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Design Optimization of Pivoting 3 Finger Robotic Gripper Links Parameter Using Genetic Algorithm Technique

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ABSTRACT

Robot gripper design is an important field of research, due to its widespread use in automation. The two-finger gripper is intended for a specific pick and place operation. Its job is to choose a workpiece and position it correctly in a flexible manufacturing cell. While two-finger grippers provide benefits such as simplicity and low cost, three-finger grippers offer more flexibility, stability, dexterity, and manipulation control. Three-finger robotic grippers are a common choice for many advanced robotic applications needing a high degree of flexibility and object handling due to these advantages. The additional figure of gripper support the movement of object and better centering in pick and place operation. So, In this project, we consider a 3 finger robotics gripper. The actuator, however, had been seen as a blackbox in earlier studies. By including an actuator model in the robotic gripper issue, the system model has been altered. Consider a general actuation system that produces force, which is directly proportional to the input voltage. The individual actuator parts are placed in series and parallel arrays in four distinct configurations to represent the actuating system as a stack. A multi-objective evolutionary method is used to solve the modified two-objective problem, which also allows for the best determination of the size of robotic gripper links and joint angles. Each of the nondominated solutions yields a force-voltage relationship that aids the user in determining the appropriate voltage based on the application. Further innovative research is conducted to identify appropriate associations between the choice factors and the objective functions.

[Keywords-Gripper, NSGA, MOGA]

INTRODUCTION

A robotic gripper is a device used to grasp and manipulate objects in the robotic place. Typically it is mounted on the end of a robotic arm and is used to perform tasks such as picking up and moving objects, assembling parts, and performing precision tasks. The design of a gripper can vary greatly depending on the application, and often involves different factors such as gripping force, weight, size, and cost.

There are several types of robotic grippers, each with its own unique characteristics and suitability for different applications. Some of the most common types are Pneumatic grippers, Electric grippers, Mechanical grippers, Magnetic grippers, Vacuum grippers, and soft grippers. All of these grippers have benefits and drawbacks, and the choice of a gripper will be determined by the application's unique needs.

Specially mechanical grippers are divided into the following types - Pivoting or Swinging Gripper Mechanisms, the swing block mechanism, the cam-actuated gripper, and the cam and follower arrangement. I have implemented pivoting gripper mechanism in my work.

A three-fingered robotics gripper is a type of end-effector used in industrial robots and automation systems to handle and manipulate objects. The design of a three-fingered gripper consists of two opposing fingers that can move towards each other to grip an object and away from each other to release it , and 3rd finger is used to support the object.

My research seeks to build a pivoting gripper that can choose and place various diameter nuts, as well as compute the link lengths and joint angle of a 2-D robot gripper by fulfilling geometric and force constraints and optimizing objective functions. As an optimization method, I employed a genetic algorithm in my work.

A genetic algorithm (GA) is a metaheuristic technique based on natural selection and genetic principles. They are frequently used to determine the optimal solution to a problem by modelling the evolution process. A GA begins with a population of solutions and develops this population over time by using genetic operators such as crossover and mutation to produce new solutions. These new solutions are then evaluated, and the best ones are chosen to produce the population's next generation. This procedure is repeated until a sufficient solution is obtained or a stopping criterion is met. Engineering, robotics, finance, medical, game design, and manufacturing are all frequen applications for genetic algorithms. These are just a few examples of the many fields where genetic GA is used.

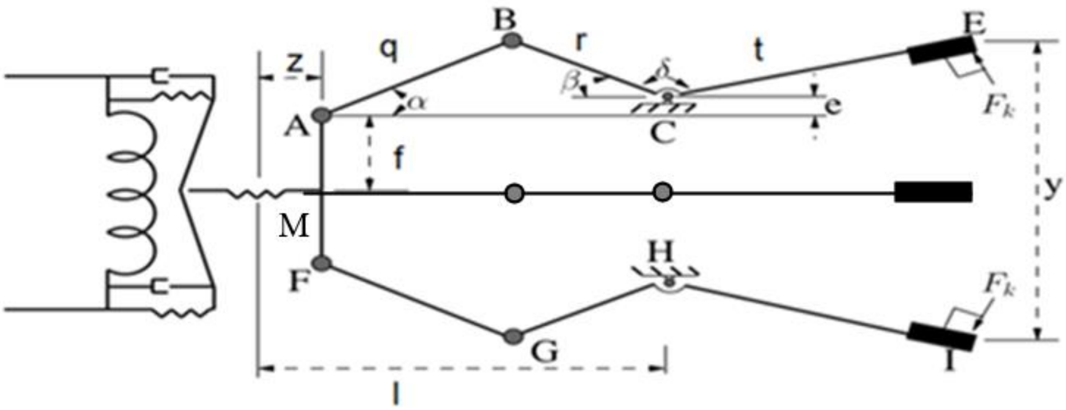
An optimization problem is the challenge of determining the optimal answer from among all possible options.In some optimization problems, many competing goal functions must be optimized at the same time. In other words, rather than a single solution that optimizes a single objective function, the goal is to identify a group of solutions that provide the optimum compromise among numerous competing objective functions. Multi-objective optimization is the name given to this sort of optimization approach. Engineering, finance, logistics, and environmental management are among industries that apply multi-objective optimization. Typically, the method entails employing mathematical models and algorithms to find the set of solutions that best balances the various objectives. This can be done using techniques such as Pareto optimization, evolutionary algorithms, or other optimization techniques that can handle multiple objectives.

