Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 28 No. 2s (2025)

Using Genetic Methods to Solve Nonlinear Retrogression Analysis

Iraq T. Abbas[1], [2]Elaf Mohammed Abd and [3]Abdul Jabbar Khudhur Bakheet
[1,2] Department of Mathematics, [1]University of Baghdad, Baghdad 00964, Iraq
[3]University of Mashreq, College of Administrative Sciences, Baghdad 00964, Iraq.
[*]Corresponding author: E-mail address: Iraq.t@sc.uobaghdad.edu.iq, elaf.m@sc.uobaghdad.edu.iq

Article History:

Received: *19-09-2024*

Revised: *29-10-2024*

Accepted: *11-11-2024*

Abstract:

Whilst mathematical approaches in order managing Non-linear The reduction Using the Further Effective Genetic Algorithm (EPNGA) to Estimation of the following factors are always available, the application of algorithmic evolution (EAs) In order these kinds of issue offer an outline In order dealing with a broad range of Multi-Objective Conflicts (MOPs). Non-linear Retrogression A factor estimation using generalized estimating equations It is possible to synthesize a Genetic Algorithm (GA) by using this method. Since the Tchebycheff Strategy is used in the leader recruitment procedure, addressing the multi-objective problem (MOP) in the context of the Genetic Algorithm (GA) at the identical time may result in quick results.

When building the leader's library, predominance is crucial since it allows the selected leaders to include less dense areas, which in turn reduces international optimization challenges and produces a more varied Pareto front approximation. Six non-linear common functions were used to arrive at this conclusion. GA seems to be effective than combined BAT and PSO. All of the results were produced using MATLAB (R2020b).

Keyword: Estimation A factor, Practice Swarm Algorithm, Non-Linear Retrogression.

2010 AMS Subject Classification: 90x90.

1- Introduction

The following part discusses the present state of investigation. The context is taken into account, and the study's objectives, question, meaning, scope, and limitations are spelled out. Nonlinear Residuals are those in which the modeling in order mutation involves a nonlinear relationship between two or more of the model A factors. There are several scientific and commercial sectors that make use of nonlinear designs, which are utilized to model delicate connections between variables. Numerical approaches include an extensive range of representations in order physical, biological, commercial, and econometric phenomena [1] and [2], including progression, yield intensity, and dose-response equations.

A factor estimation in linear designs has a well-developed mathematical framework, but several issues with Retrogression functions have yet to be addressed.

Non-linear training works on the exact same idea as linear Retrogression designs, which is to associate an outcome y with a set of predictors $x = (x_1., x_2.. x_k)$. Non-Linear Inference is characterized by the fact that the in order to equation is non-linearly dependent on any number of unknowable factors. Whenever there are empirical indications that the response-predictor association takes a non-linear shape, analysts turn to non-linear Retrogression. Non-Linear Retrogression is utilized provided there are sufficient empirical reasons to believe that the connection involving the outcome with the influencing variables adheres to a defined In order m in mathematics, in contrast to the Retrogression method, which is commonly used to construct a purely econometric method. Considering a set of data points denoted by $(x_i . y_i)$, a Non-Linear Retrogression model can be constructed.

y = $(x.\beta) + \varepsilon . i = 1 \ldots \ldots . n$. The ε_i are frequently assumed to be uncorrelated with mean zero and constant variance.

In the estimating scenario, the in-order of the Non-Linear Retrogression function is well-known, but the values of $\beta_1 . \ldots . \beta_p$ are unknown. Non-linear Retrogression functions often have unidentified variables that can be calculated using a normal linear model [3]. By reducing the A factor $\beta = \sum_{\square=1}^{\square} e_i^2 = \sum_{i=1}^{n}(yi - F(Xi\,.\,B))^2$.(the add multiplied of mistakes), the following method can be used to derive the estimates of $\beta 1 . \ldots . \beta p$. Nonlinear estimating problems that include optimizing the target function $S(\beta)$ are examples of efficiency issues.

