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Optimization of Steel Truss Using Genetic Algorithm

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ABSTRACT

In this paper, an optimization study is presented, focusing on steel trusses. The main goal of this study is to reduce the weight of truss structures using a Genetic Algorithm (GA), which is a widely acknowledged evolutionary-based method known for its efficiency in solving intricate optimization problems. The design problem formulation takes into account various constraints, such as displacement, tensile stress, and minimum size requirements. These constraints are implemented in MATLAB, utilizing the ANSI/AISC 360-16 Specification as a guideline for designing tension and compression members. To determine the optimal design, the approach involves considering discrete design variables. This is achieved by selecting sections from a database containing all available steel sections specified in the AISC Steel Construction Manual, ensuring practical and feasible design solutions. The efficiency of the algorithm is validated through its application to several plane truss types. Through a comparison of the outcomes obtained from the proposed algorithm with the results generated by CSI-ETABS software, it is demonstrated that this approach consistently yields better weight optimization. Overall, the study showcases the effectiveness of the GA-based algorithm in optimizing the weight of steel trusses. The results and implications of the findings are thoroughly discussed in the paper; this study has the potential to make a substantial contribution to the field of structural optimization and design.

KEYWORDS: Truss Structures; Sizing Optimization; Genetic Algorithm; Weight Optimization

1 INTRODUCTION

The central aim of structural optimization is to achieve the most cost-efficient "objective function" while meeting specific requirements. In the context of structural optimization problems, the primary emphasis is often placed on minimizing the weight of the structure. Over the past few decades, truss structural optimization has emerged as a crucial and challenging field in structural engineering, attracting considerable attention from researchers (Omidinasab & Goodarzimehr, 2020).

While taking into account every other pertinent restriction, the primary objective of structural design optimization is to figure out the ideal cross-sectional area, hence reducing the use of materials for each member. (Kumar et al., 2021). This research area has garnered significant interest among scholars and has become a vital subject of investigation in recent decades.

Researchers have conducted extensive studies to improve optimization methods and expedite the structural analysis process. Genetic algorithms have been widely utilized in the sizing and topology optimization of truss structures. These algorithms are particularly advantageous in searching for an optimum in multimodal objective functions without the need for calculating gradients (Delyová et al., 2021).

Genetic algorithms, inspired by natural selection and genetics, have successfully resolved a variety of scientific and technological issues. They are considered an efficient means of finding optimal solutions in various problem domains (Feng et al., 1997).

In practical applications, it is often desirable to choose design variables, such as cross-sectional areas of members and shapes of rolled sections, from commercially available options provided by manufacturers. However, optimization procedures sometimes yield non-commercially available sizes, and attempting to approximate them with the nearest available commercial sizes can make the design unfeasible and unnecessarily heavier. This challenge becomes more pronounced when dealing with discrete design variables (Kumar et al., 2021).

The suitability of genetic algorithms for discrete structural optimization of trusses has been studied, revealing their efficiency in handling discrete variables (Rajeev & Krishnamoorthy, 1992). They have also been successfully applied to topological optimization problems, including stress, buckling, and displacement constraints in trusses. Genetic algorithms serve as effective exploratory tools for evaluating topologies in discontinuous design space (Hajela & Lee, 1995).

Real-coded genetic algorithms (RCGAs) have been successfully applied to optimize the sizing, topology, and layout of trusses, as demonstrated by (Deb & Gulati, 2001). Additionally, to improve the topology, size, and form of planar trusses, investigators like Cazacu and Grama suggested parameterization and encoding approaches utilizing evolutionary algorithms and finite element approaches. (Cazacu & Grama, 2014). These advancements have significantly contributed to the field of truss structural optimization.

Weight optimization of plane trusses has been achieved using genetic algorithms (Neeraja et al., 2017). Moreover, advanced optimization techniques, such as genetic algorithms, have been employed as auxiliary tools in structural design, leading to a considerable reduction in the volume of concrete used in foundations (Ede et al., 2018) (Lopes et al., 2019).

Various studies have focused on optimizing truss structures with discrete cross-sectional areas (Kaveh & Mahdavi, 2014) (Stolpe, 2016) (Ho-Huu et al., 2016) (Wang & Ohmori, 2010). Fuzzy multi-objective methods utilizing genetic algorithms have been proposed for truss optimization, especially when dealing with systems involving fuzzy goals and constraints (Kelesoglu, 2007). Additionally, topological optimization has been employed to modify the size and relationships of truss bars, resulting in significant volume and weight savings (Assimi et al., 2017).

Hybrid algorithms that combine genetic programming with the Nelder-Mead method have been developed for the topology and size optimization of trusses, taking into account both static and dynamic constraints (Assimi et al., 2019). These algorithms introduce topological bits to determine the presence of bars in the structure, enabling faster variations in topology compared to using only zero-cross-section sizes (Delyová et al., 2021).

Another hybrid technique, known as Particle Swarm Optimization and Genetic technique (PSOGA), was presented for getting the optimum design of the truss using discrete variables. Additionally, several new algorithms, such as HPSO, HPSACO, and improved versions of genetic algorithms, have been developed to achieve optimum designs with discrete variables (Omidinasab & Goodarzimehr, 2020).

While continuous optimization procedures may lead to non-commercially available sizes, rounding off these values to the nearest accessible commercial sizes can render the design infeasible or uneconomical (Kumar et al., 2021). In structural engineering, many problems are inherently discrete, necessitating the introduction of effective algorithms capable of optimizing with discrete variables. Genetic algorithms have proven to be efficient in this regard, enabling the attainment of optimal solutions. Ongoing research aims to further enhance these algorithms and develop hybrid approaches to optimize truss structures more efficiently(Omidinasab & Goodarzimehr, 2020)(Delyová et al., 2021)(Sokół, 2011).

In the realm of structural optimization, the pursuit of cost-efficient design while adhering to specific constraints remains a paramount objective. A focal point in this pursuit is the optimization of truss structures, with an emphasis on minimizing weight. This endeavour, however, is complicated by the discrete nature of design variables and the need for compatibility with commercially available sizes. While continuous optimization techniques offer valuable insights, they may generate non-commercial sizes that compromise feasibility and cost-effectiveness. This paper addresses the challenge of optimizing truss structures, particularly in the context of discrete design variables, and explores the efficacy of genetic algorithms and their hybrids in achieving optimal solutions. By considering the interplay between structural efficiency, available materials, and discrete design variables, this research aims to enhance the applicability of optimization methods for practical engineering solutions.

