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Multi-Objective Design Optimization of 3d Printed Parts Using Hybrid Evolutionary Algorithms in FDM

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Abstract

The revolutionary ideas and prototypes made possible by the advent of 3D printing, often called additive manufacturing, is revolutionizing the industrial industry. Given the characteristics of the substance, there are number of 3D printing processes. 3D printed products have significant applications in Aerospace, Automotive, Construction, Tissue Engineering, Medical, Electronics areas. Fusion Additive manufacturing includes the use of deposition modelling predominantly used for printing ABS, PLA and Composite filament-based wire-feeds to form required geometry. The designs are realized through CAD designs and sliced through Slicer software. FDM possess simplicity having smaller machine unit and provides design freedom. There are more than 150 filaments compatible with the technology including metal mixed plastic material. Printing sensors is one of the key 3D printing applications. Existing E-beam deposition of metals are fairly complex and costly. Certain process involves vacuum and pressure processing to print metals. Metals are mostly processed through fusing powder particles at very high temperature using high power laser. These are applied for macro and micro-objects. Nevertheless, FDM based process are mostly used for macro-objects. Resolution is poor for micro printing objects. Therefore, product quality needs improvement for micro printing scenario. Clogging issues during dispensing are more. Further, layering metal on a substrate is a key challenge for existing 3D metal printing processes. FDM supports layering on substrate. However, limitations exist for conductive metal layering for sensor fabrications as the current filaments are not conductive. Currently, the vertical printing resolution using plastic and plastic with metal is 50 µm. For electrochemical applications such as heavy metal ion sensors, the metal layering requires in micro or nano sizes. Hence, FDM 3D printing needs improvement in improving z-resolution or reducing the layering height for more precision.

Keywords: Mechanical, academics, parameters, revolutionary, Optimization

Introduction

A large number of academics are interested in finding the optimal process parameters since the printed items' mechanical qualities change depending on those factors. Items made using FDM machines have recently sparked interest from academics who want to learn more about their structural performance. Recent years have seen a deluge of Studying the effects of input factors on mechanical properties, with a focus on flexural and tensile strengths. Layer thickness, orientation, raster angle, raster width, air gap, feed rate, print speed, filling ratio, extruder temperature, nozzle diameter, and shell number are some of the parameters that renowned researchers have examined. According to Dhinesh *et al*. (2011) [5], the tensile strength of PLA is greater than ABS, and it is much higher when an 80/20 mix is used. Mixed with half PLA and half ABS, it has the best flexural strength. More investigation into different percentages of PLA and ABS is now possible because to this. S. Singh *et al*. studied PLA reinforced with chitosan and found that compressive strength increased but tensile and flexural strengths dropped as the chitosan weight % raised. According to research, the most important aspect for wood PLA composites is the thickness of the layers. When it came to the mechanical characteristics of PLA+

samples, Günaya found that infilled density was the most critical element. Printing at a faster pace decreased tensile strength, but an orientation of 0 or 90 degrees increased it. As the layer height was raised, Camargo *et al*. discovered that the mechanical qualities of PLA-graphene improved. Rajpurohit and Dave and Gebisa and Lemu demonstrated both parameters are inversely related, with layer thickness being the more important. There was an effect of raster angle and raster width on FDM specimen flexural strength, which was also found. In order to maximize mechanical qualities like tensile and flexural strength, Chacón *et al*. propose orienting the edges. Using response surface analysis, Anoop Kumar Sood, Ohdar, and Mahapatra found the best combination of parameters for tensile and flexural strength.

3D Printing Process

The 3D printer adds layers of material by subsequent physical layers of powdered metal or plastic bound components to create three-dimensional solids. It is based on a digital model file. This is distinct from traditional removal materials and due to this quality, It's another name for AM technology, which stands for additive manufacturing. With the development of 3D printing, it is now possible to manufacture complex 3D objects without the need for traditional tools or moulds may transform it into a series of 2D manufacturing overlays. Parts that are almost arbitrarily complex increase flexibility and efficiency of manufacturing. As a result, the 3D printing sector's growth has drawn more attention domestically and internationally and it will also influence how future manufacturing will go.

