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Shape optimization of Star Crash Box Using Particle Swarm Optimization and Bayesian Optimization

by

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A THESIS

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ABSTRACT

Crash box is energy-absorbing component to ensure the passive safety of vehicles during frontal crash. For crash-boxes - lightweight design, safety requirements absorbing energy are relevant. This research aims to determine the value of geometric design parameters in design space of star crash box optimizing specific energy absorption (SEA). The geometric modelling, meshing and finally input file for LS dyna is created using python scripting. Crash simulation is performed in LS Dyna. The energy absorption is taken from glstat of binout file and mass is taken from massout file. The particle swarm optimization is done using skopt python module. The geometric design parameters used are height (a), width (b), x-intrusion (u), y- intrusion (v) and thickness (t). For each simulation reference material Mild steel with density 7830 kg/m^3, Young's modulus 200 GPa and cowper-symond parameters $c = 40s^{-1}$ and $p = 5$ is used. The impactor of 250 kg mass with speed of 15 mm/ms is used. The values of geometric parameters in baseline geometry of star crash box were a= 90 mm, b = 90 mm, u = 15 mm, v = 15 mm and t = 1.85. From the simulation result, the SEA of 37948.57 J/Kg is obtained. Using PSO optimization algorithm, 480 simulations was run in batch mode. The maximum SEA of 63777.547 J/Kg was obtained at the values a = 60 mm, b = 112.420 mm, u = 13.876 mm, v = 0 mm and t = 0.987. In case of Bayesian optimization, the simulation is run for 129 in batch mode to obtain the optimized value SEA is obtained to be 68897.182 J/Kg at geometric parameter values of a= 72.291 mm, b=75.314 mm, u = 20.162 mm, v = 4.978 mm and t = 0.985. Both the optimization gives significantly more value of SEA than that of baseline geometry. In between optimization algorithms, Bayesian optimization gives more value of SEA than PSO. Also, computational time is also less in case of Bayesian optimization. Other crashworthiness parameters like peak crushing force, mean crushing force and crushing force efficiency are also compared. In all these cases, the values of these optimized result from PSO and Bayesian optimization are better than that of baseline geometry. Further, the result from Bayesian optimization is better in terms of these crashworthiness parameters than PSO. Bayesian optimization can be better algorithm to perform crashworthiness optimization in future study.

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The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a thesis entitled **"Shape optimization of Star Crash Box Using Particle Swarm Optimization and Bayesian Optimization"** Submitted by Bikki Chhantyal in partial fulfillment of the requirements for the degree of Master of Science in Mechanical Systems Design and Engineering.

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LIST OF SYMBOLS

ρ	Density
A	Area
V	Volume
μ	Poisson's ratio
σ	Stress
ε	Strain
E	Young's modulus
$\dot{\varepsilon}$	Strain rate
a	Height
b	Width
u	Intrusion in x-direction
v	Intrusion in y-direction
t	Thickness
c, p	Cowper-Symonds strain rate parameters
τ	Shear stress
δ	Displacement
P	Load/Force
m	Mass
W_T	Total work done
W	Inertia factor
c_1,c_2	Cognitive learning rate

LIST OF ACRONYMS

NPR	Negative Poisson's Ratio
CFRP	Carbon Fiber Reinforced Polymer
EA	Energy Absorption
SEA	Specific Energy Absorption
PCF	Peak Crushing Force
MCF	Mean Crushing Force
CFE	Crushing Force Efficiency
PSO	Particle Swarm Optimization
RSM	Response Surface Method
DoE	Design of Experiments
GA	Genetic Algorithms
FEM	Finite Element Method
FEA	Finite Element Analysis
HMnS	High Manganese Steels
DE	Differential Evolutionary

CHAPTER ONE: INTRODUCTION

1.1 Background

With the increase in population, the number of automobiles is also increasing. Road traffic crashes result in the deaths of approximately 1.3 million people per year and about 93% of this case comes from middle income and low-income countries like Nepal (WHO, 2022). The number of frontal collisions is significantly more than side collisions. This has increased the need of enhancing safety of the vehicle and its occupants. Consumers are thus becoming more aware of the importance of road safety. This includes both safe driving, passive and active vehicle safety. Therefore, automotive companies are spending funds in the direction of improving the vehicle safety.

In recent years, the realm of road safety has witnessed a surge in awareness, extending beyond mere driving practices to encompass the intricacies of vehicle safety features. This heightened consciousness has prompted automotive companies to embark on a journey of intensified research and development, channeling their resources towards bolstering vehicle safety standards. These concerted efforts have borne fruit in the form of a substantial decline in road fatalities, as exemplified by the remarkable 44.3% drop in fatalities within the European Union between 2001 and 2011, despite a mere 0.2% decrease in the overall number of accidents (Andreas, 2015).

To achieve this remarkable feat, car manufacturers have embraced a synergistic approach, employing a combination of real-world crash tests and sophisticated computer simulation techniques, with the Finite Element Method (FEM) emerging as the cornerstone of their endeavors. FEM empowers designers to scrutinize and compare a myriad of design options at the early stages of the development process, offering a far more expeditious and cost-effective alternative to traditional physical crash tests.

However, the intricate nature of vehicle structures, coupled with the highly non-linear behavior they exhibit during crashes, presents formidable computational hurdles. To circumvent these challenges and complete simulations within a reasonable timeframe, car manufacturers have turned to the prowess of powerful computer clusters. These sophisticated machines harness their collective processing power to unravel the complexities of vehicle dynamics, enabling designers to optimize safety features and enhance overall vehicle performance.

The transformative impact of FEM on vehicle safety is undeniable. By enabling designers to probe the intricacies of vehicle behavior under extreme conditions, FEM has played a pivotal role in reducing road fatalities and fostering a safer driving environment for all. As technology continues to evolve, FEM's potential is poised to expand, driving innovation and propelling vehicle safety to even greater heights.

1.2 Problem Statement

Crash boxes used for automotive safety, are designed to absorb and dissipate the immense energy generated during a frontal crash. Their primary purpose is to minimize the transfer of forces to the vehicle's main structure, thereby protecting passengers from the impact. However, optimizing crash box design is no easy feat.

The balance between weight reduction and safety enhancement is needed. Every kilogram saved reducing weight of vehicle improves fuel efficiency and performance, but it also comes at the cost of reduced crashworthiness. The crash box design demands innovative solutions that maximize energy absorption without compromising safety. The crash behavior of the crash box further increase challenge. Crash box progressive buckling pattern and energy absorption exhibit highly nonlinear characteristics. This nonlinearity makes it difficult to predict and optimize crash performance using traditional analytical methods used in literature.

As a consequence, the design of crash boxes often relies heavily on the experience and expertise of engineers. While this approach has proven effective to a certain extent, it also limits the exploration of the design space. Without systematic optimization techniques, there's a risk of overlooking potential design improvements that could further enhance crashworthiness. To address these challenges, researchers are increasingly turning to advanced design optimization techniques.

These methods employ computational techniques to evaluate a wide range of design parameters and identify optimal solutions that balance weight reduction, safety, and manufacturing constraints. By exploiting population-based metaheuristic algorithms, crash box design, leading to safer vehicles with improved performance and fuel efficiency can be designed. The future of crash box design promises to be a fascinating journey of innovation and technological advancement.

1.3 Objectives

1.3.1 Main Objective

The main objective of the research is to optimize design of star crash box using particle swarm optimization and Bayesian optimization.

1.3.2 Specific Objectives

- To use particle swarm optimization in shape optimization of star crash box.
- To use Bayesian optimization in shape optimization of star crash box.
- To compare the PSO and Bayesian optimization in terms of crashworthiness simulation result.