Several articles have been written about the estimate of A factors in Non-Linear Retrogression frameworks. Component estimation and mathematical modeling become more complex and difficult due to the nonlinearity hypothesis. As well as the restrictions imposed upon these (classic) approaches to estimating nonlinear A factors. It's hard to regulate by professionals and requires a lot of supplementary data to work properly. These difficulties originate from the objective function's inherent multimodality and the large number of A factors. Minimizing the mean squared deviation’s function $S(\beta)$ assuming conventional optimization techniques is not obviously difficult [4].

In order to, the acceptance of advanced meta-heuristic procedures is reliable, robust, and useful in conquering these obstacles because of the many benefits they offer, one of which is their ease of deployment. In this research, we use a set of three meta-heuristic techniques, collectively known as the Genetic Algorithm (GA), to address the problem of Non-Linear Multiple Retrogression.

2- Non-Linear Retrogression

Non-Logarithmic Retrogression constitutes a specific instance of Retrogression research. Quantitative research is a frequently employed technique In order analyzing the relationship among a number of factors [4]. It is an indispensable tool In order precise analysis and thorough use of investigational data. $x = (x_1, x_2, \ldots, x_k)$ and the dependent or response measurement, Y, to show the relationship between autonomous or predictor observations (marked by the letter I) as well as dependent or predicting measurements (identified by the letter P).

To achieve this, we will develop a regressive model, $y = f(x, \beta) + \varepsilon$, where y is the totally reliant variable, x is a vector of separate from variables, β is a vector of characteristics, ε is a constant, s is a collection of standards characterized by zero indicates and typical deviations [1] and [2]. The two most common kinds of Retrogression evaluations are linear and nonlinear.

The coefficient of determinant [5] constitutes a very popular quantitative deductive deductive technique when the Retrogression product f is linear Retrogression. In 1894, Sir Francis Galton was the initial person to present the theory of linear Retrogression [5]. Nonetheless, rectangular patterns aren't universally applicable appropriate; as a result, a nonlinear quantitative technique is usually utilized, where f is nonlinear in β[j]. Non-linear A factors and characteristics, non-linear measures, and non-linear characteristics may all be included in non-linear Retrogression analysis. The model is referred to as a non-linear Retrogression model if The attributes include non-stationary, even though the In order ecast's components are linear (Gujarati, 2004) [6].

Whenever data needs to be converted to fit a linear interpolation as the the Non-Linear Resistance approach is very helpful In order evaluating scientific inIn order mation. Consequently, proportional Retrogression is a subset of non-linear Retrogression, which represents a broader idea [7]. Nonlinear patterns are employed in various fields of study, including physical sciences, biology, statistics in order inference, commerce, architecture, mathematics, and governance. The creation of nonlinear designs is a recent and intriguing area of study in mathematical applications. The challenge of creating a multiple linear Retrogression model will almost certainly be encountered by a researcher in arithmetic or any other scientific field.

A multitude of nonlinear patterns has been delineated and effectively implemented across diverse real-world contexts pertaining to various research problems inside numerous quantitative modelling fields in the available literature. Nonetheless, due to the complexity of the circumstances or their intractability in statistical and mathematical terms, quite a few of instances remain nonlinearly unrepresented [8]. Next, we will analyze two instances of quadratic regressors. Calculated techniques contain a wide range of uses in reality.