In the current scenario, high fluctuation in the global manufacturing industries economy forces the manufacturers to develop and deliver end-use manufactured parts with improved mechanical and physical properties. Traditional manufacturing techniques, high tooling costs, design, geometrical complexity constraints, time-consuming pre and post-processing processes, and so on are all factors that have forced the researcher to consider a new technology that overcomes all of these factors Wong & Hernandez (2012) [6]. As a result, meeting end goals such as customer requirements and realization have shifted the manufacturer's focus to a new technique that fabricates parts in an additive rather than subtractive manner, i.e., Three-Dimensional Printing (3DP).

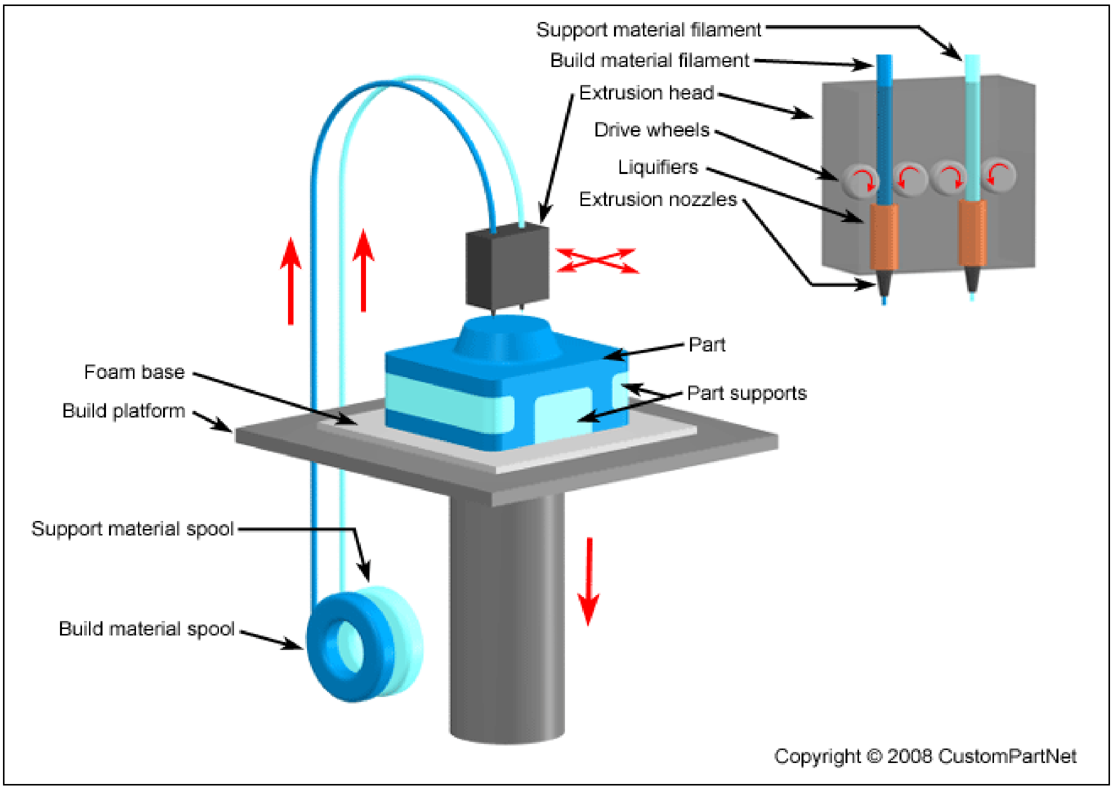

Fig 1: Fused deposition modelling

Literature Review

To make things more efficient, Raju *et al*. (2022) [1] suggested the components in Additive Manufacturing (AM). The components produced by the AM process had a broader range of applications in a variety of domains. One of the AM methodologies used for component fabrication was fusion deposition modeling. Due to its biodegradability and the addition of carbon nanoparticles, PLA was the ideal substitute for plastics and might be used for many technical purposes. Using specific independent process variables, Taguchi's experimental design was identified as a concept for organizing experiments. Taguchi's method was used to optimize specific aspects. The samples' hardness, roughness, and tensile strength were used to measure their performance. A strategy for multi-faceted optimization was grey system theory. The ideal process variables were found for various experimentation techniques. Interaction analysis was conducted to ascertain how combinatorial variables affected the results.