1.4 Assumptions and Limitations

The assumption and limitation of this research are listed as follows.

- The experimental validation of the optimized result is not performed.
- The material used is mild steel in all simulations for the reference. It is one of the traditional crash box materials and material properties are available in literature. The material optimization is out of scope of this research. Recently, novel materials with negative poison’s ratio (NPR), carbon fiber reinforced polymer (CFRP), auxetic core are in research for material of crash box.
- The research focuses on energy absorption capability of crash box. Afterwards, the safety requirement is check using peak crushing force but the multi-objective optimization is not done using both energy absorbing and safety requirement criteria.
- Design space is explored in this research but study of manufacture of material isn’t done. The manufacturing constraints are not studied and hence included in this research.

CHAPTER TWO: LITERATURE REVIEW

This chapter presents a brief review of the literature used throughout the thesis.

2.1 Crash box

Crash box is important component of vehicle for passive safety of vehicle and its occupants during frontal crash. During a collision, it acts as a kinetic energy absorber. It is a tube shape thin-walled structure located behind bumper. During collision, it undergoes progressive buckling plastic deformation thereby absorbing most of the energy prior to the transfer the main cabin of a vehicle. The specific modes of deformation observed in crash box design and collapse behavior are concertina mode and diamond mode.

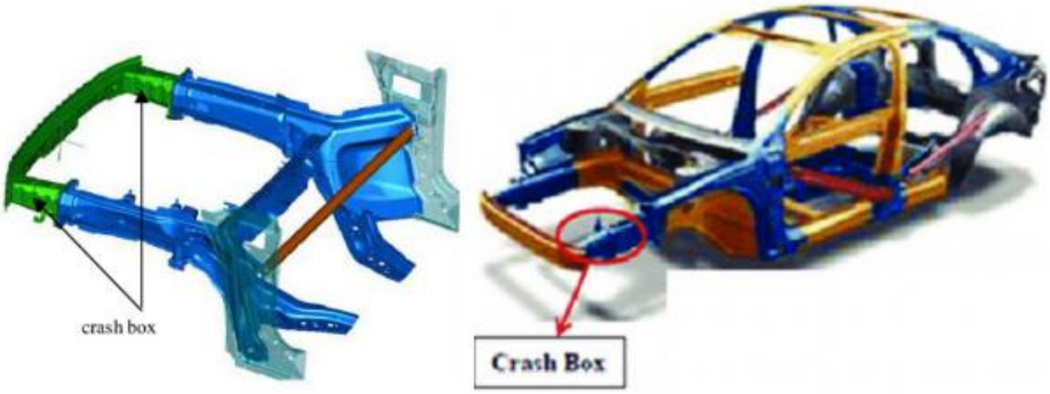

Figure 2-1: Crash box

Concertina mode is a deformation pattern characterized by a series of accordion-like folds or wrinkles along the length of a structure, resembling the folds of a concertina musical instrument. Diamond-shaped deformation occurs when a thin-walled structure undergoes a collapse, and the resulting folds or distortions take on a pattern resembling diamond shapes. The failure of the crash box should ensure crashworthiness.

2.2 Crashworthiness of Crash box

Crashworthiness is a fundamental concept that delves into the intricate science of safeguarding individuals within various structures when faced with accidents. This critical attribute finds its most prominent application within the domains of automobiles, aircraft, and trains.

Vehicle safety is usually measured by safety parameters like the contact forces applied on the occupants or the accelerations during the crash, measured in specific points (US Department of Transportation, 1998). These safety parameters are highly related to the energy that is absorbed by the structure such that neither acceleration of the occupants is high nor intrusion into the safety cabin around them.

According to (Galganski, 1993), the problems of crashworthiness can be summarized as:

- Displacement and energy;
- Crash pulse;
- Crash position;
- Automobile capability.

Since crashworthiness measures the structure's ability to protect the passages during impact, it should fulfill the following requirements (Ibrahim, 2009):

- High energy absorption by controllable plastic deformation;
- Preservation of a minimum survival space in order to prevent injuries.

In order to find the best design, taking into account not only the safety but also other design objectives, optimization is needed. Optimization has always been a very popular idea. It reflects the desire of achieving a certain goal using the least possible sources. It involves scanning the whole design space trying to find the best feasible solution according to well-known objectives. Applying optimization directly to the non-linear finite elements model would require extremely high computational effort. To overcome this, a variety of approximation methods are used. Approximation methods consist in mathematical models that are much simpler than the original FEM model. With the help of FEM the crash response is estimated, rather than exactly computed. In general, due to the highly non-linear nature of crash phenomena, non-gradient based optimization techniques are preferred.

2.3 Crashworthiness Parameters

Crashworthiness parameters include energy absorption, mean crush force, specific energy absorption, and crush force efficiencies.

2.3.1 Energy Absorbed (EA)

Energy absorption is the process of releasing energy from external loading through fracture or plastic deformation. The energy absorbed (EA) is represented by the area under the load-displacement curve and it can be calculated from the equation:

$$W = \int_{S_i}^{S_f} P d\delta \tag{1}$$

Here, P is instantaneous load and δ is displacement.

There are two regions that make up the area under the load displacement curve. The first one is known as pre-crushing, and its area can be determined by locating the triangle's underside.

$$A = \frac{1}{2} P_i \delta_i \tag{2}$$

The area in the second region (post-crushing) can be calculated from Eq.1, total work done (W_T) is the area under force in force displacement graph.

Normally, it is expressed in SI unit KJ.

2.3.2 Specific Energy Absorption (SEA)

Specific energy absorption (SEA) is a common parameter used to indicate energy absorption capability. When designing components for vehicles that need to reduce weight, the specific energy absorption plays a critical role. SEA is the energy absorbed per mass of the specimen. It is expressed in KJ/Kg.

$$\text{Specific Energy absorption, SEA} = \frac{EA}{m} \tag{3}$$

2.3.3 Peak Crushing Force (PCF)

Peak crushing force (PCF) is a commonly used metric in axial crush deformation to assess thin-walled beam crashworthiness. PCF is a thin-walled beam's maximum force value. It cannot absorb energy if this is greater than the bearing capacity of other structures when they are crushed. The energy absorbed by a thin-walled structure's deformation is known as energy absorption. The impact on other structures decreases with increasing energy absorption.