Table (1): Designs of Non-Linear Dependent variable

N	Problems Name	Function
1	Meryer1	$\frac{\beta 1\beta 2x1}{1+\beta 1x1+\beta 2x2}$
2	Meryer4	$\beta 3(e^{-\beta 1x1}+e^{\beta 2x2})$
3	Meryer7	$\beta 1+\beta 2e^{\beta 3x}$
4	Militky4	$\beta 1e^{\beta 3x}+\beta 2e^{\beta 2x}$
5	Militky5	$\beta 1x^{\beta 2}+\beta 3^{\beta 2}/_{x}$
6	Gompertz	$\beta 1e^{-e(\beta 2-\beta 3x)}$
7	Logistic	$\frac{\beta 1}{1+e^{(\beta 2-\beta 3x)}}$
8	Richards	$\frac{\beta 1}{(1+e^{(\beta 2-\beta 3x)})^{1/\beta 4}}$
9	Jennrich	$e^{\beta 1x1}+e^{\beta 2x2}$
10	Militky2	$e^{\beta 1x}+e^{\beta 2x}$
11	Ratkowsky2	$\frac{\beta 1}{1+e^{(\beta 2-\beta 3x)}}$
12	Eckerle4	$\frac{\beta 1}{\beta 2}e^{\left(-\frac{(x-\beta 3)^2}{2\beta_2^2}\right)}$
13	Ratkowsky3	$\frac{\beta 1}{(1+e^{(\beta 2-\beta 3x)^{1/\beta 4}}}$
14	BoxBOD	$\beta 1(1-e^{-\beta 2X)}$
15	Thurber	$\frac{\beta_1+\beta_2X+\beta_3X^2+\beta_{4\,X^3}}{1+\beta_5X+\beta_6x^2+\beta_{7x^3}}$
16	MGH09	$\frac{\beta 1(x^2+X\beta_2)}{x^2+X\beta_3+\beta_4}$
17	Misrald	$\frac{\beta_1\beta_2X}{1+\beta_2x}$
18	Misrala	$\beta_1(1-e^{-\beta_2x})$

19	Chwirut2	$\frac{e^{-\beta_1 x}}{\beta_2 + \beta_3 x}$
20	Rat42	$\frac{\beta_1}{1 + e^{(\beta_2 - \beta_3 x)}}$

3- Classical methods

The Mean Squared Error (MSE) as well as the Least Squares Estimator (LSE) belong to the many prevalent techniques In order component predictions [9]. MSE is favored by researchers and is thought to have superior quantitative features. Additionally, the LSE approach only subjects data to a summing the residuals measured in squares as the target in order minimization. LSE is incredibly practical, which is why practitioners adore it. In this study, Kernel Density estimation Estimation and Least Squares were used to estimate the A factors of four non-linear Retrogression designs.

4- Genetic Algorithm Technique (GA)

Search techniques known as biological algorithms (GAs) are founded on the ideas of natural selection and genomics [10]. We begin by giving a quick overview of elementary GAs including the terms that are used in them. GAs converts a search problem's decision variables to finite-length alphabetic strings with a specific cardinality. The letters are called genes, the strings that are potential answers to the research question are named mitochondria, and the numerical contents of genes are termed alleles. For instance, in a problem like the travelling salesman problem (TSP), a gene might stand in for a city, and a chromosome for a route. GAs operates with the programming of variables rather than the parameters one another, compared to conventional optimization methods. The steps that follow can be used to begin evolving solutions to the search problem after the problem has been chromosomally transcribed and an appropriate fitness metric for differentiating between outstanding and inferior remedies having been selected:

Initialization: The first set of candidate solutions tends to arise arbitrarily throughout the entire search area. Nevertheless, the initial sample can be readily generated by incorporating domain-related expertise or extra data.

2. Evaluation: The viability characteristics of the potential remedies are assessed when the population has been initialized or an offspring community has been produced.

3. Selection: Choice forces the survival-of-the-fittest process on the prospective solutions by allocating more copies to answers with higher fitness scores. Preferring enhanced options over inferior ones is the fundamental idea behind selection. A variety of methods of selection, a few of and this are discussed in the following section, are those suggested to achieve this goal. These techniques include assessing selection, events selection, stochastic universal selection, and roulette-wheel selection.

4. Recombination: The process of recreates new, potentially superior approaches (i.e., offspring) by combining fragments of more than one father answers. The main idea to remember is that the product produced under reproduction will not be the same to any specifics parent and will rather incorporate the parental characteristics in a unique way. There are numerous ways to achieve this, certain of which are covered in the following subsection, and competent performance depends on effectively developing the replication systems [11].

5. Mutation: The process of re affects two or more paternal chromatin, whereas mutation alters a solution locally yet at arbitrary. Once more, mutation can take a variety of shapes, but it often entails one or more modifications to a person's trait or qualities. To put it another way, mutation walks randomly around a potential answer.

6. Replacement: Choice, a process of and variation produce offspring that act as substitutes for the original maternal population. GAs makes use of several restoration methods including arrogant substitution, generation-wise renewal and constant state substitution approaches.

