE | 25 | 90-100 | 100 |

Table 3. Statistical Results of Different Methods for Pneumatics Force Problems (23, 24, 25)

| **Design Variables** | **Best** | **Mean** | **Worst** | **Standard Deviation** | **Fitness Value** |
|---|---|---|---|---|---|
| hEA | 1.72 | 1.73 | 1.75 | 0.005 | 0.80 |
| Haitao Qi, Gary M.Boone, yile Zhiang (2019) | 1.72 | 1.74 | - | 0.03 | 0.65 |
| H. Kazerooni (2005) | 1.73 | 1.76 | 1.82 | 0.02 | 0.56 |
| James E. Boodrow, Brian W. Mcdowell (1998) | 2.38 | N/A | N/A | N/A | N/A |

Table 3 compares the statistical simulation results in MATLAB for pneumatics force problems found in literature. Simultaneously taking into account the fitness value, premier solution calculated and the statistical evaluation results, it is concluded that the hEA provided better options for this case problem compared to the evaluations given in literature. The best solutions found by James E. Bobrow et al (1998) are still lower than the worst solution found by the hEA. Using the proposed hybrid technique improves the convergence rate by calculating the best value 1.72 with the best fitness value of 0.8 closest to 1 and standard deviation 0.005. Compared to best results given in literature, hEA gives better results for pneumatics force problem, as can be seen in Table 3.

## 5. Conclusion

This paper has presented a hybrid Evolutionary search algorithm combining Differential Evolution, Memetic Algorithm and MONEE Implementation. In MATLAB simulations, this algorithm has shown to develop optimum holding force significantly faster than the stand alone algorithms. The experimental results show that the proposed hEA can improve fitness by providing quickly a set of near optimum conditions. The hEA based optimisation approach introduced combines established computing methods in a hybrid framework for combined internal adaptation and environment task driven optimisation of a climbing robot Bernoulli based holding pad. The framework consists of: 1. Objective function modelling based on the Derivative rule, 2. Fitness function value for parameter inclusion, 3. An evolutionary based hybrid optimisation algorithm and 4. MATLAB modelling and simulation. The framework has been implemented and tested in MATLAB. The results of the application presented show that the approach can find an optimal holding force and that the system parameters can be determined. The tests realized in this paper will now allow holding force design problems of the same class to be solved by using the best combination of operators found in this article. It is now also possible to move on to the next stage of the project and represent these findings in a suitable control scheme.

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## Biography

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