Afrin *et al*. (2021) [7] analyzed the data using Taguchi and

G-Code. One of the technologies that is currently being developed is 3D printing. Easy, quick, and exact product production is possible with this machine. Models, prototypes, instructional tools, medical supports, product design, and many more 3D things are produced via 3D printing. The majority of 3D printers employ Fused Deposition Modelling. To sum it up, you won't need any adhesives or solvents to keep it in good repair. Easy access to replacement components affordably available. In this study, Autodesk inventor was used to create objects known as human dentures. Simplyfy3D software version 4.1.2 was used to convert it to G-Code. The product was produced by Using G-Code files for the 3D printer. The product's creators decided on the printing parameters. In this study, the optimal parameters for the relationship between the product hardness and the shrinkage were established. The research examined the following variables: print speed, print temperature, layer height. Pla + filament was used to make the denture for the human mouth. For these data, we resorted to the Taguchi and Grey analyses. Here are the optimal analysis parameters: Print settings were set at 210 °C with a layer height of 0.15 mm and a speed of 25 mm/s.

Zhang *et al.* (2021) [2] added a One prominent feature of the emerging corporate landscape was 3D printing, an abbreviation for additive manufacturing. A new technology with several potential uses, Additive Manufacturing (AM) grows new materials and exhibits spectacular mechanical, physical, and chemical qualities of things. The base up added substance fabricating strategy is more advantageous than customary hierarchical methodologies in all viewpoints with the exception of certain impediments, for example, creation time; Item aspects; Establishment charge; arrangements of regulation. Notwithstanding the difficulties, there is as yet an edge of commercialization of AM items in the worldwide market, bringing about creation reserve funds of under half and a creation speed increment of over 400% contrasted with negligibly prohibitive strategies.

Harris *et al.* (2018) [8] studied about Additive Manufacturing (AM) which is a quickly developing innovation because of its many benefits over conventional assembling processes. Materials that can be treated with AM are restricted and have poor mechanical execution, which restricts the innovation's true capacity in assembling practical parts. The most unfavourable aspect of the material has limited its applicability to prototyping, even if FDM is the most well-known and creative method. Nanocomposite materials enhance FDM objects' temperature, mechanical stress, and electrical output. Almost all polymer nanocomposites have practical applications; in fact, several studies have shown that they can even surpass more conventional materials. Some of the main reinforcements used to make thermoplastics include carbon nanotubes, carbon fiber, graphene nanosheets, and nano-clay. Our investigation centers on the most recent developments in nanocomposites for the FDM cycle, as well as the impact of nanofillers on the mechanical properties of the emerging product.

Khoo *et al*. (2015) [3] the late 1980s. There has been remarkable progress in the sector, but there is always room for improvement. To address the numerous remaining problems, a lot more study is needed. Substance assembly of clever materials and designs has recently emerged as one of the domains of dynamic research. Clever materials may change their shape or properties in reaction to outside forces. The fourth characteristic is that AM-produced items may alter their form or qualities over time (thanks to applied external enhancements) with the help of clever materials. It was for this reason that the phrase "4D printing" was coined to describe the process of structural reconfiguration in the long run. Printed novel smart nanocomposites, shape memory polymers, actuators, and form memory combinations, and other recent notable breakthroughs in 4D printing were covered in this article for delicate robots, self-created structure, against duplicating framework, dynamic origami and controlled consecutive collapsing and a portion of our continuous examination discoveries. Likewise, various 4D bio printing research exercises were additionally included, trailed by conversations on challenges, applications, research headings and future 4D printing patterns.

Materials and Methods

Fused deposition modeling (FDM) uses a mechanically modified material extrusion method to deposit layers sequentially throughout the manufacturing process (Yan, Lin *et al*. 2018) [9]. Thermal bonding, a diffusion welding process, holds the adjacent deposited layers together. Some problems, such as low mechanical strength and poor quality of FDM to make end-use items for any manufacturing business, have limited the precise usage of the predetermined performance. (Ippolito, Iuliano *et al*. 1995, Kim and Oh 2008) [10, 11].

Furthermore, manufacturers are unable to provide high-quality components because to variations in FDM input settings (s and Oh 2008) [11]. In this approach, an intuitive methodology might be a productive strategy to consider collaboration between diverse aspects and qualities of components manufactured utilizing fused deposition modeling methods. The efficiency of FDM must be understood while fabricating components at various factor levels and rages, so that they are reliable for current applications. The present part displays the materials and procedures used to examine FDM generated items by conducting testing on various features. It explains the complexities of the component manufacturing procedure and the many tests undertaken to determine performance.