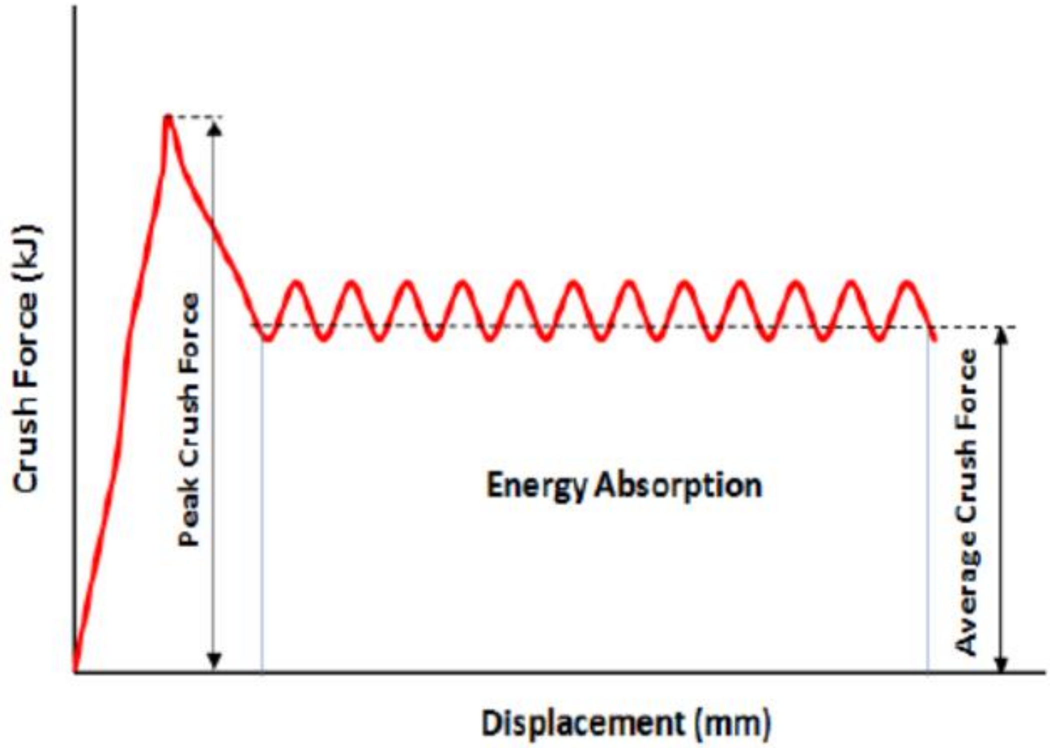

Figure 2-2: Peak Crushing Force (Djamaluddin et al., 2015)

As shown in the Figure 2-1, the force reaches to peak and comes down to mean position to oscillate about it. The maximum of crush force is called peak crushing force.

2.3.4 Mean Crushing Force (MCF)

It is the average crush force experienced during the crash moment in the crash box. It is calculated by following formula.

$$\text{MCF} = \frac{\text{Energy Absorbed}}{\text{Total deformation}} \tag{4}$$

2.3.5 Crushing Force Efficiency (CFE)

Crush force efficiency, or the ratio of the mean crush average load to the peak crush load, is another crucial indicator of crush performance. The crush force efficiency (CFE) of an energy absorber device should be taken into consideration when assessing its crashworthiness. Crush force efficiency, or CFE, has been identified as a crucial crushing attribute. The crush started load in the crash box's load-displacement curve dropped significantly, and the collapse continued with low value load. It is value that illustrates the failure mechanism catastrophic or progressive failure.

This value is used to assess the risk of head and neck injuries in the event of a collision in the aerospace and automotive industries. It can also be used to estimate the amount of force that would be transferred to cargo or other supplies.

$$CFE = \frac{MCF}{PCF} \times 100\% \tag{5}$$

2.4 Optimization

Optimization is the method of finding the optimum solution for a given function within a defined set of possible solutions. The crash behavior is highly nonlinear, making it complex to find an optimized design that maximizes energy absorption. Population-based optimization is a type of optimization strategy that involves maintaining a population of candidate solutions and iteratively evolving this population to improve the overall performance with respect to an objective function. This approach is particularly useful for complex and nonlinear optimization problems like crash behavior of crash box.

The general mathematical form of an optimization problem always contains the following functions (Christensen and Klarbring, 2009):

- Objective function: For every possible design a value is used to evaluate the design. Usually, this function must be minimized. It can also be a set of functions when there are multiple criteria optimization problems.
- Design variables: A vector or function of input parameters that is changed during optimization and that can describe the design.
- Constraints: They are limits in the values of the design variables. There can be equality and non-equality constraints. In some cases of structural optimization problems there might be no constraints.

Thus, optimization is defined as the process of maximizing or minimizing an objective function while satisfying specific constraints (Chandrupatla and Belegundu, 2011). The general mathematical form is:

Minimize $f(x)$ (6)

w.r.t $g_i(x)$, $i = 1,\ldots,m$

and $h_j(x)$, $j = 1,\ldots,n$

and $x^L \leq x \leq x^U$

Structural optimization problems are classified, based on the design variables, in the following types (Schumacher et al., 2005):

- Material Optimization;
- Topology Optimization;
- Shape Optimization;
- Sizing/Dimension Optimization.

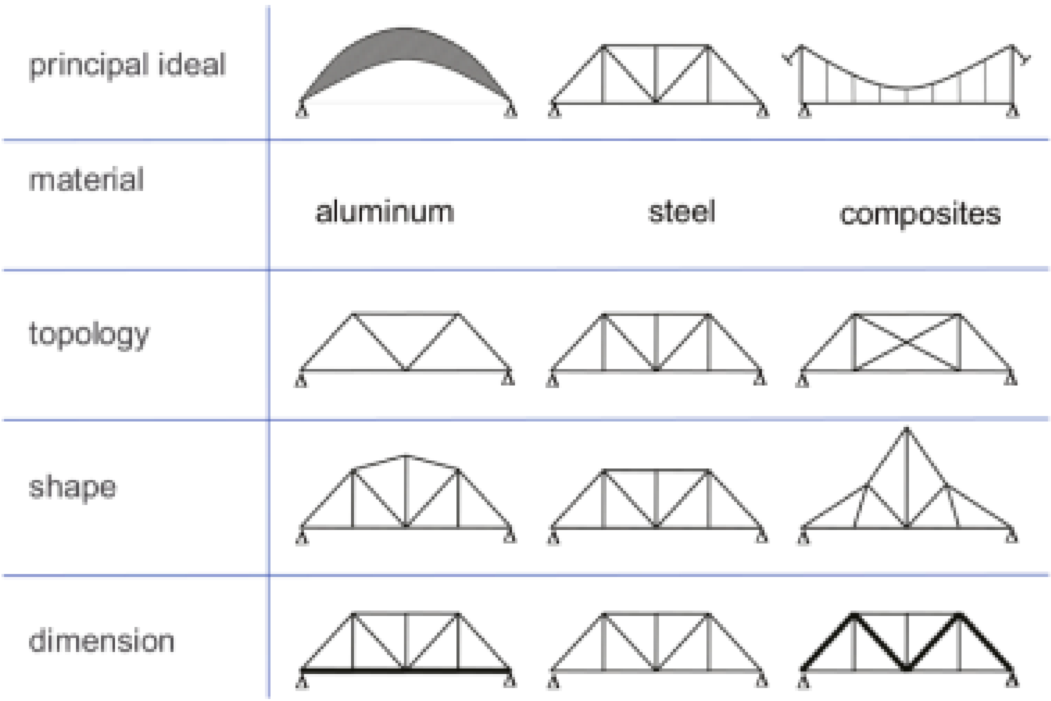

Figure 2-3: Classification of design variables (Schumacher et al., 2005)

2.5 Optimization in crashworthiness

Usually design (shape) optimization involves a lot of iterations. As building real models would be both expensive and time consuming, virtual models are used instead. Closed form solutions cannot be used due to the high complexity of crash phenomena. In crashworthiness study, responses are highly non-linear and noisy (Ibrahim, 2009). As a result, usual methods, like gradient-based, cannot be used, since the complexity of the problems makes it very difficult to acquire gradients for the objective and constraints functions. Moreover, the computational costs would also be very high.

From the literature research stands out that different optimization objectives are used. The most common is minimizing the structure's mass (Marklund and Nilsson, 2001; Craig et al., 2002; Stander et al., 2003; Hamza and Saitou, 2004, 2005; Liao et al., 2007). However, in (Nilsson and Redhe, 2004) the minimization of maximum acceleration is used as objective. In (Redhe et al., 2002) the objectives are to maximize the internal energy and to minimize of the maximum rigid wall force. Also (Wu and Xin, 2009; Wu et al., 2011; Wang et al., 2011) use as objective the maximization of the internal energy. (Schramm et al., 1998) designs the system such that it absorbs the maximum amount of energy. (Redhe and Nils- son, 2004) searches for optimum 19 crashworthiness assuming as objectives the maximization of the time that it takes to the rigid wall crashing against a beam to stop and the minimization of area between the velocity curve and a line connecting its first and last value. The goal is in this way to reduce the maximum acceleration and make the deceleration more linear. In almost all the previous cases, the optimization was constrained. Either the maximum acceleration, intrusion, time to stop, weight or maximum velocity were constrained. Sometimes, also combinations of these objectives are considered.