It is expected that authors will submit carefully written and proofread material. Careful checking for spelling and grammatical errors should be performed. The number of pages of the paper should be from 4 to 8.

Papers should clearly describe the background of the subject of the author's work, including the methods used, results and concluding discussion on the importance of the work. Papers are to be prepared in English, and SI units must be used. Technical terms should be explained unless they may be considered to be known to the conference community. The references should be numbered [1], or [2, 3], or [1, 4-6].

2 DISCRETE AND CONTINUOUS OPTIMIZATION

Truss optimization problems involve design variables that can take either discrete or continuous values. In the specific context of this paper, the sizing variables considered are discrete in nature. Whenever the choice of cross-sectional areas for members is restricted to a given range of profiles, the issue of truss design optimization necessitates a discrete formulation. Consequently, the member cross-sectional areas were directly obtained from a comprehensive database of AISC manual section profiles. As a result, the suggested algorithm is capable of handling simultaneously discrete and continuous variables in an efficient manner, accommodating the specific requirements of truss design optimization.

3 THE DEVELOPMENT OF OBJECTIVE FUNCTION USING GENETIC ALGORITHM

The genetic algorithm (GA) is a widely popular and easily implementable algorithm used in various research fields. Inspired by genetics and evolution, it represents design variables as binary individuals called chromosomes (Omidinasab & Goodarzimehr, 2020). The GA aims to create increasingly strong individuals within a population, making it suitable for optimization problems (Delyová et al., 2021) (Assimi et al., 2019). The encoding of design variables is crucial for the effective exploration of the design space, while the formulation of the objective function and constraints should accurately reflect the specific requirements of the problem (Delyová et al., 2021). Holland's 1975 monograph (Hayes-Roth, 1975) and Goldberg's work from 1989 are significant contributions to the GA literature. The GA operates iteratively, selecting solution candidates from the population (Omidinasab & Goodarzimehr, 2020) (Delyová et al., 2021). A typical flow chart of the program is shown in Figure 1.

In general, GA is defined as:

1. Initialize the population P.
2. Evaluate each individual in P.
3. Repeat the following steps until a stopping condition is met:
    a. Select at least two individuals from P.
    b. Apply crossover process.
    c. Apply mutation to the individuals.
    d. Create new individuals in a separate population P’.
    e. Evaluate the individuals in P’.
    f. Update P to be equal to P’.
4. Stop and end the algorithm.

Utilizing a genetic algorithm (GA) together with the finite element method to find the optimal truss structure(Delyová et al., 2021). The FEM expresses the structural behaviour through a system of linear equations,

$$K(x).uj(x) = Pj(x);\ (j = 1, 2, .., n) \quad (1)$$

where the stiffness matrix (K), nodal displacements (u_j), and load vectors (P_j) are considered for each load case, and x is the vector of bar cross-section area indexes in AISC Database tables.

Based on the correlation between stress and bar displacements, the nodal displacement vector may be used to calculate the stress in each bar (σ_{ji}) (Delyová et al., 2021) (Sokół, 2011). Constraints are imposed on the stress (σi) and displacement (u_{jk}) magnitudes, ensuring that they do not exceed specified limits.

The objective of the paper is to minimize the weight of the truss while satisfying compliance constraints. The weight (w(x)) is calculated as the sum of the product of the cross-sectional area (A_i), length (L_i), and material weight density (ρ) for each member. Additionally, stress (σ_i) must be below the allowable stress (σ_M) and Euler buckling constraint (σ_{Ei}) for all members (Sokół, 2011).

The objective function is to minimize w(x) subjected to constraints Ci(x) < 0, i = 1,2,3, . . . where i is the number of constraints.

$$w(x) = \Sigma\ \rho AiLi \tag{2}$$

As this is a constrained problem and GA performs better with unconstrained problems, it is necessary to transform the problem into an unconstrained one to optimize it using GAs. Some constraints cannot be directly expressed in terms of design variables and require the analysis of the truss structure (Kumar et al., 2021).