LITERATURE REVIEW

A significant amount of study has been conducted on this topic. There is a comprehensive survey on robotic grasping available. Where (Datta, Pradhan and Bhattacharya 2016) have discussed a nonlinear multiobjective optimization problem that was initially created to solve the modified bi-objective issue and discover the optimal of the size of robotic gripper links and joint angle. Each of the non-dominated solutions yields a force voltage relationship, which aids the user in determining the voltage to be provided based on the application. (Krenich and Osyczka 2000)performed a atudy about the multicriteria optimization model of the robot gripper and is presented using the G.A technique, with one bicriterion optimization model solved at each stage. (Saravanan, Ramabalan, et al., Evolutionary multi criteria design optimization of robot grippers 2009) investigates the use of intelligent approaches to determine the best geometrical dimensions for a robot gripper. And discover the Pareto optimum solution for a problem with five objective functions, nine constraints, and seven variables. (Design optimization of robot grippers using teaching-learning-based optimization algorithm 2015) proposed the Teaching-learning-based optimization (TLBO) method in determining the optimal geometrical dimensions of a robot gripper and reveal that the TLBO method outperforms or is competitive with other optimization techniques. (Ho, et al. 2017) have performed the optimization of the design parameters of the gripper using the Taguchi technique and the gripper's statics and dynamics have examined using finite element analysis in ANSYS software. (Anil K B 2019) have implemented an algorithm for determining the optimal configuration from a list of potential alternatives. They have used static force analysis to determine an equation linking input force applied and output obtained for each configuration. (Dörterler et al. 2021) considered four different multiobjective metaheuristic algorithms, which were applied to two different configurations of a highly nonlinear and multimodal robot gripper design problem with two objective functions and a certain number of constraintsParticle swarm optrimization (MOPSO), artificial algae algorithm (MOAAA), grey wolf optimizer (MOGWO), and non-dominated sorting genetic algorithm are only a few examples. (NSGA-II). The major goal is to reduce the force differential between the minimum and maximum for the expected range of gripper end displacement. The second goal is to produce a high force transmission rate, which is defined as the ratio of actuator force to the gripper ends' lowest holding force. Particle swarm optrimization (MOPSO), artificial algae algorithm (MOAAA), grey wolf optimizer (MOGWO), and non-dominated sorting genetic algorithm (NSGA-II) are only a few examples. The main aim is to decrease the force difference between the lowest and maximum gripper end displacement for the projected range of gripper end displacement. The second aim is to achieve a high force transmission rate, which is defined as the ratio of actuator force to the lowest holding force of the gripper ends. The performance of the optimizers was evaluated individually for each configuration using pareto-front curves and the hyper-volume (HV) metric. The optimizers' performance on the given issue was compared to the results of previously recommended methods under the identical conditions. In these comparisons, the best-known setup results were achieved. In addition, the pareto optimum solutions are carefully analysed in order to show the link between design features and target functions.

ANALYSIS

As discussed before, We have considered pivoting gripper in this work. The line digram of gripper is same as the line digram of (Datta, Pradhan and Bhattacharya 2016) , in which we only add a extra finger for our 3 finger robotics gripper. they have considered a voice coil actuator to give input to the gripper. This actuator is used to provide linear motion to the gripper and it's other advantages are compact size and simple construction. Based on the Lorentz force theory, voice coil actuators employ a permanent magnet and a coil winding (conductor) to produce a force, which is directly proportional to the current provided to the coil. The gripping force 'F_K' is generated by the actuating force 'P'.



[Fig-1]

The following equation provides the relation between the force delivered and the current provided-

$$P = K \times B \times L \times N \times I \quad (1)$$

Where K is a constant, B is the magnetic field strength, L is the coil length, N is the number of windings , and I is the current flowing through the coil.

If an external voltage V is applied, the current generated may be computed by considering the coil's net resistance (R). i.e.- V=I×R. After putting the value (I) in equation 1, We get-

$$P = \frac{K \times B \times L \times V \times N}{R} \quad (2)$$

If the L, B, N, R are kept constant, equation (2) can be expressed as follows:

$$P = Ac \times V \quad (3)$$

Where, $Ac = K \times B \times L \times N/R$

GRIPPER CONFIGURATION DESIGN-

A constant actuator force has been taken into account in this research.

In multi-objective optimization, there is no single objective function, but rather a set of objective functions that are simultaneously optimized. These objective functions represent the different goals or criteria that need to be met. The objective functions are typically defined in terms of a set of decision variables, which represent the choices or actions that can be taken to achieve the goals. The decision variables can be continuous, discrete, or a combination of both.

Two objective functions were considered in the multiobjective optimization-

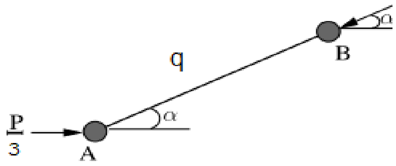
(1) A force's range between its greatest and least.
(2) the ratio of force transformation.

Design Variables

The link lengths and joint angle are represented by the seven design variables $x = (q, r, t, e, f, l, \delta)^T$, where q, r, t, e, f, and l represent the link lengths and δ represents the joint angle between components r & t.

Force analysis

Any 2-D mechanism with an attached link operates as a truss because the actuator can move to change its position in order to prevent the link from bending.