Various parameters such as dimensional precision, tensile and compressive strength, surface roughness, and wear are used to assess product quality when considering current needs. All test runs are completed according to the various ASTM standards. This section of the thesis also discusses the approach for the RSM-based experimental design method, as well as evolutionary methods such as ANN, ANFIS, and Fuzzy aided with GA.

Different characteristics measurement

Dimensional Preciseness

The test item that was made to measure the dimensional precision of the FDM process. We employ micrometers (with a minimum count of 0.01mm) to measure various exterior measurements (length, width, thickness). It is a precise instrument for taking measurements of inside and outside dimensions with the use of mechanical interpolation, a micrometer can precisely measure the distance between any two points on a linear scale.

The test specimen is clamped between two sets of external jaws, with one set of jaws being stationary and the other set to move, in order to get the external measurement dimension mentioned before. In addition, the jaw's two arms are snugly clamped, and the measurements are collected precisely by looking at the scale.

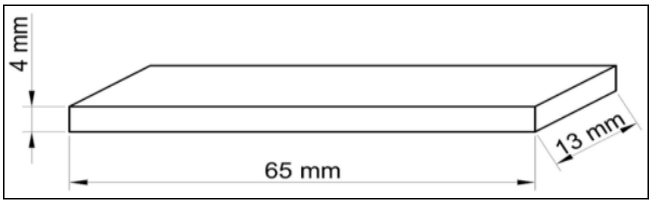

Fig 2: Test specimen for dimensional preciseness

Wear Testing

Measurements of wear were taken using a pin-on disc machine. The cylindrical test specimen with dimensions according to the ASTM-G99 standard is shown in Figure 3. Estimating the amount of sliding wear on a component using this method is standard practice.

Table 1: Surface roughness tester parameters

Condition	Value
Measuring speed	0.5mm/sec
Filters	Gaussian, 2CR75
Standard	ISO 1997
Cutoff length	2.5mm
Skid force	Less than 400mN

Results and Discussion

Experimental Work: Fabrication of all test specimens is carried out in accordance with the method. To quantify the dispersion as a percentage, three values are obtained at each face of the specimen using a digital micrometer device: width, thickness, and length. The output value is determined by averaging the three readings on each face.

Levels and ranges for four variables infill-density, number of contours, build direction, and layer thickness. We compute the range of values for the specified parameters in terms of alpha to fit the demands of the FDM machine, but we leave all other parameters unchanged. Parts manufactured by FDM could be measured more precisely because to a core composite design that has five levels for every process parameter.

Experimental Design Matrix

Reason being, it can reduce the number of trials needed to find the optimal combination of machine input parameters and output goal, all while enhancing the link between the two, CCD is used based on RSM, the experimental design matrix is shown.

Table 2: Dimensional accuracy input parameter ranges and levels

FDM input parameters	Notation	Unit	Range	(-alpha)	(+alpha)
Layer thickness	A	mm	0.12-0.4	-1	1
Build orientation	B	Degree	0-90	-1	1
Infill-density	C	% (percentage)	0-100	-1	1
Number of contours	D	No.	2-10	-1	1

The four input elements are all subject to five levels of change, as shown in Table 2. Throughout the experiment, all Everything else that may be entered into the FDM is left at its default settings. The mathematical model was constructed using a second-order polynomial fitting model. The accuracy of the connection between the input process parameters and the equation was examined (3.1). There are a total of 30 experimental run orders with 6 center points that were obtained. Table 2 displays the values of the observed and expected output dimensional precision

Experimental Data Learning and Training utilizing ANN: Indeed, neural networks are so good at fitting that they can consciously execute fitting functions, meaning they suitable for any purpose. So that the network may receive a clear picture of the issue, we load the input data as a 4x30 matrix (.mat format) with 30 values that correspond to four factors: layer-density, build-direction, infill-density, and contour-count. A 1x30 matrix (.mat format) with 30 values per factor (variation in length, breadth, or thickness) was used to create the intended network output. next data collection, Validation and test data are the following steps. In the past, this was accomplished by randomly assigning 15% of a 30-value data set to testing, 15% to validation, and 70% to training. During training, the network is fed training samples and fine-tuned based on its mistakes. We utilise validation samples to measure the network's speculation and stop training when speculation stops progressing. You can calculate the network's performance independently by evaluating samples both during and after training, as they don't affect the data used for training.