7. Repeat steps 2–6 until one or more stopping criteria are met.

5- Practical Swarm Optimization (PSO)

The coordinated movement of fish schools and avian flocks served as the inspiration In order the PSO metaheuristics (Kennedy and EberDiagram, 2001) [12] and [13]. The PSO is a swarm of matter that each represent a possible remedy In order the present problem. Particles "flow" around the problem's hyperdimensional search space, and adjustments to their positions are predicated on individual social mental inclination to imitate the accomplishments of others inside seeking space. Everyone who is part of a society —in this case, a society of particles—has the ability to assess the worth of their own life experiences. Being sociable creatures, they are aware of how well their neighbors possess conducted. These two categories of knowledge represent, correspondingly, the cognitive component (individual learning) and the social component (culture transmission). As a result, each individual makes a choice whilst taking into account both the cognitive and social aspects, which causes the society (the swarm) to engage in a spontaneous action.

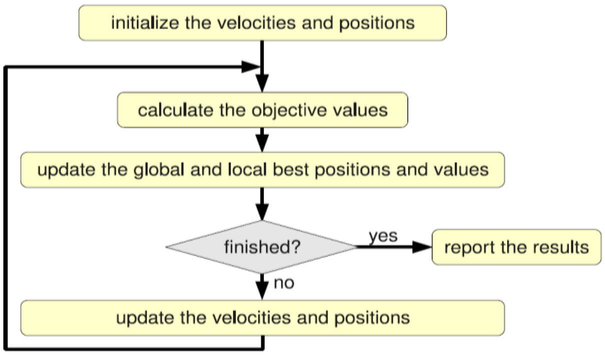

Figure (1) Flow Diagram of PSO

6- Bat Algorithm

The SI family includes the biologically-inspired Bat Algorithm (BAT). In 2010, Xin-She -Yang developed the Bat Algorithm [14] and [15], which is now widely used. Bats employ a type of echolocation using a sonic signal called sonar echolocation to navigate their environments and identify potential dangers. Yang focused on the following three guidelines In order proper bat execution:

Although the capacity and wavelength can vary, bats always fly at the same arbitrary speed and regularity toward the same fixed location. So bats naturally adjust their frequencies to sound like their prey. In addition, all bats rely on acoustic signals to gauge how far away an object is.

In conclusion, the contributor suggested that capacity be adjusted from loudest to quietest rather than the other way around. In order to replicate the variation in the luminance and heartbeat exhaust gases encountered by bats throughout hunting, BATA makes use of automatic zooming throughout its searching phase [16] .

The following is an introduction to the BAT Method's processes:

Initiate BAT society at $(x.\beta)$, set the goal function at v_i, and calculate pulse regularity f_i at x_i

using the BAT Algorithm's fitness function, $\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}$ Capacity (A) and heart rate (r_i) are set to their default values. . $r_i \in\{0,1\}$.

Second, by changing the regularity, an entirely new answer is In order med, which in turn updates the locations and velocities.

Third, if ($random > r_i$), shape the best an approach pick it, and then produce a neighborhood solution centered on the best solution picked.

Fourth, if that doesn't work, just let the dice roll and come up with something fresh.

The fifth step is to check if the goal function f(x) is satisfied if (random <A_i and $f(x_i)$ < $f(x_0)$).Take the new advice, raise r_i , and lower A_i.

Step 6, The present best (x_0) can be determined.

Step 7, When iteration count reaches a maximum.

Interpretation and follow-up results of the procedure. At the end of the algorithm, the optimal global answer is found.

7- The Proposed Method (EPNGA)

The article will begin with a glossary of MOP terms. Then, the structure of the proposed estemation A factor of nonlinear regresion with Genetic Algorithm method is displayed. The process In order allocating grades will be discussed afterward. Lastly, we will cover the mechanisms of ambient adjustment and the strategies In order mating.