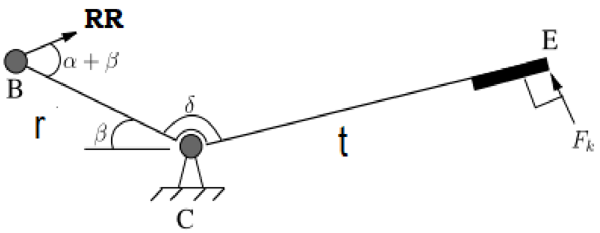


[Fig-2]

This figure shows the FBD of robot gripper link AB. P, the actuator force, is considered to be the sum of three point forces at positions A , F&M. The reaction force at point B is denoted by RR.

i.e. –

$$\frac{P}{3} = RR \times COS\alpha \tag{4}$$



[Fig-3]

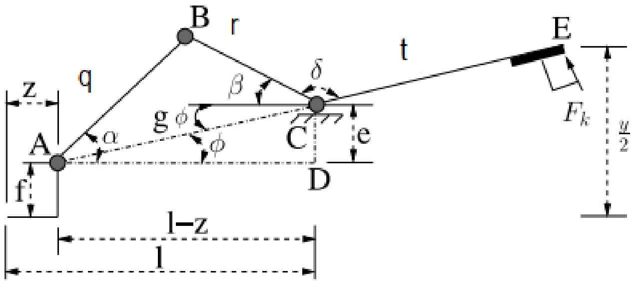
FBD of robot gripper link 2. (α + β) denotes the angle formed by the reaction force and link 2. β is the angle formed by link 2 and the manipulator's motion direction .δ is the angle formed by links 2 and 3.

Taking moment about 'C'-

$$\sum Mxc = 0 \tag{5}$$

$$F_k = [P \times \frac{r\sin(\alpha + \beta)}{3 \times C\cos(\alpha)}] \tag{6}$$

The reaction force on links an in the equation above is denoted by RR. P is the actuation force used to operate the gripper from the left side.



[Fig-4]

The gripper mechanism's geometrical dependencies. The distance between A and C is given by g, while the angle formed by AC and AD is given by φ, α is the angle made by link AB with horizontal, and β is the angle made by link BC with horizontal.

So,

$$\alpha = \arccos\left[\frac{q^2 + g^2 - r^2}{2 \times q \times g}\right] + \varphi$$
$$\beta = \arccos\left(\frac{r^2 + g^2 - q^2}{2 \times r \times g}\right) - \varphi$$

$$\varphi = \arctan\left(\frac{e}{l - z}\right)$$

For this paper, the following constrains have been taken into account.

(1) The distance between the gripper's two ends should be smaller than the gripping object's smallest dimension for maximal actuator displacement

$$g_1(x) = Y_{min} - y(x, Z_{max}) \geq 0$$

In the above equation,

$$y(x, z) = 2 \times [e + f + t \times \sin(\beta + \alpha)]$$

(2) For maximum actuator displacement (Z_{max}), there should be more space between the gripper ends and should be greater than zero.

$$g_2(x) = y(x, z_{max}) \geq 0$$

(3) The distance between the gripper's two ends should be bigger than the largest dimension of the object to be grasped for zero actuator movement.

$$g_3(x) = y(x, 0) - y_{max} \geq 0$$

(4) The gripper's end displacement should have a maximum range that is larger than or equal to the distance between the ends of the grip that corresponds to zero actuator displacement.

$$g_4(x) = YG - y(x, 0) \geq 0 \quad (7)$$

(5) The geometric constraints are as follows:

$$g_5(x) = (q + r)^2 - l^2 - e^2 \geq 0$$

$$g_6(x) = (l - z_{max})^2 + (q - e)^2 - r^2 \geq 0$$
$$g_7(x) = l - z_{max} \geq 0$$

(6)The specified limiting gripping force should be larger than or equal to the minimal force required to grasp the object.

$$g_8(x) = \min F_k(x, z) - FG \geq 0 \quad (8)$$

where FG is the assumed minimal griping force.
Objective Functions
The following two goal functions have been developed based on the link geometry analysis.

1) The first objective function is the difference between the maximum and lowest values of the gripping force. The least amount of variation in the gripping force would result from the minimum difference between the highest and minimum values.

$$F_1 = \max F_k(x,z) - \min F_k(x,z) \tag{9}$$

2) The gripping force that is achieved for a specific actuation force is a crucial part of the gripper problem. The mechanism would be more effective the greater the value of the minimum gripping force. We select the force transmission ratio as our second goal function to take this into consideration. The ratio between the applied actuating force P and the resultant minimum gripping force at the tip of link c is known as the force transmission ratio.

$$F_2(x) = \frac{p}{\min F_k(x,z)} \tag{10}$$

The actuator force P is no longer constant in this study and now fluctuates with actuator displacement. In light of this, the second goal function (force transformation ratio) is changed to –

$$F_2(x) = \max\left(\frac{p(x,z)}{F_k(x,z)}\right) \tag{11}$$

CONVENTIONAL ACTUATOR

For this study, a typical actuator with a force that is linearly proportional to voltage is used. This behaviour is analogous to that of the voice coil actuator. The following work tries to produce force and voltage interactions for a stack of such actuators. To do so, it is first assumed that a proper force-voltage relationship exists for a single actuator. The individual actuators are then stacked together in various combinations.

The electrical and mechanical models of the component are then arranged by series and parallel combinations. Which is described in table-1 along with the reason for acceptable and unacceptable combination of electrical and mechanical system.