The objectives of the evaluation of energy absorbing structures, as described in (Anselm, 2000) are:

- Deformation Characteristics: This describes the conversion of energy by plastic deformation. Good deformation characteristics would cause the worst possible deformation to a limited part of the structure.
- Specific Energy Absorption: Is defined as the absorbed energy with respect to the mass of the deformed structure. The goal is a high specific energy absorption.
- Force-Displacement curve: The integral value of force over displacement represents the energy absorption of the structure. The aim is to get a structure that absorbs the highest possible value.
- Energy-Displacement curve: This is used to estimate the deformation stiffness. The steeper the curve rises, the stiffer the structure.

2.6 Optimization Algorithms

There exist many optimization algorithms that use different methods and approaches. They are applied in many different applications. But as stated before there is no optimization algorithm that can be considered to be the best. For each application a different algorithm fits. In the scope of crashworthiness optimization usually Response

Surface Method is used. In this work, different optimization algorithms will be used, evaluated and compared.

2.6.1 Genetic Algorithms

An approach to constrained and unconstrained optimization problems based on a natural selection process that emulates biological evolution is called a genetic algorithm (GA). Genetic algorithms (GAs) are search methods based on principles of natural selection and genetics (Fraser, 1957; Bremermann, 1958; Holland, 1975). A basic vocabulary of the GAs, as summarized in (Sastry et al., 2005), is:

- Chromosomes: Candidate solutions to the search problem.
- Genes: The alphabets of the chromosome strings.
- Alleles: The values of the genes.
- Fitness: A measure for distinguishing between good and bad solutions. Usually, the objective function.
- Population: A sum of candidate solutions. The size of the population is one of the most important factors affecting the performance of the algorithm.
- Selection: In selection, chromosomes are selected from the population to act as parents in crossover. Selection favors solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions. Some algorithms use different selections. In general, the selection can be either deterministic or stochastic. The selection can be done between parents and offspring or just offspring.
- Crossover: Often called recombination, it is the creation of a new individual by combining properties of parents. It is explorative, it makes big jumps in areas between parents. This is good for finding promising areas in the search space.
- Mutation: Is the slight change of one individual by random. Mutation is exploitative, it favors optimizing within a certain region of the design space.
- Replacement-Elitism: The offspring replace the parents in the population. It is possible that the parents are fitter and thus it is possible to lose some good solutions from the population. In order to preserve the very best solutions during the optimization procedure, elitism is applied. This enables the transfer of a predefined number of the best chromosomes to the new population.

2.6.2 Particle Swarm Optimization

Kennedy and Eberhart (1995) developed Particle Swarm Optimization (Kennedy and Russell, 1995; Eberhart and Kennedy, 1995). This algorithm, which mimics the collective behaviors of animals like fish schools and flocks of birds, is a population-based search. Each particle in PSO represents a person in the population. In turn, the population is referred to as a swarm. PSO takes into account a group of birds foraging in an unidentified food source. Each solution to the optimization problem is represented by a bird, and it is frequently called a particle that flies across the search space. Each particle has three associated parameters: its current velocity, its position in the search space, and its fitness 21 value. In addition, every particle is a potential solution that is influenced by its surroundings and its own experiences.

2.6.3 Differential Evolutionary Algorithm

Differential Evolutionary (DE) algorithm is simple yet powerful population-based algorithm. It uses the same operators, selection, crossover and mutation like GAs. It was introduced in (Storn and Price, 1995; Storn, 1996) and has been successfully used in solving single-objective optimization problems. The algorithm uses mutation operation as search mechanism and directs the search with the selection operator.

The main steps of the DE algorithm are the same with the GAs. First, an initial population is created and evaluated. Then, the population is mutated and recombined. The result is evaluated and the process continues until the termination criteria are met.

2.6.4 Response Surface Method

Response Surface Method (RSM) is a method that consists in constructing and approximating response in terms of polynomial functions. They are ideal for noisy responses and can be used effectively in gradient or gradient free based optimization algorithms. RSM where introduced in (Box and Wilson, 1951). They suggested a linear model to approximate output responses. The first application was chemical engineering experiments. Much work has been done for developing suitable experiments with large variations. RSM are reviewed in detail in (Myers et al., 2009).

2.6.5 Bayesian Optimization

Bayesian optimization is a powerful approach for optimizing objective functions that are computationally expensive and may involve noisy evaluations. It is particularly useful when optimizing functions over continuous domains with a limited number of dimensions. Here's an overview of how Bayesian optimization works (Frazier, 2018):

- Objective Function: You start with an objective function that you want to optimize. This function may be expensive to evaluate and could have noise in its evaluations. The goal is to find the input values (parameters or configurations) that maximize or minimize this function.
- Surrogate Model (Gaussian Process Regression): Bayesian optimization builds a surrogate model for the objective function. The most commonly used surrogate model is Gaussian process regression (GP). GP is a probabilistic model that captures the uncertainty in the function evaluations. It models the objective function as a random process and provides a probability distribution over the function values at different input points.
- Acquisition Function: With the surrogate model in place, Bayesian optimization uses an acquisition function to decide where to sample the objective function next. The acquisition function quantifies the trade-off between exploring uncertain regions and exploiting regions that appear promising. Three common acquisition functions are: Expected Improvement (EI): EI measures the expected improvement over the current best value found so far. It encourages sampling in regions where there is a high probability of finding a better solution. Entropy Search: Entropy search aims to reduce uncertainty about the location of the optimum. It selects points that maximize the reduction in uncertainty about the location of the global minimum. Knowledge Gradient: Knowledge Gradient measures how much new information about the objective function can be gained by evaluating it at a particular point. It seeks to maximize the knowledge gain.
- Sampling: Based on the acquisition function, Bayesian optimization selects the next set of input values to evaluate the objective function. These evaluations are typically costly and time-consuming.
- Updating the Surrogate Model: After obtaining the objective function's values at the selected points, the surrogate model (GP) is updated with this new data. The uncertainty estimates in the surrogate model are refined.

- Iteration: Steps 3 to 5 are repeated iteratively. Bayesian optimization continues to select new points to evaluate, update the surrogate model, and refine its understanding of the objective function.
- Termination: The process continues until a stopping criterion is met, such as a predefined number of iterations or a convergence threshold.
- Final Result: The best solution found so far during the optimization process is considered the final result.

Bayesian optimization is highly effective in scenarios where evaluating the objective function is resource-intensive, and its ability to model uncertainty makes it robust to noisy function evaluations. It has applications in hyperparameter tuning for machine learning models, optimizing simulations, and various engineering design problems.

2.7 Review of Past Researches

This section includes the research done by past researchers and included in literature. This section of searches is divided into research in mechanics, research in material and research in optimization.

2.7.1 Research in Mechanics of Crushing

Crash box design is based on energy absorption of thin- walled structure. The mechanics and analysis of thin-walled structures dates back to 1960s. Initially J.M. Alexander studied progressive folding of thin cylindrical shells under axial loading during concertina mode failure (Alexander, 1960). An approximate theory for the process is derived, leading to a solution of the type

$$P = Ct^{1.5}\sqrt{D} \tag{7}$$

Where, P is the collapse load, t the shell thickness, D the shell diameter, and C a constant for any given material.