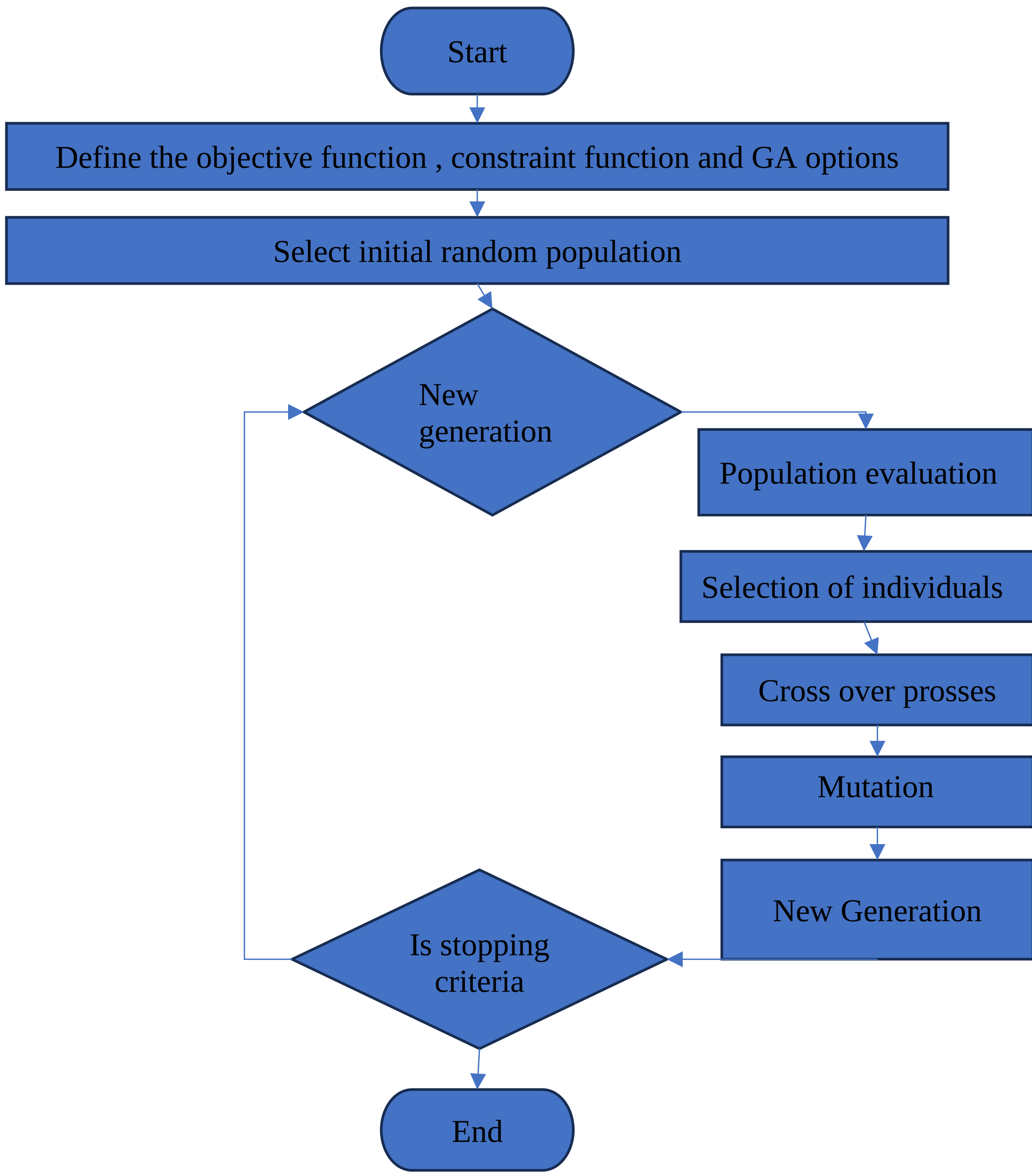

Figure 1" Typical flow chart of GA used in optimization

3.1 Tension member

SLENDERNESS LIMIT

For sections in tension, there may be no upper limit to slenderness *L/r*, preferably should not exceed 300.

$$\frac{L}{r} \leq 300 \tag{3}$$

Slenderness Constraint for Tension member

$$\frac{L}{r} - 300 \leq 0 \tag{4}$$

Tensile strength limitation

The permissible tensile strength, $\emptyset_t P_n$, and the allowable tensile strength, P_n/Ω_t, of tension members must be calculated. The smaller value is determined by the maximum tensile yield conditions in the gross section.

Allowable force constraint

For allowable stress design (ASD)

$$Pa \leq \frac{Pn}{\Omega t} \leq \frac{Fy\ Ag}{\Omega t} \qquad (D2-1) \tag{5}$$

Tensile strength Constraint

$$Pa - Fy\frac{Ag}{\Omega t} \leq 0 \tag{6}$$

Ultimate member force constraint

For Load and resistant factored design LRFD

$$Pu \leq \varphi t\ Pn \leq \varphi t\ Fy\ Ag \qquad (D2-1) \tag{7}$$

Tensile strength Constraint

$$Pu - \varphi t\ Fy\ Ag \leq 0 \tag{8}$$

Where

Ag gross area of member

Fy specified minimum yield stress, ksi (MPa)

φt= 0.90 (LRFD), Ωt = 1.67 (ASD)

3.2 Compression members

Compression members can fail in various modes, each with distinct characteristics and causes. These failure modes and their corresponding limit states are addressed in the AISC Specification in sections E3, E4, and E7(Committee, 2016)[32] as shown in table AISCM Table E1.1. Understanding these modes is essential for ensuring the structural integrity and safety of compression members under axial compression loads.

One such mode is flexural buckling, which can be either elastic or inelastic, depending on the slenderness ratio of the member (Sokół, 2011).

Another failure mode is torsional buckling, where the member twists about its longitudinal axis without experiencing any lateral displacement.

Lateral-torsional or flexural-torsional buckling is a combined failure mode observed in wide flange sections. It arises from the flexural compression stresses on the compression flange of a beam or column with large unbraced lengths.

Lastly, local buckling occurs when certain slender components of the structural member, such as the web and flanges, undergo local buckling.

SLENDERNESS LIMITATIONS

According to AISC, to ensure the stability of members designed for compression, it is preferable that Lc / r, is not more than 200.

$$\frac{Lc}{r} \leq 200 \tag{9}$$

The Slenderness constraint for compression member is

$$\frac{Lc}{r} - 200 \leq 0 \tag{10}$$

where

K is the effective length factor for pin-connected members as per AISC Table C-A-7.1; K = 1.

Lc is the effective length of a member.

L is unbraced length.

r is the radius of gyration.

LOCAL BUCKLING OF COMPRESSION MEMBERS,

Slenderness of member elements

This section focuses on examining local instability of each element inside a compression member (refer to *Figure 2*). Instability occurs when these elements become slender, leading to reduced strength and limiting the compression member's axial compression capacity.

To prevent local buckling (see *Figure 3*), the AISC specification (Committee, 2016) sets specific limits for the width-to-thickness ratios (λp and λr) of elements forming the compression member. These restrictions can be found in section B4 of the AISC Specification (Table B4.1a).

In members with slender elements, the cross-section does not reach yield point, and the strength is controlled by local buckling, which is not recommended due to their inefficiency and lack of cost-effectiveness (Sokół, 2011).

Their width-to-thickness ratios influence the axial compression buckling strength of compression elements, λ. The value of λr categorizes a column element as non-slender (λ ≤ λr) or slender (λ > λr), depending on whether the element is stiffened or unstiffened. These critical values are provided in AISCM Table B4.1a.

It's crucial to note that the value of λ is accessible in the AISC section database, which is then utilized for analysis.

In addition to the previous classification, it is essential to categorize each element as either stiffened or unstiffened based on their support conditions (see *Figure 3*). The proposed algorithm takes into account different constraints and limitations specific to each element.

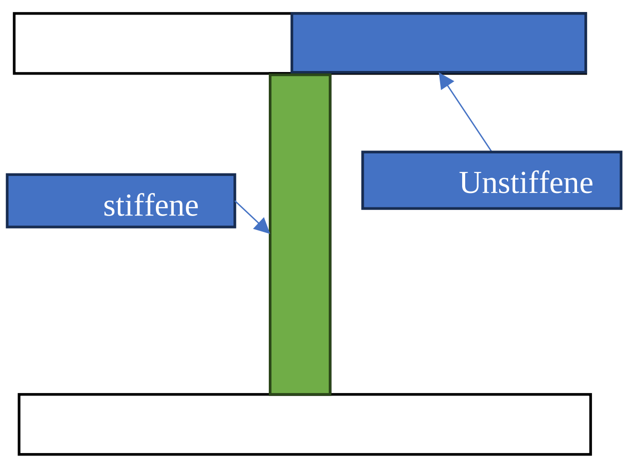

Figure 2 element type in W shape

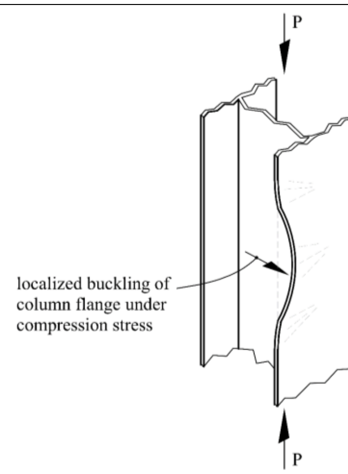

Figure 3 local buckling of an element

Euler critical buckling load for the members is provided by Equations (11 and 12) for the x and y directions, respectively.