[TABLE-1: Comparison between four different arrangements of actuating element in actuator.]

CASE N0.	MECHANICAL SYSTEM (SPRING)	ELECTRICAL SYSTEM (CAPACITOR)	REMARKS	REASONS
A	Parallel	Series	Acceptable	In this case, the value of force transformation ratio is very low and the gripping force range is also very low.
B	Series	Parallel	Acceptable	In this case, the value of the force transformation ratio is quite low, as the range of the gripping force.
C	Series	Series	Unacceptable	There are no feasible solutions are determined for both electrical and mechanical systems in series connection. Because the proportionality factor between force and voltage in this situation is very small. So, we get very small force for a particular voltage. This suggests that in this situation, a high actuator stiffness value is required to both achieve workable solutions through optimization and to produce significant gripping forces.

D	Parallel	Parallel	Unacceptable	This is due to the fact that ideal configurations do not change the force transformation ratio, which is a ratio of two forces, each of which increases in value by a factor of n. (number of components in a stack). If the identical research had been done using the first objective function for range of gripping force, the values on the x-axis would have been n times greater than in the prior situation.

METHODOLOGY

To optimize the design of pivoting grippers, the links parameter are to be optimized. The design variables are mentioned in the table-2.

[Table-2:The range of decision variables used in NSGA-II]

Sl. No.	Design variable	Minimum value	Maximum value
1	q	10mm	250mm
2	r	10mm	250mm
3	t	100mm	300mm
4	e	0mm	50mm
5	f	10mm	250mm
6	l	10mm	300mm
7	δ	1 rad	Π rad

The NSGA (Non-dominated Sorting Genetic Algorithm) algorithm's operation will be broken down into the following steps: Begin by developing a sample of possible solutions to the situation at hand. Sort the population's solutions into different levels of non-domination. Solutions that are not dominated by any other solutions are placed in the first level, solutions in the first level that are dominated by only one solution are placed in the second level, and so on. Calculate the crowding distance for each level's answer. The crowding distance is used to determine the extent of variety among solutions. Selection Choose solutions for the next generation depending on their level of non-domination and crowding distance. Lower non-domination levels and greater crowding distances are more likely to be chosen. To develop novel solutions for the following generation, use genetic operators such as crossover and mutation. For the new solutions, repeat the non-dominated sorting and crowding distance assignment processes. Repeat the preceding procedures until the termination requirements have been fulfilled. A certain number of generations, a minimal level of solution quality, or other relevant constraints can be used as termination criteria. Pareto-optimal solutions are those that are not dominated by any other solutions in the final population, illustrating the trade-off between the many conflicting aims. This is a broad overview of the NSGA's working method. The precise selection and genetic operators utilized, the computation of crowding distance, and the termination criteria may vary based on the unique problem and application needs. The NSGA pseudocode is provided below.

Pseudocode I: NSGA-II

Input: population (P), mutation rate (R), crossover rate (C) , population size (N)
Output: Optimum value of design variable

Begin with population "P1";
Generate a random population of size "N";
Analyse the objective function;
Assign rank based on Pareto sort;
Create a child population;
Binary tournament solution;
For i=1 to g, **perform the following:**
  Do the following for every parent and child in the population:

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Based on the Pareto principle, assign a rank
Make a collection of non-dominant solutions;
Determine the crowding distance;
Loop (inside) by adding solutions to the next generation starting from the first front until "N"

End

Choose points with a high crowding distance on the bottom front;
Create the future generation;
Binary tournament selection;
Recombination and mutation;

End

The NSGA parameters can have a significant impact on the performance and convergence of a Genetic Algorithm, so it is important to carefully consider their values when designing and running an NSGA. The parameters of an NSGA typically include Crossover Rate, Mutation Rate, Population Size, and Population Size. The values of NSGA parameters are mentioned in table-3.

Table-3:The values of parameters of genetic algorithm.

Sl no.	Parameters	Value
1	Crossover Rate	0.25-0.45
2	Mutation Rate	0.015-0.025
3	Population Size	1000
4	Number Of Generation	1000

The crossover rate in the context of the Non-dominated Sorting Genetic Algorithm (NSGA) refers to the potential of using crossover during the reproduction phase.

NSGA is a multi-objective optimization method that creates new offspring from parent individuals by using genetic operators that include crossover. The crossover operator is used in order to combine the genetic information of two parents to create new offspring solutions.

In NSGA, the crossover rate influences the possibility of using crossover during reproduction. A larger crossover rate indicates a larger the potential of crossover, whereas a lower crossover rate indicates a lesser the potential of crossover. It has an impact on the exploration and exploitation balance within the search phase.

The optimum crossover rate in NSGA is determined by various factors, including the nature of the problem, population diversity, and the trade-off between exploration and exploitation. A larger crossover rate allows search space exploration, allowing for the generation of varied solutions. A smaller crossover rate, on the other hand, allows exploitation by maintaining excellent solutions in the population.

NSGA, like other evolutionary algorithms, frequently determines the ideal crossover rate by practical testing and fine-tuning. It includes experimenting with various crossover rates and assessing their influence on the algorithm's performance, such as convergence speed, variety of solutions, and the quality of the Pareto front produced.

In this paper, We have done a comparison between pareto front graph, Which are obtained due to the varying value of cross over rate from 0 to 1, allowing to NSGA model to run for 1000.