This relationship and the experimental data show good agreement. He studied the mechanics for nuclear application. But the study was limited to concertina or axisymmetric failure case. And, the technique is upper bound technique. The more general case of failure is diamond shape failure. The crumpling of thin cylindrical column under diamond pattern of deformation is studied by A. Pugsley and M. Macaulay. The empirical relation of load required to crumple is obtained by equating internal and external work. And the critical buckling load was much below from the classical theory based on small deflection (Pugsley, 1960).The load required for progressive folding is obtained. During deformation, the circular cross section changed first to square type and finally to rhomboid type appearing diamond shape during observation.

The concertina mode of failure is in thick tubes and diamond mode of failure is in thin tubes. When the R/t ratio is higher than 45, the buckles show up as several lobes or depressions in the tube walls that resemble diamonds. If compression is applied, the buckles continue to develop plastically by folding about their circumferential diagonals, replacing the original circular appearance with a polygonal one in plan. The transition is calculated at R/t value of 45 and the transition is due to post elastic behavior (Pugsley, 1979).

Even though the zones of extensional deformations only make up a small portion of the shell's overall area, they consistently account for up to one-third of the energy dispersed throughout the structure. Two thirds of the energy are produced by in-extensional deformations at both stationary and moving hinge lines. The average crushing force for a shell is significantly influenced by the shell's thickness. However, there is significantly less reliance on the linear dimension (Wierzbicki and Abramowicz, 1983).

They later gave mean crushing load for the design of metal honeycomb as energy absorbers, the approach is predicated on energy considerations combined with the plasticity minimum principle. The issue is demonstrated to be analogous to the analysis of a system of collapsing angle elements subject to deformations in both the bending and extension directions (Wierzbicki, 1983).

Then, W Abramowicz modified alexander's theoretical solution. He considered effective crushing distance in static crushing and influence of material strain rate sensitivity is retained in case of dynamic crushing, the experimental validated the result (Abramowicz and Jones, 1984).

Then, the specific energy absorption of the foam filled structures was analyzed (Wierzbicki, 1988; Hanssen et al., 2001). It gave interaction between the thin-walled tube and filling foam (polyurethane foams). It showed distinct collapse mode with increased energy absorption capacity of the column but significant increase of bending stiffness of a deformed cross-section is observed. The specific energy absorption somewhat increased in case of axial loading but in case of oblique loading result was opposite. In both cases the change from hollow wasn't significant (Borvik et al., 2002). Borvik et al. used LS Dyna for the result. The specific absorbed energy is somewhat reduced for the foam-filled columns with a central hole in the foam core, but the effect was not dramatic. DYNA3D, an explicit finite element code that was presented in his study, is used to simulate highly nonlinear and complex structure crushing behavior. Using the design-of-experiment technique, the response surface approximation technique is used to create an approximated design sub problem in the preassigned design space in cylindrical and tubular tube. It is discovered that the ideal tubes have dimensions that allow them to achieve the maximum number of symmetric progressive wrinkles until column buckling happens, as well as the allowable limit of the mean axial impact force (Yamakazi, 1998). Then, (Reyes et al., 2002; Reyes et al., 2003) studied crashworthiness during oblique loading.

2.4.2 Research in Material of crash box

The crash box material is light weight metal structure. But the number of researches has been in different materials. At first, thermoplastic composite was used as crash box material. In the comparative analysis of crash performance between an optimized composite crash box and an optimized aluminum tube, empirical findings by Zarei et al. (2008) reveal noteworthy differentials. The optimal composite crash box exhibited a superior capacity for energy absorption, surpassing the optimum aluminum tube by approximately 17%. This outcome underscores the enhanced crashworthiness of the composite material in absorbing and dissipating impact energy during collision events. Number of researches were done during negative poison's ratio (Zhou et al., 2016), CFRP/aluminum hybrid material (Ma et al., 2020), auxetic core (Wang et al., 2020) as crash box material. Improved specific energy absorption was achieved by combining material and structural design. The results of the simulation show how well structural and material design can be combined for a high total specific energy absorption of 27 kJ/kg. The fully recrystallized HMnS tension parts exhibited exceptional specific energy absorption of 67 kJ/kg. (Wesselmecking et al., 2022).

2.4.3 Research in Optimization of crash box

The optimization of crash box crashworthiness involves topology considerations, as investigated by (Mayer et al., 1996) and (Patel et al., 2009). Evaluation of various geometric shapes revealed that the square section with a diagonal welding line, as determined by (Li et al., 2009), emerges as the most effective configuration based on simulation results. This finding underscores the significance of geometric parameters in enhancing crashworthiness within the context of crash box design. The use of optimization algorithm was limited to response surface approximation and radial basis functions (Wierzbicki, 1988; Fang et al., 2005; Liao et al., 2008) earlier. In recent trend, the use of metaheuristic optimization models is in use due to their global search approach, iterative method, and simple heuristic and less computational time. Also, these can find optimal solution in difficult and complex optimization problems (Zhou et al., 2016; Andreas, 2015). The objective function of the crashworthiness problem is used as specific energy absorption (Wesselmecking et al., 2022; Andreas, 2015), energy absorption (Wierzbicki, 1988; 1 Hanssen et al., 2001; Fang et al., 2005), area in between displacement curve (Redhe and Nilsson, 2004), strain energies weighted at specified times (Mayer et al., 1996) etc. Other objective functions suggested are internal energy, mass, maximum force, maximum acceleration and time for wall to stop (Andreas, 2015). The constraint can be volume (Mayer et al., 1996) and maximum displacement (Patel et al., 2009). The optimization objective of area between displacement curve and among metaheuristic optimization model, particle swarm optimization was suggested (Andreas, 2015).

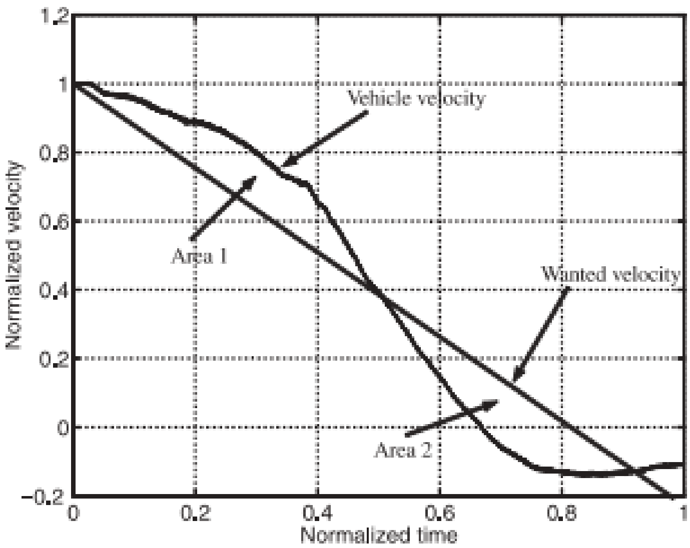

Figure 2-4: Area minimization objective function

CHAPTER THREE: RESEARCH METHODOLOGY

The research methodology is delineated in a schematic representation, encapsulated within a figure. The procedural chronology of the study is articulated through various tasks integral to its fruition. The sequential progression of the research commences with the identification of the research topic, delineation of objectives, exhaustive literature review, and subsequent engagement in model simulation.