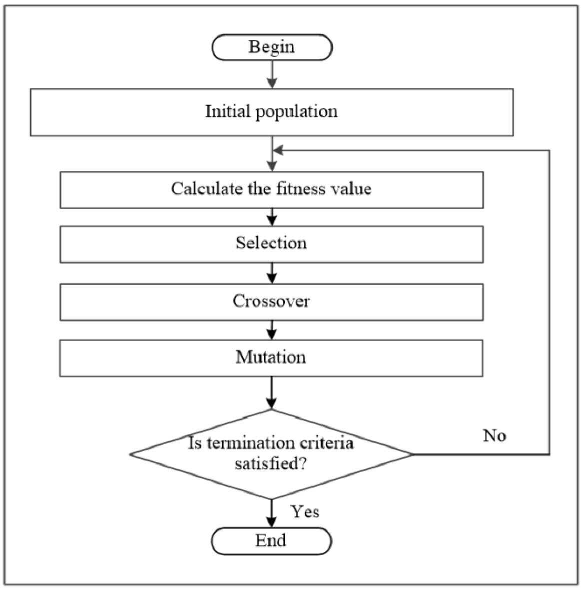

Figure (2) Flow Diagram of EPNGA

Moreover, there has been no systematic investigation into the relationships between the attributes and convergence rates. To generate better optimal strategy, predict Non-Linear Retrogression Designs, the researcher presents a hybrid method called EPNGA by adding two extra components, repository and leader, uncovered Within the MOPSO method that [17] suggested. The repository's main purpose is to keep and access the greatest non-dominated, non-controllable Pareto strategies that have been discovered.

The central processing unit (CPU) of the storage is also present.

Pseudo-code of the EPNGA

```
GA Steps
Create initial generation function
Find fitness value for the First one
Find fitness value for the last one
Create initial generation function
parent selection function
Crossover function
Mutation function
Find fitness value for the new gene
Find probability of contribution
Stopping Criteria
Print the near optimal
End
Find the non − dominated solutions
Update the archive concerning to the obtained non − dominated solutions
If the archive is full
Run the grid mechanism to omit one of the present archive members
Add the new solution to the archive
end if
If any of the new added solutions to the archive is located outside the hypercube
Update the grids to cover the new solution(s)
end if
Set k := k + 1;
End
```

8- Observation as well as Computation Study

8.1 -Indicators of Achievement

The $EPNGA$ algorithm is calculated using data from quantitative associations and is then compared with different methods. Pareto Diagrams showing the outcomes of meaningful comparisons are shown. The mathematical concepts of gravitational distancing (GD), inverted gravitational distancing (IGD), and hyper capacity (HV) [18] are used to make quantitative comparisons. GD, or gravitational dispersion. It is acceptable to use the phrase metric when referring to the (GD) [19] since it analyzes the typical divisions between various sets of groupings of Q as it continues with P: in evaluating whether or not arrangements of Q can be included with the configuration of P^*.

$$GD = \frac{\sqrt[p]{\sum_{n=1}^{R}(d_i^p)}}{R} \quad \ldots (13)$$

$$IGD = \frac{1}{R}\ (\sum_{n=1}^{R} \min\ (\sqrt[p]{\sum_{n=1}^{R}(d_i^p)}\ )) \quad \ldots (14)$$

Inverted transmissible distance (IGD) is a mean distance within each possible solution in the dataset being tested and the closest the fluid It displays the expansion of options in the most nearby group of possibilities. Using the ideas of scattering and improving the IGD calculation, sometimes called the Pareto front (PF) P^* assessment, measures how cohesively generated structures develop.

The determination of hyper capacity (Hyper capacity) (A) calculates how much of the objective space a PF approximation pitifully commands. Hyper amount v* serves as a point of comparison and also designates a broad objective with a cap v^* is described as possibly the most appallingly low objective appreciates present in A (In order example) v^* is referred to be one of A's highest extremely low self- and outside perceptions (In order example) (Λ), and the hyper capacity is stated as:

$$HV(A) = \Lambda(\cup \{x \mid a < x < v^*, a \in A\}) \quad \dots (15)$$

Table (1) lists the $IGD's$ residual consequences. The second table displays the outcomes of employing hyper capacity HV. The final paragraph displays the p-estimation. Powerful text style reveals a factually significant difference in the two subsequent matched t-test between the $EPNGSA$ and other approaches. Figuring 2 in order each of the five estimations being taken into consideration, calculate the difference between PF valid and PF Determined.