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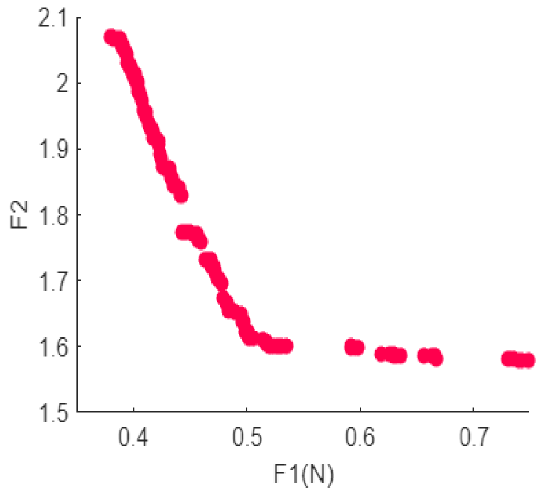
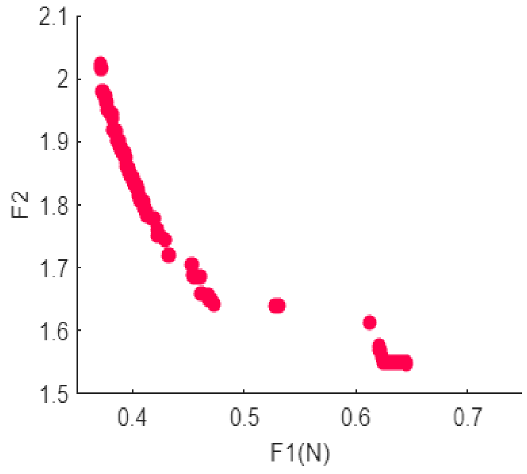
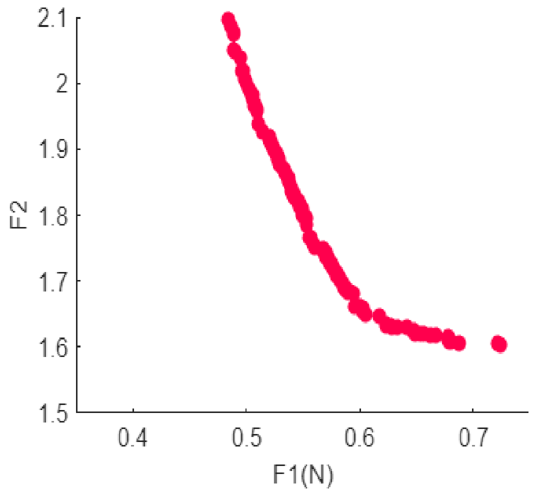


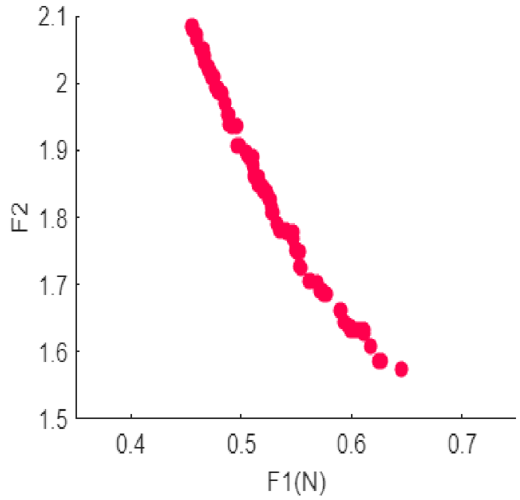
[Fig-5]
The graph represent the pareto optimal front at crossover rate 0.35



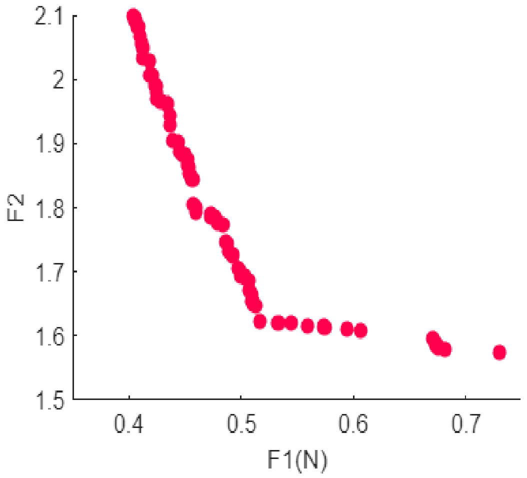
[Fig-6]
The graph represent the pareto optimal front at crossover rate 0.39



[Fig-7]
The graph represent the pareto optimal front at crossover rate 0.4



[Fig-8]
The graph represent the pareto optimal front at crossover rate 0.45



[Fig-9]
The graph represent the pareto optimal front at crossover rate 0.5

As we know pareto optimal front contains non dominated solution and the optimal solution always stay close to the origin of the graph. The graph-5&9 are rejected, Because the pareto front of the graphs are become straight line, which indicates that one objective function is highly dominated to other objective function. The graph-8 is also rejected due to its high objective functions value (i.e- F1=1 ,F2=2.8).In graph-6&7 we get good result and the pareto front are curve shape. But, Between these 2 graph, graph-5 has less distance between the point on pareto front graph to origin. which, indicates that the graph-5 has good optimal solution as compare to the graph-6. So, we take 0.39 as cross over fraction in this project.