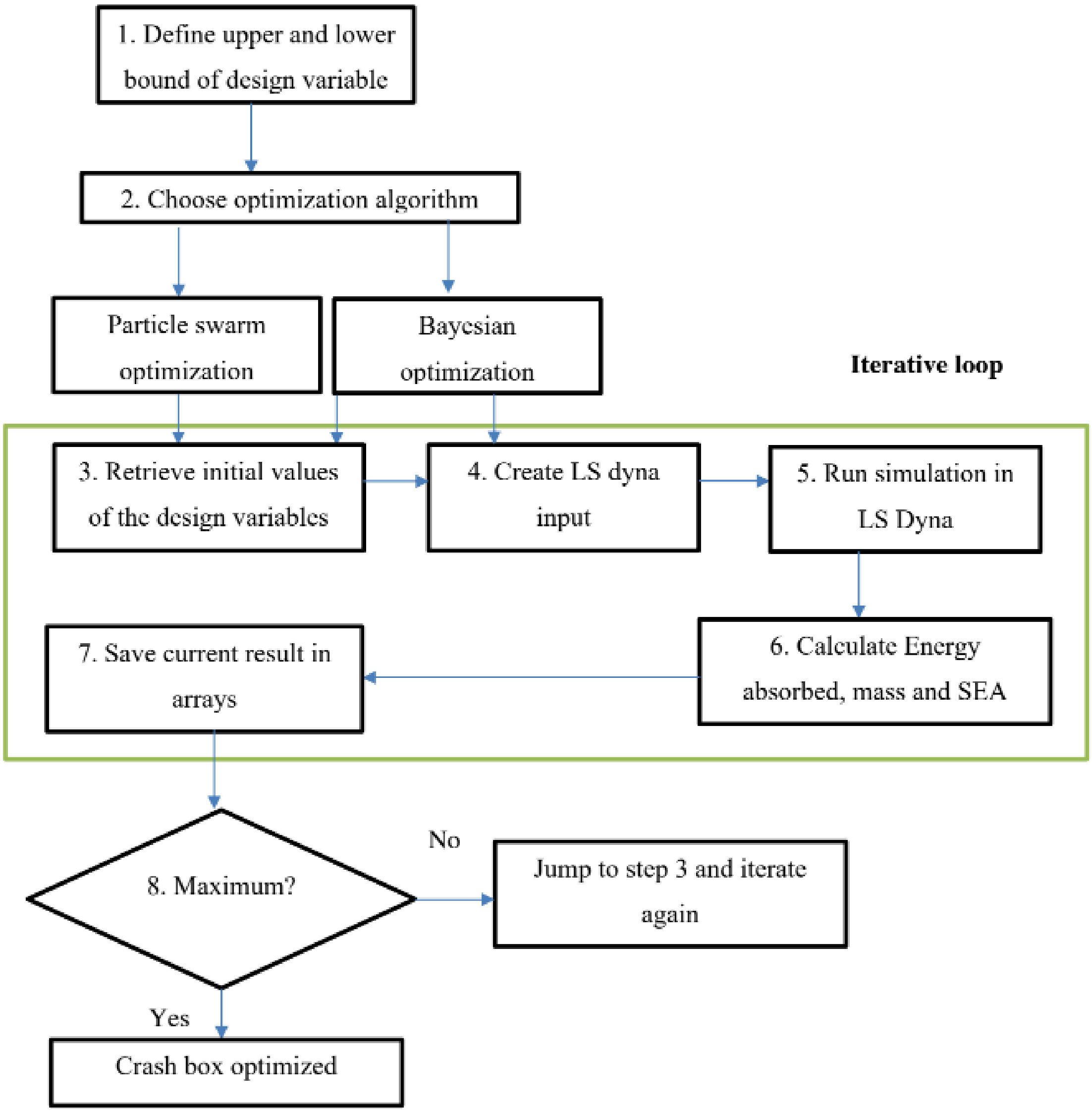

Figure 3-1: Research Methodology

In the course of this study, an extensive array of scholarly resources, including articles, journals, publications, books, and other pertinent sources, were systematically consulted. This comprehensive review informed the delineation of the research focus on the optimization of the crash box, and subsequently, facilitated the establishment of clear and relevant objectives. Given the pivotal role of the crash box as a critical automobile component, a wealth of literature was available. The selection process involved the meticulous shortlisting of research documents closely aligned with the study's thematic contours and objectives, thereby serving as foundational guidance for the seamless execution of the research endeavor.

3.1 Literature Review

The research works in the related topic of crash box optimization are collected from various sources. These researches are then reviewed to identify the problem statement. Other literary researches are reviewed in order to find a suitable solution to the research gap identified.

3.2 Finite Element Model

The Finite Element Method (FEM) serves as a numerical tool within Finite Element Analysis (FEA), enabling the simulation of diverse physical phenomena. Leveraging FEA software, engineers can optimize components during the design phase, reducing reliance on physical prototypes and experiments. This approach accelerates and streamlines product development, presenting a more cost-effective methodology. In the present thesis, explicit dynamic analysis employing FEM is conducted using LS Dyna. The explicit dynamics analysis process is underpinned by diagonal ("lumped") element mass matrices and the utilization of an explicit integration rule. Specifically, the explicit central-difference integration rule is applied for the integration of the body's equations of motion.

Explicit Finite Element Program has two main features:

- FEM Program with explicit time integration.
- Only transient dynamic analysis is possible.

LS-DYNA is a finite element analysis (FEA) software that is used to simulate complex, transient problems involving nonlinear material behavior, large deformations, and contact interactions. It is a powerful tool that can be used to solve a wide variety of engineering problems, including:

- Crash simulation: LS-DYNA is widely used to simulate crash events, such as car crashes, plane crashes, and explosions. It can be used to predict the behavior of materials under crash conditions, and to design safer products.

- Manufacturing simulation: LS-DYNA can be used to simulate manufacturing processes, such as stamping, forging, and casting. It can be used to predict the behavior of materials during these processes, and to optimize the process parameters.
- Biomedical simulation: LS-DYNA can be used to simulate biomedical problems, such as bone implants and prosthetics. It can be used to predict the behavior of materials in the human body, and to design safer and more effective medical devices.

LS-DYNA is an explicit FEA code, which means that it solves the equations of motion using an explicit time integration scheme. This makes LS-DYNA well-suited for simulating transient problems that involve large deformations and contact interactions.

LS-DYNA is a versatile tool that can be used to solve a wide variety of engineering problems. It is a powerful tool that can be used to improve the safety and performance of products, and to optimize manufacturing processes.