8.2- Multi-Objective Test Functions

Six benchmarking functions are compared and utilized to validate the proposed EPNGA algorithm in order to demonstrate its effectiveness. The comparison features [20]. In order the test capacity of nonlinear functions is shown in detail in Exhibits tables below.

8.3- Decision space

The variety of possibilities that are open to us is represented by the choice spectrum. The choices we provide will be the sole factor in determining the criterion's weights. A similar issue It is possible to specify in the selection domain as a result. In order instance, whilst developing items, we make decisions about the design requirements (with regard to cost), each of which affects the quality metrics (criteria) Our efforts employ to evaluate it. True Pareto front: is a quantitative technique in order determining the most important choices among a large number of possibilities.

8.4- Results and Discussion

The accuracy of the provided method is the focus of this essay. The suggested method (EPNGA) is run in Matlab, and depending on the subject under discussion, registration takes a few seconds to less than a second. Several factors are used to test it, such as the total society (n=20, 40, 80, 160, and 200), the quantity of shots M, and the size D.

The usefulness of the suggested technique in balancing accessibility and diversity has been confirmed by the results of the experiment. The numerous studies showed how well a theoretical policy balanced proximity and variety. On the other hand, scientists have developed numerous mathematical estimation techniques in order non-linear Retrogression employing hybrid methods.

We announce the MSE demonstration applying the latest EPNGA calculations in the following paragraphs and other PSO, and BAT computations.

These tables 3.1 and 3.2 display the median square variance of prediction values from BAT and PSO techniques based on Meyer's Non-stationary the regressive model (Meyer (7)) alongside A factors **($\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$ and $\boldsymbol{\beta_3}$)**= (600,1.5,1.5) and (700,2,1). Best-Determined characteristics are blue.

These tables showed that EPNGA method provides the lowest median square error and produces the most accurate results for all datasets.

The integrated EPNGA method's applicability shall be tested utilizing several design considerations. Evaluate an approach with alternate ways that tackle the precise same challenge to see its true value.

The MSE characteristics are used to compare the new EPNGA algorithm to PSO and BAT. All strategies use deviate numbers and regular functions to solve.

Tables (1, and 2) show the MSE indicator's performance with Meyer (7), Meyer (4), Militky (4), Militky (2), Misra 1d, and MGH09 contrasted to the new EPNGA method with PSO and BAT methods. The new EPNGA method has normal mean performance in both the median and arithmetic mean calculations, but the remainder of the methods perform more fully in the ranking as well as specifications.

TABLE 1. EPNGA, PSO, BAT, and MSE Comparative Results Using β1=600, β2=1.5 and β3=1.5

n	Techniques	Important events	β1	β2	β2	MSE
20	GA	Determined	5.246	1.227	1.588	1.417
		MSE	1.056	6.129	3.423	NaN
	PSO	Determined	6.145	1.480	1.506	2.246
		MSE	9.176	1.766	1.424	NaN
	BAT	Determined	5.773	1.404	1.515	1.640
		MSE	1.316	6.699	6.669	NaN
40	GA	Determined	5.455	1.273	1.543	9.897
		MSE	4.556	3.682	1.125	NaN
	PSO	Determined	5.774	1.480	1.503	4.814
		MSE	5.107	8.934	4.435	NaN
	BAT	Determined	6.025	1.741	1.489	1.031
		MSE	2.958	9.598	6.022	NaN
80	GA	Determined	5.070	1.467	1.509	4.128
		MSE	1.013	1.928	1.454	NaN
	PSO	Determined	6.273	1.429	1.506	3.673
		MSE	1.213	4.982	4.006	NaN
	BAT	Determined	4.484	1.569	1.497	2.153
		MSE	1.793	9.103	3.601	NaN
160	GA	Determined	5.590	1.154	1.570	9.830
		MSE	1.532	6.446	2.749	NaN
	PSO	Determined	5.192	1.472	1.501	1.681
		MSE	3.426	6.284	1.098	NaN
	BAT	Determined	1.730	1.406	1.507	7.912
		MSE	7.609	2.715	9.216	NaN
200	GA	Determined	6.512	1.681	1.495	1.350
		MSE	7.990	3.787	5.517	NaN
	PSO	Determined	4.666	1.457	1.506	6.960
		MSE	2.069	1.705	6.726	NaN
	BAT	Determined	2.890	1.540	1.500	9.933
		MSE	1.400	1.070	3.570	NaN