$$Fex = \frac{\pi^2 E}{\frac{Lcx^2}{rx}}; \qquad (E3-4) \qquad (11)$$

$$Fey = \frac{\pi^2 E}{\frac{Lcx^2}{ry}}; \qquad (E3-4) \qquad (12)$$

COMPRESSION MEMBER STRENGTH,

The AISC Specification defines the design compressive strength (φcPn) and allowable compressive strength (Pn / Ωc) for the flexural buckling limit state. The nominal compressive strength (Pn) is determined based on the lowest value obtained after considering the applicable limit states of flexural buckling, torsional buckling, and flexural-torsional buckling.

$$\phi_c = 0.90\ (LRFD) \quad \Omega_c = 1.67\ (ASD)$$

The nominal axial compression strength is given as

$$Pn = FcrAg \quad (E3-2) \qquad (13)$$

The calculation of the axial compressive strength according to the LRFD technique is provided as

$$P_u \leq \left(\phi_c\, P_n = \phi_c\, F_{cr} A_g\right) \qquad (14)$$

Thus, the Compressive strength Constraint is determined as

$$P_u - \phi_c\, P_n \leq 0 \qquad (15)$$

While permitted axial compressive load using the ASD technique is stated as

$$P_a \leq \frac{P_n}{\Omega_c} = \frac{F_{cr} A_g}{\Omega_c} \qquad (16)$$

So, the compressive strength Constraint using the ASD method

$$P_a - \frac{P_n}{\Omega_c} \leq 0 \qquad (17)$$

Where Pn is the nominal compressive strength, Fcr is the flexural buckling stress, ϕ_c*is* 0.90, and Ωc is 1.67.

FLEXURAL BUCKLING OF MEMBERS WITHOUT SLENDER ELEMENTS

The nominal compressive strength, *Pn*, shall be determined based on the limit state of flexural buckling:

In equation E3-2.

The AISC critical flexural buckling stress, *Fcr*, is determined as follows:

Critical stress in for buckling about x-axis

when $(\frac{lcx}{rx} \leq 4.71\sqrt{\frac{E}{Fy}})$ i.e inelastic behavior (the member buckles inelastically)

$$Fcrx(i) = 0.658^{\frac{Fy}{Fex(i)}} * Fy; \quad \%(E3-2) \qquad (18)$$

when $(\frac{lcx}{rx} > 4.71\sqrt{\frac{E}{Fy}})$ i.e elastic behavior (the member buckles elastically)

$$Fcrx(i) = 0.877 * Fex(i); \quad \%(E3-3) \qquad (19)$$

Minimum critical stress in both directions will control the design

$$Fcr(i) = min\left(Fcrx(i), Fcry(i)\right) \qquad (20)$$

Equations (18) through (20) address the global flexural buckling of the compression member; however, they do not take into account the local buckling of the individual components within the compression member.

TORSIONAL AND FLEXURAL-TORSIONAL BUCKLING OF MEMBERS WITHOUT SLENDER ELEMENTS

Some doubly symmetric members without slender elements, are considered slender when the lateral unbraced length exceeds the torsional unbraced length. In such cases, the nominal compressive strength (Pn=Fcr Ag) is determined based on the limit states of torsional and flexural-torsional buckling.

The critical stress, Fcr, is calculated using the flexural buckling equations (18) to (20). Additionally, elastic buckling stress Fe, for such a case, must be computed as shown below:

For members that are doubly symmetrical and twist about the shear centre (W, M, S, HP, and HSS),

$$Fe = (\pi^2 * E.* Cw./Lcz.^2 + G.* J).* 1/(Ix + Iy) \quad (21)$$

MEMBERS WITH SLENDER ELEMENTS

As described in Section B4.1 AISC, such compression members have a width-to-thickness ratio that exceeds λr, making them classified as slender-element sections.

To determine compressive strength (Pn), a minimum value is chosen depending on the limit states of flexural buckling, torsional buckling, and flexural-torsional buckling, taking into account their interaction with local buckling. For members with slender elements, the Determination of axial compressive strength follows the guidelines provided in Section E7 of the AISC Specification.

Note that all of these criteria are taken into account in the design program.

Program Description

The software was developed by combining the Genetic Algorithm (GA) and the Finite Element Method (FEM). The GA, inspired by natural selection, finds optimal solutions for complex problems where traditional methods are inadequate. It lacks a user-friendly interface, operating in a batch mode via MATLAB input and output files. FEM is employed for structural analysis.

In ETABS (Extended Three-Dimensional Analysis of Building Systems), the "Auto Select Design" method automates selecting optimal design sections for structural members. It utilizes predefined codes and criteria, considering loads, member properties, and constraints, streamlining the design process while ensuring structural integrity.

3.3 Numerical Examples & Comparison between ETABS and GA

This section introduces various truss structures that incorporate discrete variables; 3-member truss(3M1L),5-member truss(5M1L), 9-member truss(9M1L), 13-member truss(13M1L), and 17-member truss(17M1L), all are under single concentric load(1L),9-member truss(9M3L), 13-member truss(13M3L), and 17-member truss(17M3L) under three concentric loads (3L), design variables in each structure equal to the number of the members. All examples in this section involve a comparison of Genetic Algorithm (GA) results with results obtained through CSi ETABS Optimum Design. For all members in the truss structures, the stress limit is set to 50 ksi (344.737 MPa) in both tension and compression. The material density is 0.2836 lb/in.^{3} (7850 kg/m^3), and the modulus of elasticity is 29000 ksi (199948 MPa). These material properties remain consistent across all the examples. Two load cases are considered: a single concentric load and three concentric loads.

Eight examples have been solved, and their corresponding design outcomes are illustrated in the subsequent figures. Each example is accompanied by a dedicated figure that portrays the geometric configuration of the structure, the applied load conditions, the structural sections designated by ETABS, as well as the optimal sections recommended by the proposed algorithm. Furthermore, a time history profile is provided to visually elucidate the progressive optimization process. Complementary to this visual representation, a comprehensive tabular presentation in Table 3 showcases the optimal weights as ascertained by both ETABS and the Genetic Algorithm (GA), alongside the weight reduction ratio for each specific example.