In the context of Genetic Algorithms (GA), a generation refers to a particular iteration or a single population of potential solutions in the evolutionary process. Genetic Algorithms are inspired by the principles of natural selection and genetic inheritance. They are used to solve optimization and search problems. The process begins with an initial population of potential solutions, often represented as individuals or chromosomes. Each individual in the population has a set of characteristics, called genes, which encode its potential solution to the problem at hand.

The evolution of the population occurs through successive generations. In each generation, a new population is created by applying genetic operators such as selection, crossover, and mutation. These operators mimic the processes of selection, reproduction, and mutation found in natural evolution.

During the evolution, individuals with more desirable characteristics, as determined by a fitness function, have a higher chance of being selected for reproduction. Crossover and mutation operators are then applied to produce offspring with a combination of genetic material from the selected individuals. This creates a new generation of individuals that undergoes further evaluation and selection.

The process of evolving generations continues until a stopping condition is met, such as reaching a maximum number of generations or achieving a satisfactory solution to the problem. With each generation, the hope is that the population improves, converging towards an optimal or near-optimal solution.

In summary, a generation in a Genetic Algorithm represents a particular iteration or population of potential solutions in the evolutionary process. It evolves over time through the application of genetic operators, aiming to improve the fitness and quality of the population's individuals.

[TABLE-4: Programme running time at crossover rate 0.4 from 100 generation to 1000]

SL no.	Maximum Generation	Programme Run Time(sec)	F_1 (N)	F_2	Number Of Solutions
1	100	14.71	0.5746	1.7752	378
2	200	27.55	0.7237	1.6040	488
3	300	27.84	0.7237	1.6040	558
4	400	27.44	0.7237	1.6040	558
5	500	27.19	0.7237	1.6040	558
6	600	27.09	0.7237	1.6040	558
7	700	27.44	0.7237	1.6040	558
8	800	27.04	0.7237	1.6040	558
9	900	27.11	0.7237	1.6040	558
10	1000	27.50	0.7237	1.6040	558

From the table-4, We get information about the time duration to determine results by NSGA-II. From table , we found that in 100 generation we get result in less time, and in 200 generation algorithm take more time to give result. But, The results in 100 generation and 200 generation are different. So, the algorithm required more iteration after 100 generation. After 200 generation we get approximately same result. So we can stop iteration after 200 generation.

[TABLE-5: Programme running time at crossover rate 0.39 from generation 100 to 1000]

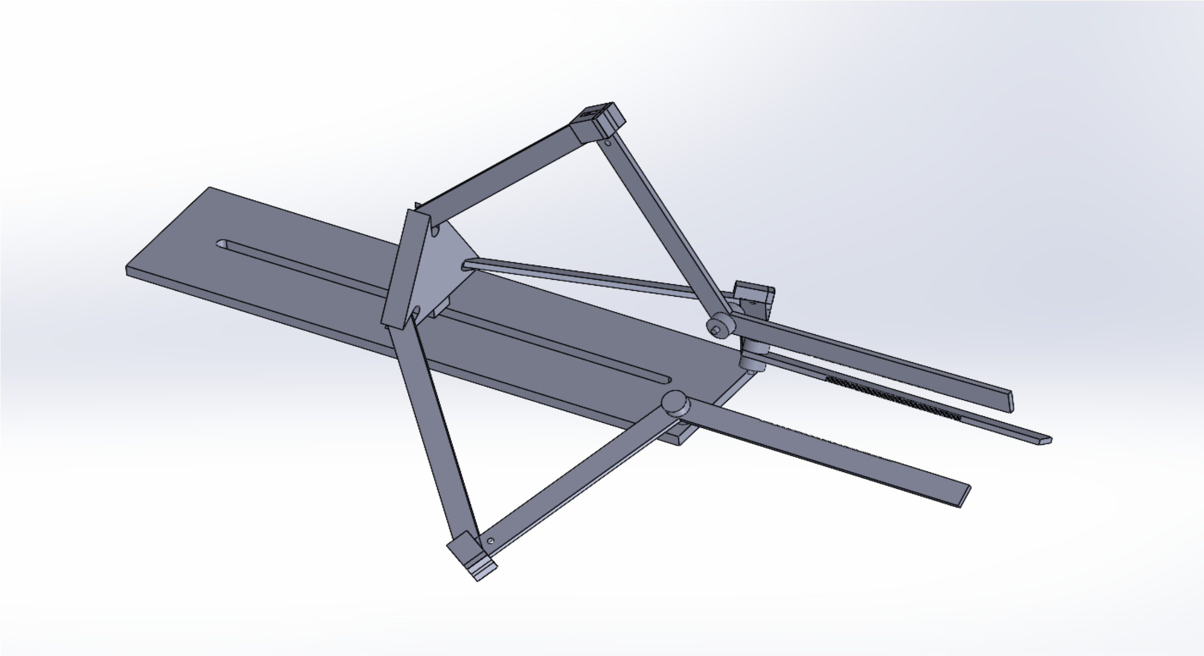
SL no.	Maximum Generation	Programme Run Time (sec)	F_1 (N)	F_2	Number Of Solutions
1	100	20.90	0.3713	2.0219	690
2	200	28.46	0.3715	2.0217	700
3	300	26.80	0.3715	2.0217	700
4	400	27.54	0.3715	2.0217	700
5	500	26.60	0.3715	2.0217	700
6	600	28.01	0.3715	2.0217	700
7	700	28.46	0.3715	2.0217	700
8	800	26.51	0.3715	2.0217	700
9	900	27.54	0.3715	2.0217	700
10	1000	27.90	0.3715	2.0217	700

According to Table-5,We can stop iteration at 100 generation, Because results of 100 generation and 200 generation are approximately same. But, in case of 200 generation algorithm take 8 sec more. Because it give 10 more number of solution. So, the result of 200 generation is acceptable as compared to the result of 100 generation. Finally, after 200 generation we get almost same result.