TABLE 2. EPNGA, PSO, BAT, and MSE Comparative Results Using β1=700, β2=1.7 and β3=1.6

n	Techniques	Important events	β1	β2	β2	MSE
20	GA	Determined	5.61	1.35	1.72	5.35
		MSE	3.94	2.66	5.09	NaN
	PSO	Determined	7.01	1.46	1.71	2.73
		MSE	4.06	1.18	4.08	NaN
	BAT	Determined	5.24	1.72	1.69	1.22
		MSE	2.76	1.36	2.53	NaN
40	GA	Determined	5.28	1.35	1.78	9.43
		MSE	3.14	7.75	2.74	NaN
	PSO	Determined	6.23	1.26	1.75	2.99
		MSE	2.70	3.82	8.91	NaN
	BAT	Determined	4.53	1.82	1.70	1.43
		MSE	1.64	1.01	6.31	NaN
80	GA	Determined	5.13	1.62	1.72	5.11
		MSE	3.82	3.25	9.42	NaN
	PSO	Determined	5.18	1.63	1.70	2.74
		MSE	1.15	1.98	7.75	NaN
	BAT	Determined	4.88	1.67	1.69	1.67
		MSE	6.56	8.05	4.79	NaN
160	GA	Determined	4.93	9.29	1.81	2.07
		MSE	4.47	9.26	2.81	NaN
	PSO	Determined	5.99	1.47	1.71	1.00
		MSE	4.80	1.37	6.97	NaN

	BAT	**Determined**	**3.03**	**1.49**	**1.71**	**4.37**
		MSE	**2.22**	**1.22**	**5.03**	**NaN**
200	**GA**	**Determined**	**4.39**	**1.54**	**1.71**	**1.13**
		MSE	**8.65**	**1.66**	**9.22**	**NaN**
	PSO	**Determined**	**3.58**	**1.53**	**1.70**	**5.57**
		MSE	**2.03**	**5.84**	**1.73**	**NaN**
	BAT	**Determined**	**4.43**	**1.73**	**1.70**	**6.97**
		MSE	**3.57**	**6.09**	**1.32**	**NaN**

9- Convergence Graphs

The merging charts were made to demonstrate how rapidly the conventional assessment merges with the number of repetitions in order to resemble the samples. One hundred thousand iterations have been performed to sort every record. The success rate of the proposed hybrid strategy in achieving the ideal value faster is seen in these subsequent graphs. The results shown here demonstrate that, when compared to other designs, meta-heuristic methods yield the smallest MSE values. But in terms of reliability, matching GA, BAT, and PSO was superior.

8-Conclusion and Future Work

The purpose about this article is to address an issue of Non-Linear Retrogression in the field of combinatorial optimization. Initially, we provide a concise summary of the studies that has been done in each section's respective sections. In doing so, we provide an explanation of the way we address the Non-Linear Retrogression difficulties that have been addressed at the outset of the paper. Subsequently, we provide particular instructions that pertain to our hybrid method (EPNGA) in greater detail. Secondly, three meta-heuristic methods were employed as an alternative approach for the order estimation of non-linear regression designs. The number of A factors varied among the six types of Non-Linear Retrogression designs. Furthermore, a variety of samples (20, 40, 160, 200) were employed.

Finally, it is imperative to conduct more tests and evaluations of the ideas. The results of this research suggest that mixed approaches can be constructed using an assortment of methods. Separation solutions, multi-purpose problems, and the EPNGA method figure among them. Additional research could concentrate on comparing the outcomes of this method to those of other optimization techniques that are frequently employed.

References

[1] W. M. Aly, "Evaluation of cuckoo search usage for model parameters estimation," International Journal of Computer Applications, vol. 78, no. 11, pp. 1-6, 2013.