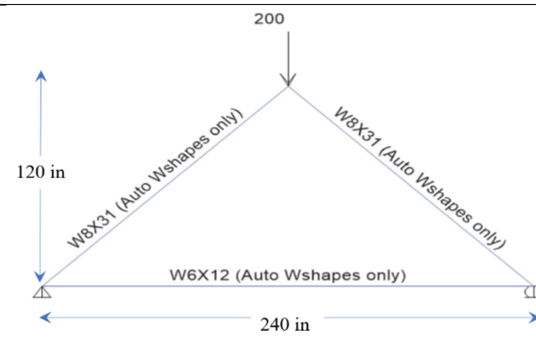

Figure 4 **3M1L** truss ETAB results

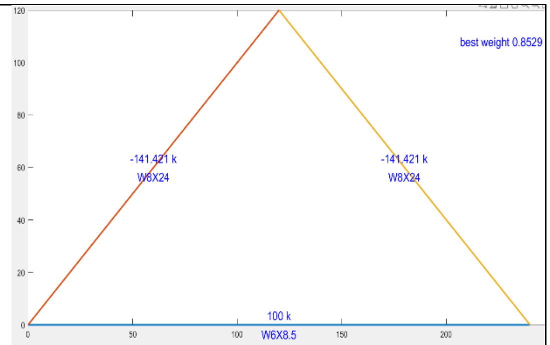

Figure 5 **3M1L** truss GA results

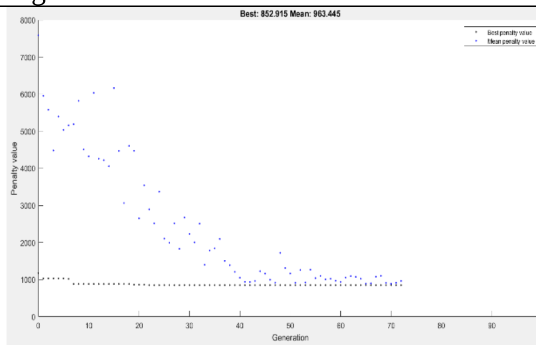

Figure 6 Optimization history of **3M1L** truss

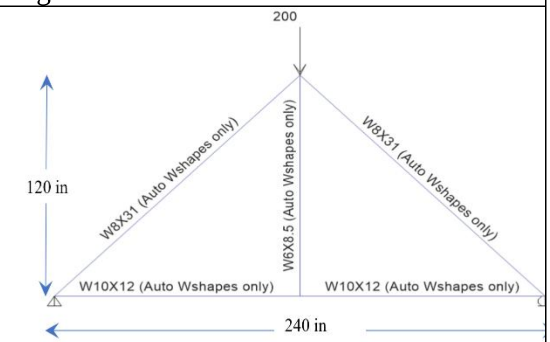

Figure 7 **5M1L** truss ETAB results

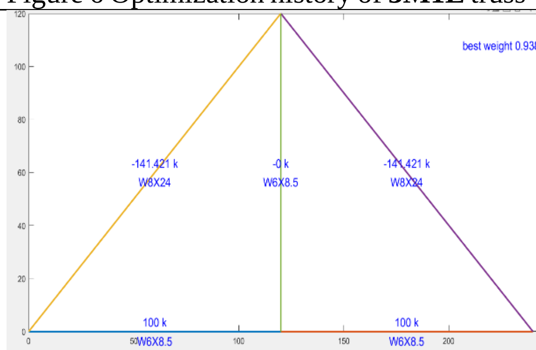

Figure 8 **5M1L** truss GA results

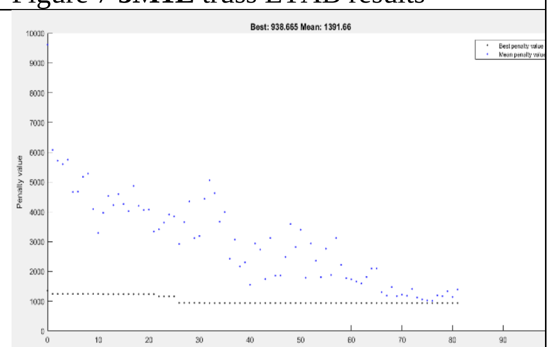

Figure 9 Optimization history of **5M1L** truss

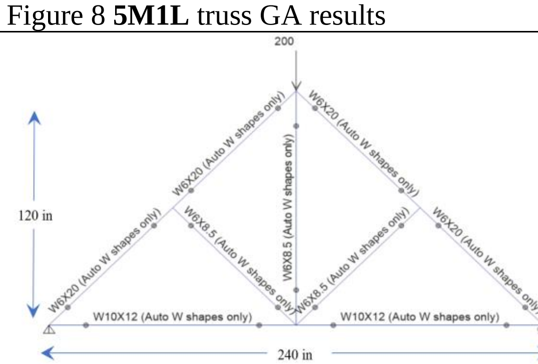

Figure 10 **9M1L** truss ETAB results

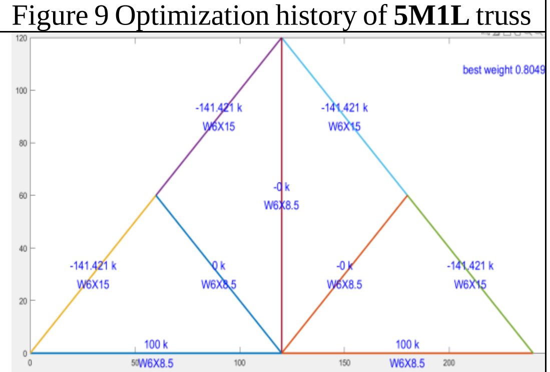

Figure 11 9M1L GA results

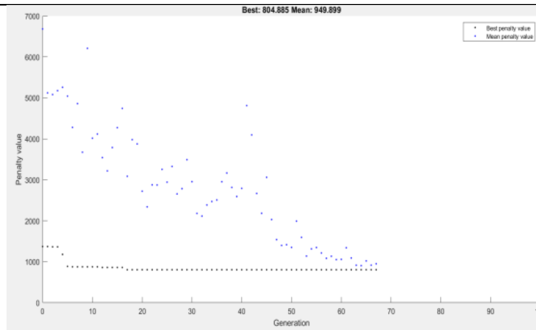

Figure 12 Optimization history of **9M1L** truss

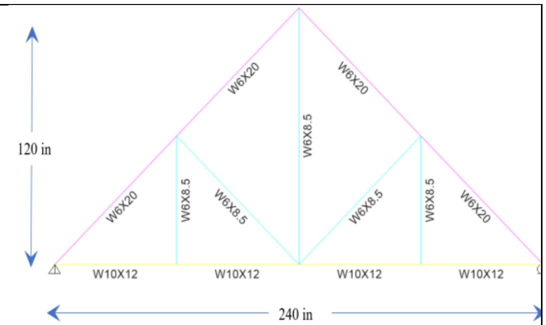

Figure 13 **13M1L** truss ETAB results

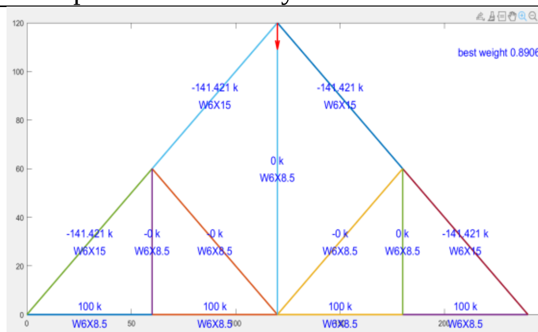

Figure 14 **13M1L** GA results

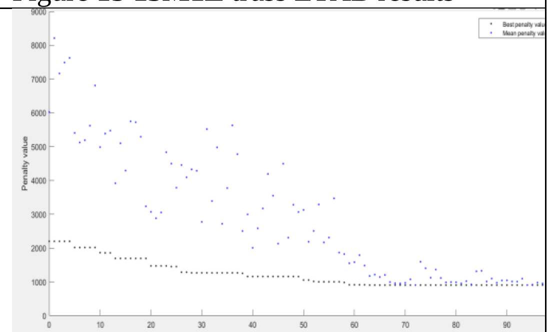

Figure 15 Optimization history of **13M1L** truss

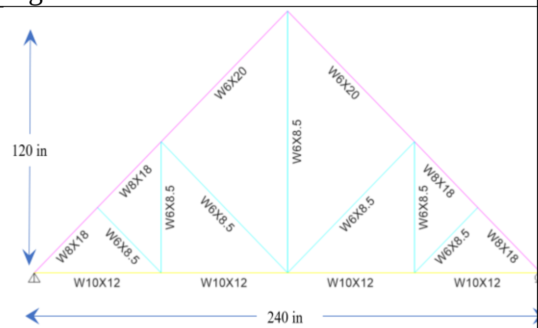

Figure 16- **17M1L** truss ETAB results

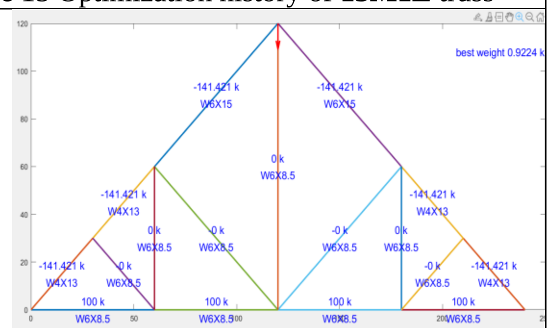

Figure 17- **17M1L** truss GA results

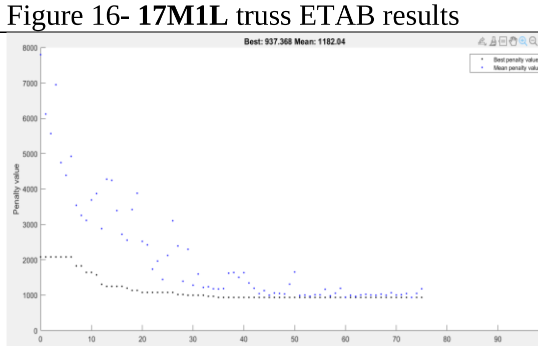