Table 3: Analytical results of length

Source	Sum of Squares	DF	Mean square	F value	Prob > F (P value)	Remarks
Model	12.07783	14	0.862702	32.69188	<0.0001	Significant
A	1.98375	1	1.98375	75.17368	<0.0001	
B	1.08375	1	1.08375	41.06842	<0.0001	
C	0.570417	1	0.570417	21.61579	0.0003	
D	0.120417	1	0.120417	4.563158	0.0496	
A^2	0.495268	1	0.495268	18.76805	0.0006	
B^2	2.953125	1	2.953125	111.9079	< 0.0001	
C^2	0.932411	1	0.932411	35.33346	< 0.0001	
D^2	0.045268	1	0.045268	1.715414	0.21	
AB	1.890625	1	1.890625	71.64474	<0.0001	
AC	0.275625	1	0.275625	10.44474	0.0056	
AD	0.075625	1	0.075625	2.865789	0.1111	
BC	0.390625	1	0.390625	14.80263	0.0016	
CD	0.140625	1	0.140625	5.328947	0.0356	
Residual	0.395833	15	0.026389			
Lack of Fit	0.2875	10	0.02875	1.326923	0.3977	not significant
Pure Error	0.108333	5	0.021667			
Cor Total	12.47367	29				
Std. Dev	0.162447				R-Squared	0.968266481
Mean	1.256667				Adj R-Squared	0.938648531
C.V.	12.92678				Pred R-Squared	0.854733973
PRESS	1.812				Adeq. Precision	24.81128775

GA-ANN Validation for Dimensional Preciseness:
By using the ideal parameter values obtained from the GA-ANN hybrid creation procedure, we were able to verify the model's correctness. The GA-ANN model's output values were validated using the data in Table 4. Three portions were executed, each with a different combination of parameters. In order to get a feel for the experimental outcomes, we calculated the percentage variance in each dimension. The minimal average variation for each dimension is 0.06344%, 0.03908%, and 0.85337%.

Table 4: Results of the GA-ANN validation for dimensional preciseness

Sr. No	A	B	C	D	Percentage variation in magnitude
For percentage variation in length					
1	0.19	40.382	25	6.013	0.0620932
2	0.19	40.381	25.001	6.014	0.0620932
3	0.191	40.409	25.002	6.015	0.0661766
Average					0.06344
For percentage variation in width					
1	0.19	56.144	25.008	S	0.03802
2	0.19	56.134	25	S	0.04082
3	0.19	56.097	25.012	7.999	0.03839
Average					0.15424
For percentage variation in thickness					
1	0.33	22.5	25	4	0.85031
2	0.33	22.506	25.015	4.005	0.84286
3	0.33	22.503	25.002	4.001	0.86786
Average					0.85337

Optimizing the GA-ANFIS Model for Tensile Strength
The input factors are transformed by merging the ANFIS model (.fis file) with GA, for example, GA-ANN may be optimized to maximize tensile strength. To optimize the input elements and intended results, several ANFIS models were trained using different MFs according to established GA issues. GA was then used to aid in this process. Table 5 displays the optimized results derived from various ANFIS MFs and GA.

Table 5: Results for tensile strength optimization using various ANFIS MFs and GA

Sr. NO.	MF Type		Epoch 3: error	Method Adopted to generate FIS	Train FIS optim. method	Optimized GA Value			Tensile Strength (MPa) [Best Value]	Tensile Strength (MPa) [Mean Value]
						Infill-Density (%)	Temp. (^{0}C)	Speed (mm/sec)		
1	Linear	gaussmf	0.17316	Grid-Partition	Hybrid	100	210	110.841	45.6147	45.6146
2	Linear	gbellmf	0.17316	Grid-Partition	Hybrid	100	210	113.574	45.8129	45.8128
3	Linear	gauss2mf	0.17316	Grid-Partition	Hybrid	100	210	115.3104	46.0758	46.0758
4	Linear	dsigmf	0.17316	Grid-Partition	Hybrid	100	210	115.781	46.1388	46.1386
5	Linear	psigmf	0.17316	Grid-Partition	Hybrid	100	210	115.856	46.1467	46.1465
6	Linear	pimf	0.17316	Grid-Partition	Hybrid	100	203.585	116.322	46.4088	46.4087

Modelling
This experiment's linear regression analysis was carried out using MiniTab 17. The dependent variable Ultimate Tensile Strength was employed in a linear regression study to determine the predictive mathematical expressions with respect to Printing Temperature and Layer Height. The predictive expressions obtained from the regression analysis are shown in equation 2.