[2] H. A. &. C. A. Sattar, "A new strategy based on gsabat to solve single objective optimization problem," International Journal of Swarm Intelligence Research (IJSIR), vol. 10, no. 3, pp. 1-22, 2019.

[3] S. A. S. R. &. R. R. Y. V. Angayarkanni, "Hybrid Grey Wolf: Bald Eagle search optimized support vector regression for traffic flow forecasting," Journal of Ambient Intelligence and Humanized Computing, vol. 12, no. 1, pp. 1293-1, 2021.
[4] N. S. W. F. &. P. G. M. Henderson, " Finding more than one root of nonlinear equations via a polarization technique: An application to double retrograde vaporization," Chemical Engineering Research and Design, vol. 88, no. 5-6, pp. 551-561., 2010.
[5] F. (. Galton, "Arithmetic by smell," Psychological Review, vol. 1, no. 1, pp. 61-62, 1894.
[6] K. A. A. K. B. &. A. G. Durai Raj, "Meta-heuristic to estimate parameters in Non-Linear Regression Models," International Journal of Mathematics in Operational Research, vol. 3, no. 5, pp. 473-489, 2011.
[7] K. B. &. W. J. E. Dorschel, "Physiological and pathophysiological mechanisms of the molecular and cellular biology of angiogenesis and inflammation in moyamoya angiopathy and related vascular diseases," Frontiers in Neurology, vol. 14, p. 661611, 2023.
[8] J. C. C. &. B. T. R. Cessna, "Multiscale retrograde estimation and forecasting of chaotic nonlinear systems," in In 2007 46th IEEE Conference on Decision and Control , 2007.
[9] J. S. H. W. Z. C. W. W. J. Z. M. .. &. F. J. Zhou, "Guidelines for the diagnosis and treatment of hepatocellular carcinoma," Liver cancer, vol. 9, no. 6, pp. 682-720, 2020.
[10] M. R. A. Z. A. D. M. I. A. Z. Z. &. A. M. B. Ramli, "Enhanced convergence of Bat Algorithm based on dimensional and inertia weight factor," Journal of King Saud University-Computer and Information Sciences, vol. 31, no. 4, pp. 452-458, 2019.
[11] D. E. &. K. C. H. Goldberg, "Genetic algorithms in pipeline optimization. Journal of Computing in Civil Engineering," vol. 1, no. 2, pp. 128-141, 1987.
[12] J. &. E. R. Kennedy, "Particle swarm optimization," in international conference on neural networks, 1995.
[13] I. T. &. G. M. N. Abbas, "Using Sensitivity Analysis in Linear Programming with Practical Physical Applications," Iraqi Journal of Science, vol. 65, no. 2, 2024.
[14] X. S. &. D. S. Yang, " Engineering optimisation by cuckoo search," International Journal of Mathematical Modelling and Numerical Optimisation, vol. 4, no. 1, pp. 330-343, 2010.
[15] R. H. &. A. I. T. Sheah, "Using multi-objective bat algorithm for solving multi-objective non-linear programming problem," Iraqi Journal of Science, pp. 997-1015, 2021.
[16] X. S. &. H. G. A. Yang, "Bat algorithm: a novel approach for global engineering optimization," Engineering computations, vol. 29, no. 5, pp. 464-483, 2012.
[17] C. C. &. L. M. S. Coello, "MOPSO: A proposal for multiple objective particle swarm optimization," in In Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600) , 2002.
[18] A. P. F. C. M. &. P. L. Guerreiro, "The hypervolume indicator: Computational problems and algorithms," ACM Computing Surveys (CSUR), pp. 1-42, 2021.
[19] H. Y. H. D. E. M. J. E. M. V. S. &. C. J. Chen, "Distance measures in gravitational-wave astrophysics and cosmology," Classical and Quantum Gravity, vol. 38, no. 5, p. 055010, 2021.
[20] T. J. Y. O. M. &. S. B. Okabe, " On test functions for evolutionary multi-objective optimization," in International Conference on Parallel Problem Solving from Nature, Springer Berlin Heid, 2004.
[21] L. Scrucca, "GA: A package for genetic algorithms in R," Journal of Statistical Software, pp. 53, 1-37, 2013.