Figure 18-Optimization history of **17M1L** truss

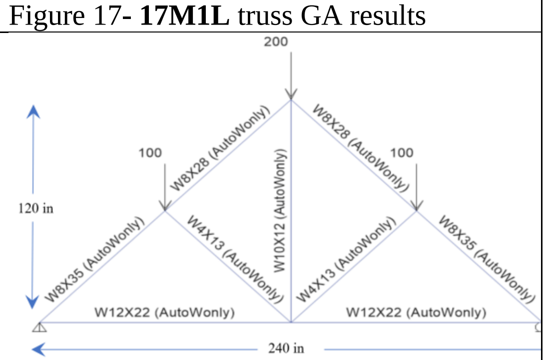

Figure 19 **-9M3L** truss ETAB results

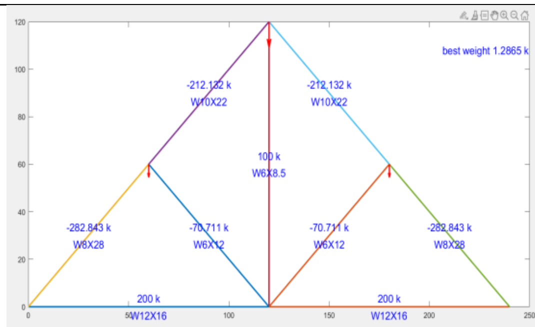

Figure 20-**9M3L** truss GA results

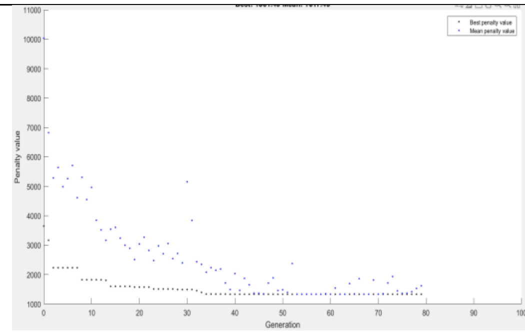

Figure 21- Optimization history of **9M3L** truss

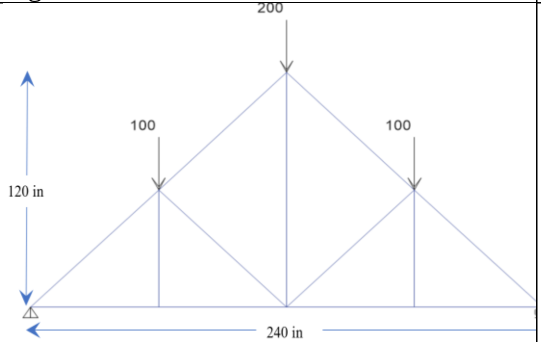

Figure 22-geometry of **13M3L**

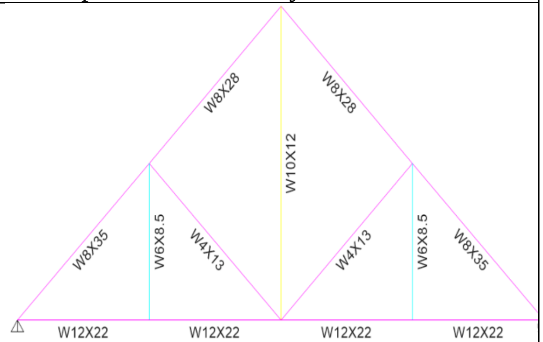

Figure 23-**13M3L** truss ETAB results

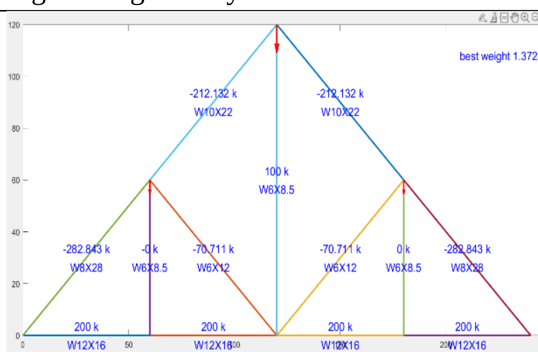

Figure 24 **13M3L** truss GA results

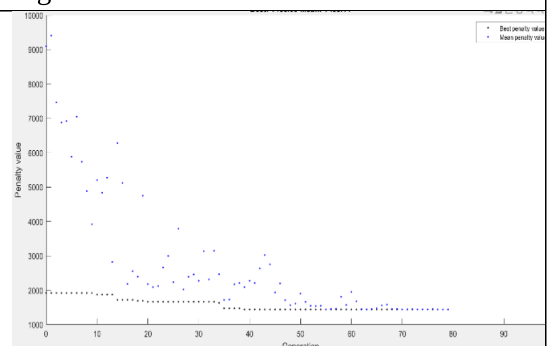

Figure 25-Optimization history of **13M3L** truss

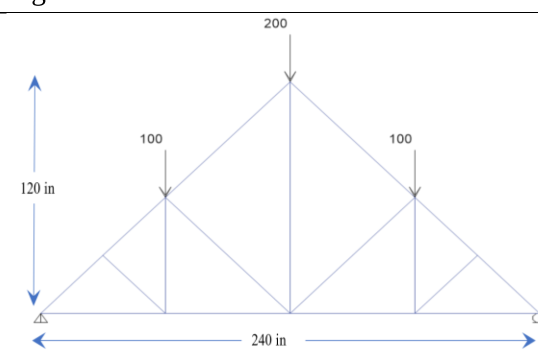

Figure 26- geometry of **17M3L**

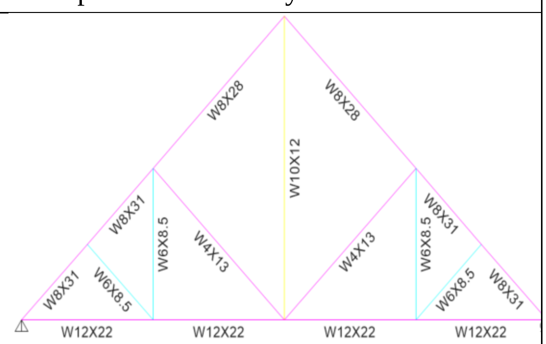

Figure 27-**17M3L** truss ETAB results

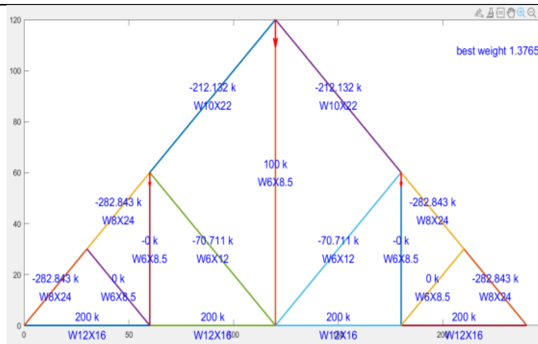

Figure 28-**17M3L** truss GA results

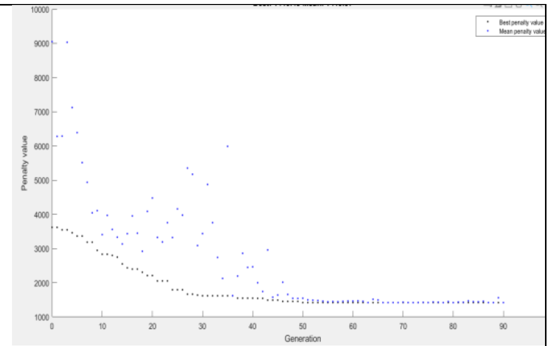

Figure 29-Optimization history of **17M3L** truss

3.4 Result discussion and conclusion

This research article presents a genetic algorithm (GA) methodology for the optimization of sizing aspects of planar truss structures, taking into consideration stress, displacement, and buckling constraints. All constraint in the AISC specification is taken in to consideration. In addition to that the program take the data for real section provided in AISC specification manual. Slender and non-slender elements is also taken in to account in calculation of local buckling. The nominal compressive strength (Pn) is determined based on the lowest value obtained after considering the applicable limit states of flexural buckling, torsional buckling, and flexural-torsional buckling. The optimization process involves an initial global search, followed by a gradual transition towards local tuning during the later stages.

The effectiveness of the proposed GA approach is assessed through the examination of nine representative weight minimization problems involving planar truss structures with discrete design variables. For each test case, ten independent GA runs are conducted. To evaluate the computational efficiency of the algorithm, a comparative analysis is performed between each test case and the auto select optimization method implemented in the CSI ETABS program. The results obtained demonstrate the efficiency, reliability, and robustness of the proposed GA methodology.

A summary of the optimization outcomes is presented in Table 1.