So, in this way after number of experiments, we get best result at mutation rate 0.020 , at crossover rate 0.39 and at generation 200.

RESULTS

CAD model of robotics gripper



[Fig-10]

Figure-10 depicts an assemble model of 3 finger pivoting robotic gripper.

A number of experiment are conducted with varying crossover rate (0.25-0.45) and mutation rate (0.015-0.025) as in table-3. After this experiment we get best result at crossover rate 0.4 and mutation rate 0.020 given in table-4.

[TABLE-6: Ten solutions were chosen from the set of Pareto optimum solutions.]

SL NO.	Q (mm)	r (mm)	t (mm)	e (mm)	f (mm)	l (mm)	δ (radian)	F_1 (N)	F_2
1	235.65	201.01	258.80	33.33	59.96	145.81	2.08	0.3715	2.0217
2	237.70	203.09	231.59	33.24	57.92	147.89	2.08	0.4114	1.7937
3	235.84	201.23	258.48	33.28	60.40	146.26	2.08	0.3717	2.0182
4	219.42	197.47	167.94	30.76	55.85	211.34	2.16	0.6207	1.5751
5	238.21	203.49	237.73	33.31	61.32	149.07	2.08	0.4000	1.8400
6	237.29	202.65	242.89	33.37	61.64	145.82	2.10	0.3933	1.8802
7	237.70	203.05	236.04	33.32	60.04	147.25	2.10	0.4042	1.8267
8	237.47	202.58	253.19	33.57	59.98	146.85	2.08	0.3767	1.9628
9	235.67	201.03	259.00	33.33	59.77	145.82	2.06	0.3711	2.0232
10	237.28	202.64	242.90	33.36	61.64	145.82	2.09	0.3927	1.8803

The designer can run the evolutionary algorithm and the collection of Pareto optimum solutions is created automatically in each scenario.

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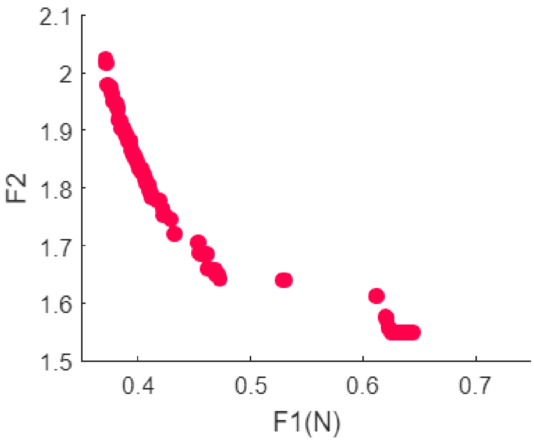
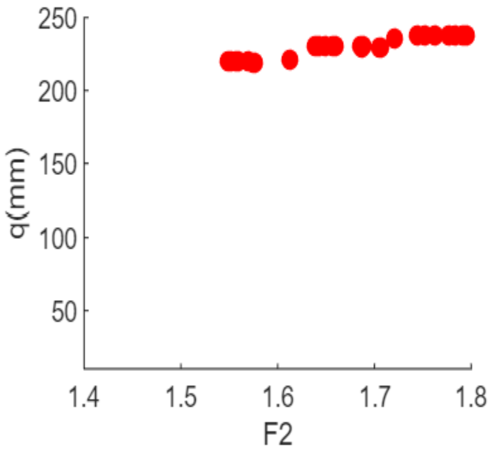


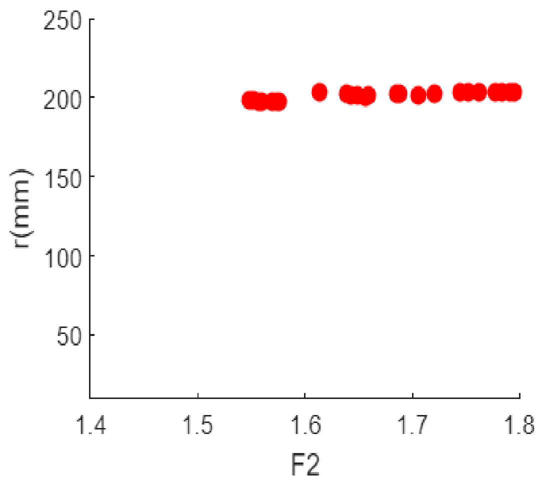
[Fig-11]

In figure-11 the nondominated solutions between the objectives using NSGA-II. Based on his preferences, the user can pick any of these points. The force transformation ratio is low on the left side of the curve, but the range of gripping force is low on the right side of the curve.