Regression Equation

Ultimate Flexural Strength = −382 + 2.36 Printing Temperature −412 Layer Height + 1.8 Infill Pattern 6.3) R^2 = 92.0%

Testing the R2 coefficient of determination allowed us to verify the efficacy of the successful models. There is a range of values for the detection coefficient, from 0 to 1. When the result is close to one, it means that the two datasets are well-matched.

Here, we found that Ultimate Flexural Strength has a well-established regression value of (R2=92.0%). In order to assess how different coefficients impacted the predicted model, the residual diagram was used. The remarkableness of the model's coefficients and the usual distribution of the residual errors are shown by the straight line, which we have got.

Remainder plots for Ultimate Flexural strength lie along the line coefficients that were set up, proving that the model is valid (Figure 3).

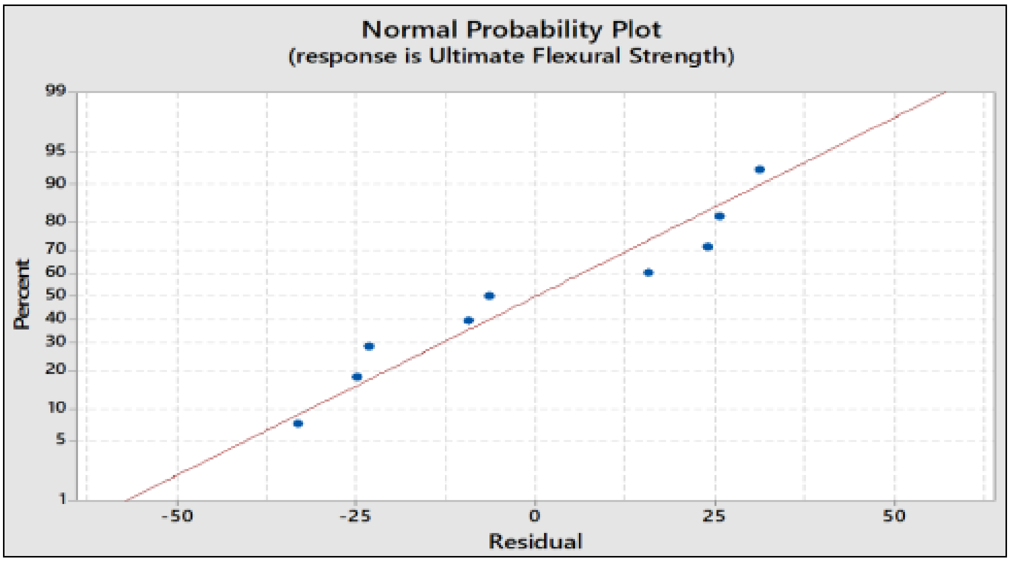

Fig 3: Normal Probability Graph

Conclusion

There is no better way to build, establish, or forecast the link between the features of FDM components and the input parameters using different conventional modeling and optimization approaches like as GRA and Taguchi. For example, when dealing with issues involving a large number of process factors, the Taguchi approach does not provide optimum solutions and is unable to generate models for higher-order polynomial fitting. To address this, the present work optimises the input process parameters using both conventional and novel evolutionary modeling and optimization techniques; the focus is on FDM components made of polymers and composites for end use.

They demonstrated their ability to calculate efficiently on their own by solving complex problems that display non-linear relationships between many parameters, such as those using FDM techniques and other soft computing approaches. There may be new possibilities for components with superior qualities when FDM and hybrid statistical approaches work together to produce them. This might lead to improvements over parts that are conventionally created. This research examined the effect of different FDM input process parameters on improving different component qualities utilizing a statistical technique that made use of a multitude of hybrid static tools, such as GA-ANFIS, GA-Fuzzy, GA-ANN, and GA-RSM.

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