Table 1 The summary of optimization results

load case	Truss			Optimum Weight (Kips)		Wt. GA/CSI	Wt. Re-duction ratio
	Type	Name	No. Mem	Csi ETABS, kip	GA , kip		
single concentric load	3 member	3M1L	3	1.203	0.853	0.71	0.29
	5 member	5M1L	5	1.2054	0.9387	0.78	0.22
	9 member	9M1L	9	1.013	0.8049	0.79	0.21
	13 member	13M1L	13	1.098	0.8906	0.81	0.19
	17 member	17M1L	17	1.1299	0.924	0.82	0.18
three concentric loads	9 member	9M3L	9	1.6385	1.2865	0.79	0.21
	13 member	13M3L	13	1.724	1.3722	0.8	0.2
	17 member	17M3L	17	1.7286	1.3765	0.8	0.2

Furthermore, Figure 30 illustrates the comparison of results, indicating that the optimal weight for the 9M1L topology is 1.013 kips for the ETABS optimization method and 0.8049 kips for the GA optimization method. This finding suggests that the 9M1L topology is the most favourable among the five cases considered. Notably, Figure 31 provides evidence that the GA consistently outperforms the ETABS method across all truss configurations.

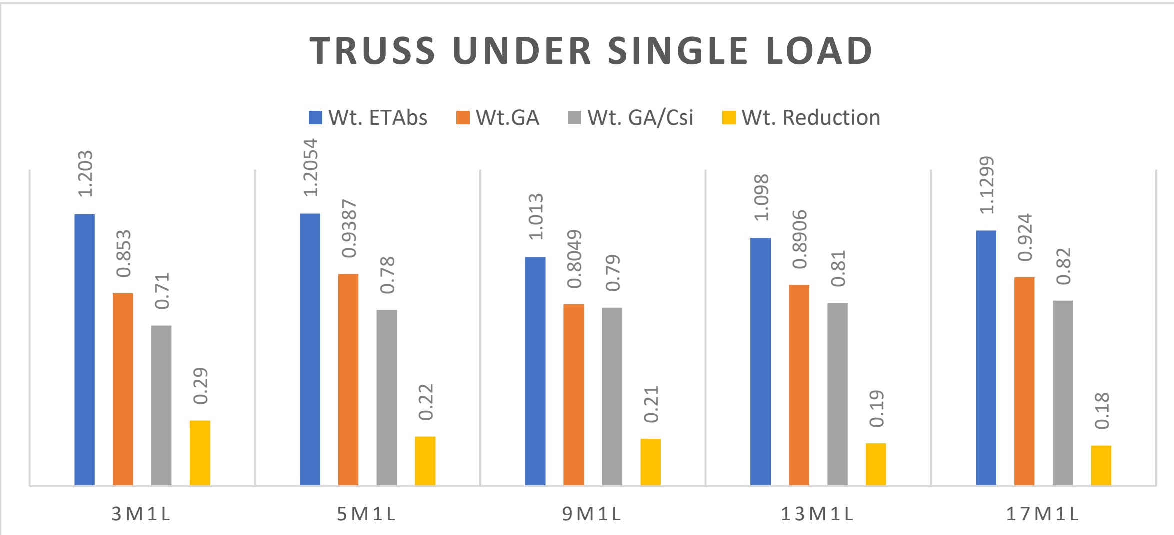

Figure 30: Results of truss under single load

Similarly, Figure 33 shows that the optimal weight for the 9M3L topology is 1.6385 kips for the ETABS optimization method and 1.2865 kips for the GA optimization method, indicating the superiority of the GA approach for this specific topology among the three cases considered. Moreover, in the case of trusses subjected to a single load, Error! Reference source not found. demonstrates that the GA consistently a chieves better results compared to ETABS across all truss configurations.

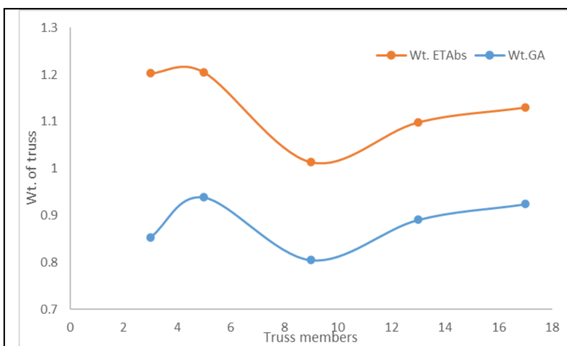

Figure 31 optimum wt. versus No. of elements for Truss under single load

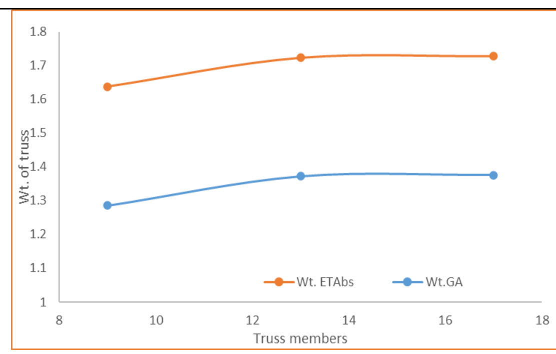

Figure 32 optimum wt. versus No. of elements for Truss under three loads

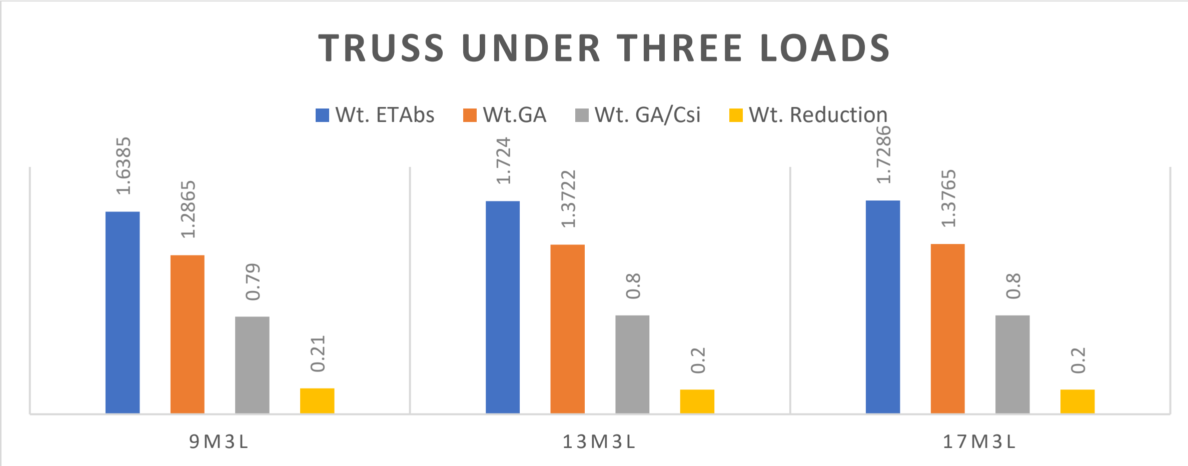

Figure 33 Result of truss under three loads

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