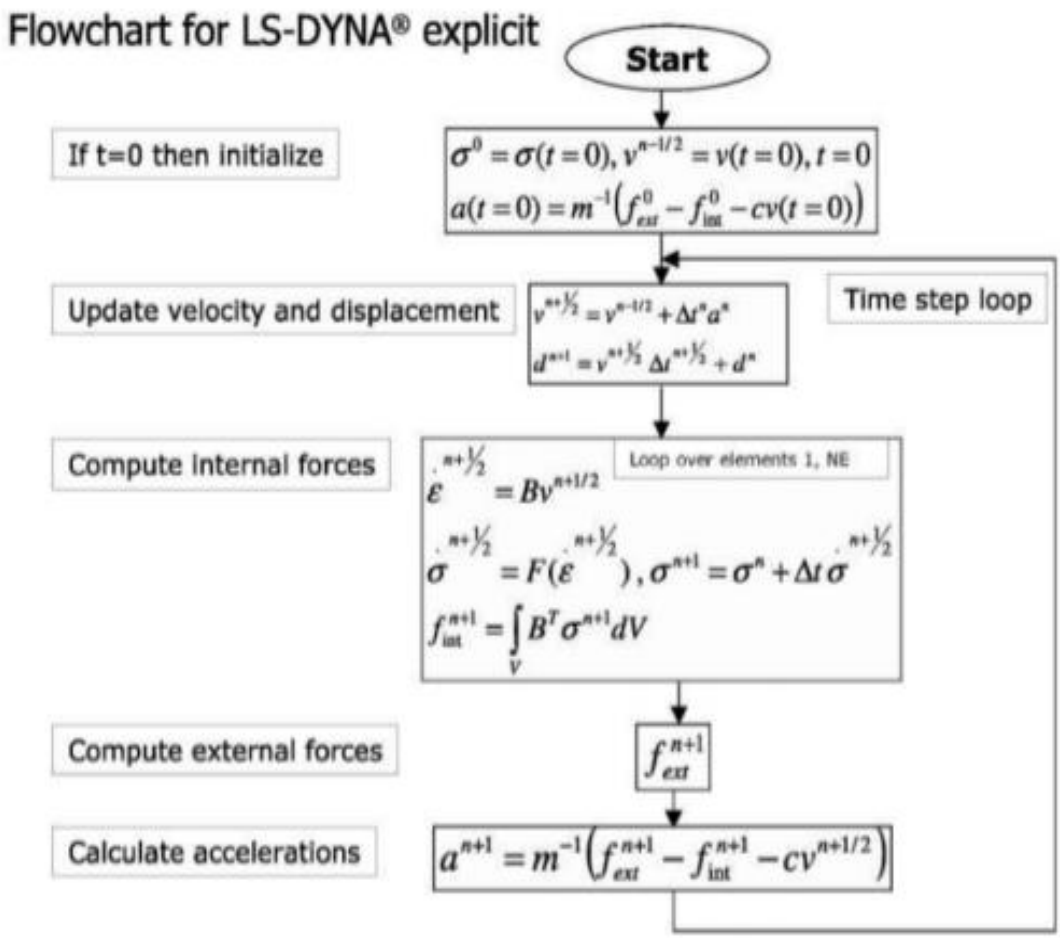

Figure 3-2: Flow Chart of Explicit Dynamics

3.2.1 Geometry design and parameters

The cross-sectional geometry of the crash box is star shaped and it is extruded to the length for a length of 120 mm. Also for the initial failure of the geometry, the trigger depth and trigger rows are defined. The number of trigger row is kept three for all simulation whereas, the trigger is taken as 5% of cross sectional length.

But we only deal with the cross-sectional design parameters. They are height (a), width (b), x –intrusion (u), y-intrusion (v) and thickness (t) as shown figure. The intrusion in x and y direction are symmetric in both sides.

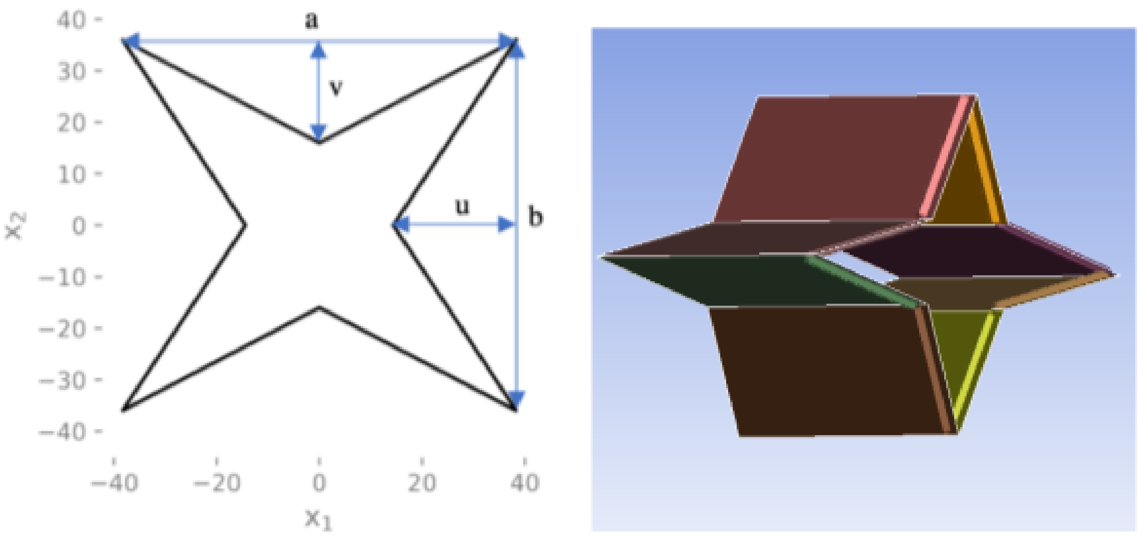

Figure 3-3: Geometry with parameters (left) and in LS Dyna (right)

The design space of the star crash box is

- a = [60, 120],
- b = [60, 120],
- u = [0, 30],
- v = [0, 30] and
- t= [0.7, 3].

It is wide design based on the physical limitation. Under certain extreme values, the cross sectional geometry of star shape changes to square, two triangles and of cross sign. These degenerate shapes are shown in figure 3-4.