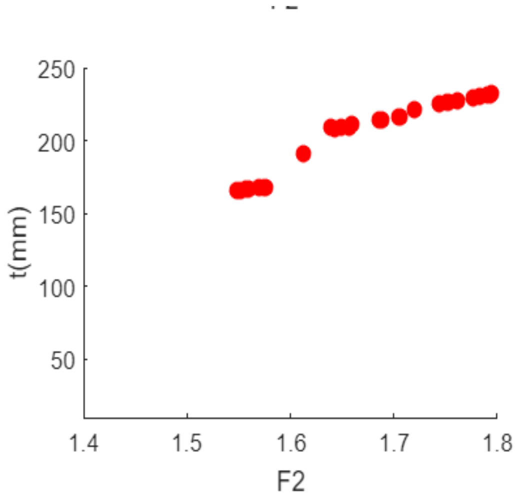
[Fig-12]

In figure-12 the second objective function is vary with the link length "q". For the various optimum configurations, the value of "q" is almost constant and may be fixed at its upper bound.



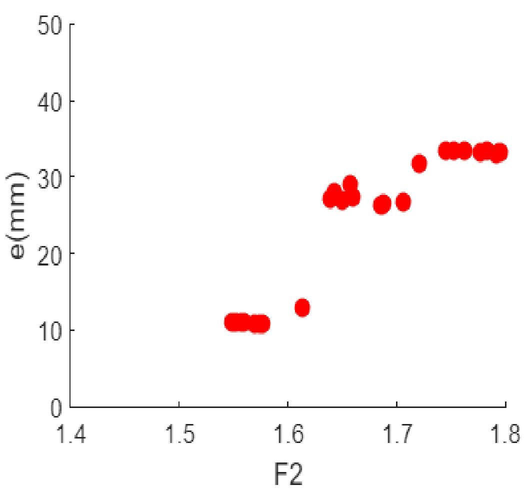
[Fig-13]

In figure-13 the second objective function is vary with the link length "r" around 200 mm. Variations can be disregarded and the value set to 200.



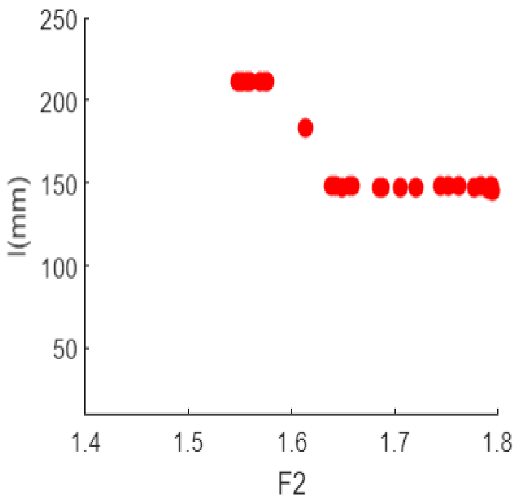
[Fig-14]

In figure-14 the second objective function is vary with the connection length "t". For the various optimum configurations, the value of "t" increases.



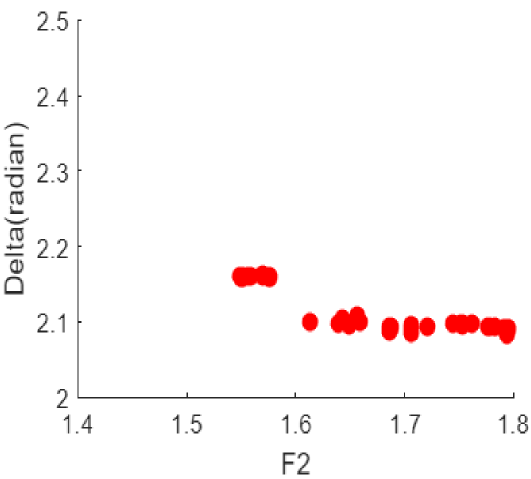
[Fig-15]

The link length "e" in figure-15 varies with the second objective function. For several ideal designs with a low value of force transmission ratio, the value of "e" is nearly constant and may be set at its lower bound.



[Fig-16]

In figure-16 the second objective function is vary with the link length "l" is varied. As can be observed, "l" is inversely related to the force transmission ratio. It is possible to say that l is the mechanism's critical component. While most other geometric elements may be set to specified values in order to obtain optimal designs, the length l defines which aim is more important to the user.



[Fig-17]

In figure-17 the angle "Delta" vary with the second objective function. The angle fluctuates significantly with the force transmission ratio, with no discernible pattern. As a result, no link can be formed between the two.

CONCLUSION

In conclusion, the use of multi-objective genetic algorithm (MOGA) for the analysis and design optimization of a robotic gripper can be a powerful and efficient approach. The MOGA can simultaneously consider multiple objectives, such as grasping force and dexterity, to generate a set of Pareto-optimal solutions. The results of this study can be used to improve the design of robotic grippers for various applications and can be extended to other types of robotic systems. Additionally, the use of MOGA can significantly reduce the time and costs associated with traditional trial-and-error design methods. Based on the results, it is obvious that this technique provides the designer with a novel and extremely effective tool for addressing fairly difficult tasks when both the optimization model and the decision-making problem are considered.

FUTURE SCOPE

In this work, It will be focused on changing the range of the input parameter, as well as addition of modified constraints function in NS-GA for obtaining improved solutions. Also, we will be implementing existing optimization algorithm i.e.- TLBO,ACO etc. for further enhancing the obtained solutions. Integrating real-world constraints, such as cost and manufacturability, into the optimization process to improve the practicality and usability of the final design. Incorporating more realistic and complex simulation models of the gripper and its environment to improve the accuracy of the optimization process. Incorporating more design objectives into the optimization process, such as durability, energy efficiency, and adaptability, to improve the versatility and robustness of the final design. Applying machine learning techniques, such as neural networks or deep learning, to improve the fitness function and speed up the optimization process.

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