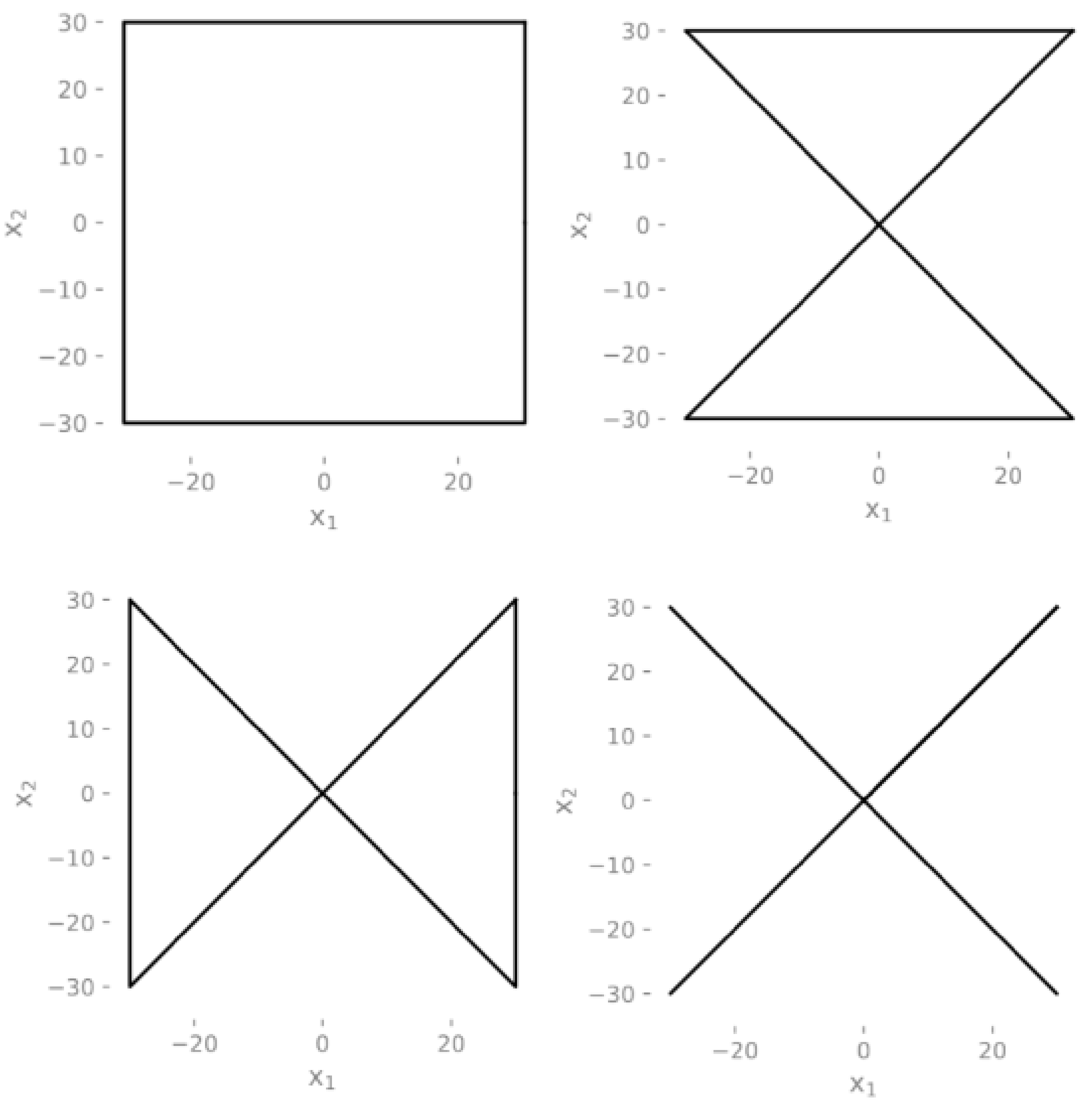

Figure 3-4: Degenerated star shaped geometry

The design space thus includes the square cross section, vertical and horizontal two triangular cross-sectional structure and section of tube with four squares in the cross section with double the thickness. These degenerated shapes can be instrumental for the direction for study of optimization in future.

3.2.2 Mesh Generation

The star crash box is meshed using Python script. Its simplified geometry allows for hex meshing on all surfaces, which reduces computational time and aids simulation convergence. The input for the mesh is the size of mesh in the code.

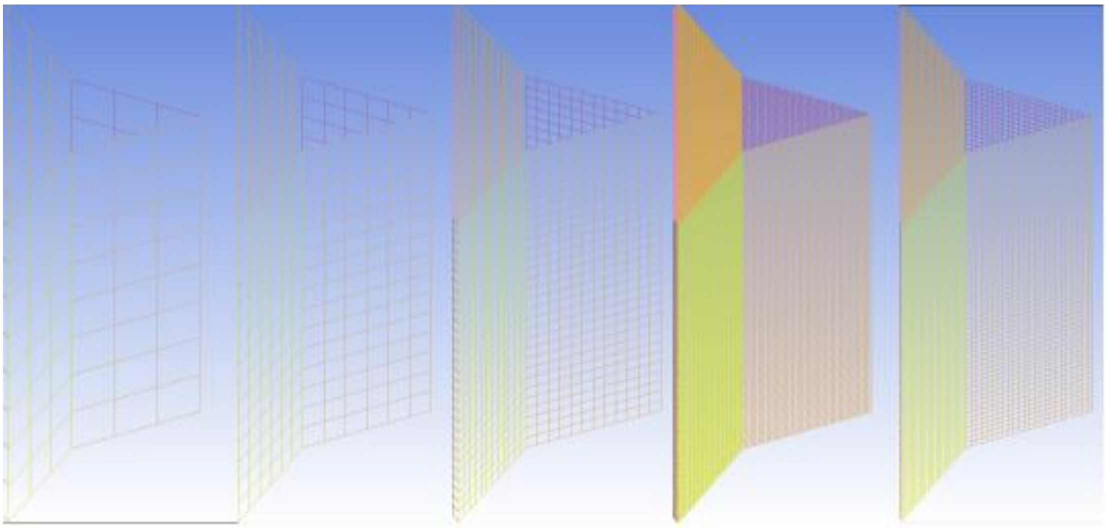

Figure 3-5: Mesh size 16 mm, 8 mm, 4 mm, 2mm and 1 mm (left to right)

The number of elements shouldn't affect the result of the simulation. So, the grid convergence study is done to find the suitable size of element. In this study, the SEA is taken as function and its value is plotted against size of element in baseline geometry. A grid convergence study (GCS) is a numerical analysis technique used to assess the convergence of a numerical solution with respect to the discretization of the spatial domain. In simpler terms, it is a process of refining the mesh of a numerical simulation and observing how the solution changes. The goal of a GCS is to determine the grid spacing at which the solution is no longer sensitive to changes in the mesh. This is important because numerical solutions can be inaccurate if the mesh is too coarse, and they can be computationally expensive if the mesh is too fine.

To perform a GCS, a series of simulations are run with successively finer meshes. The results of each simulation are then compared to determine how much the solution has changed. If the solution has converged, then it will not change significantly with further refinement of the mesh.

From the size of element 4 mm to 2mm, the change is just 0.26%, considering tolerance value of 1% as accepted, we will use 4 mm as size of element in all of our future simulation.

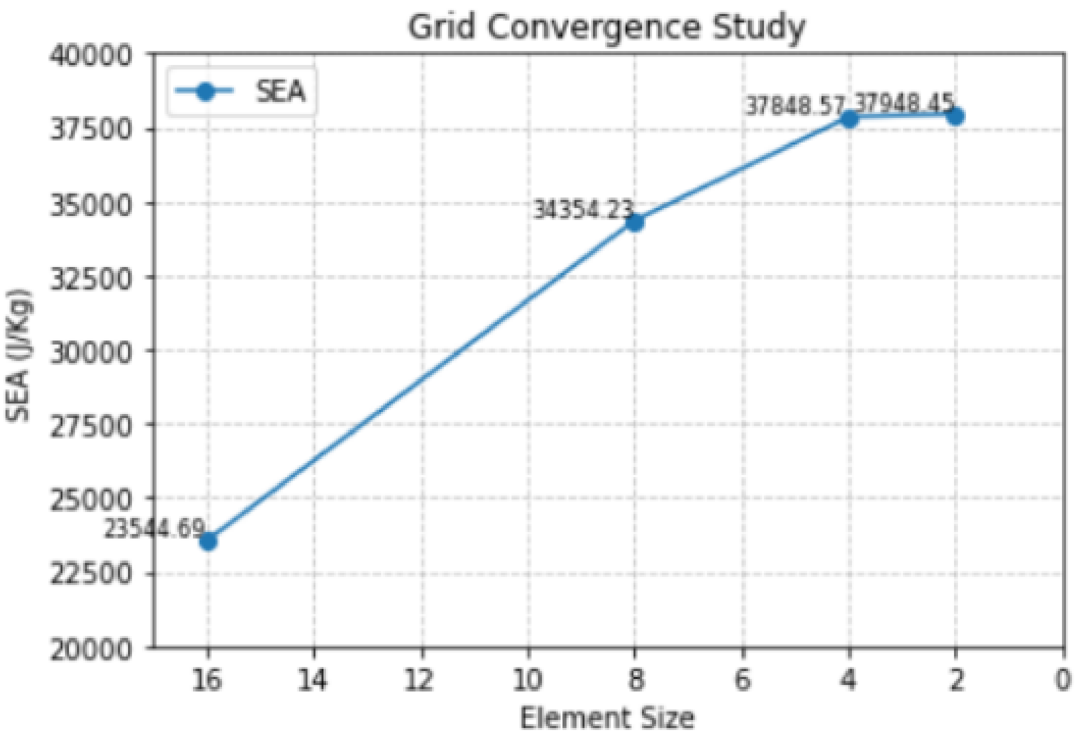

Figure 3-6: Grid Convergence Study

3.2.3 Material Properties

Conventionally, the steel and Aluminum are used as the material of the crash box. The mild steel is used due to high tensile strength and ductility. The optimize material for the crash box is out of scope of this research. Hence for simplicity, the mild steel is taken as reference material. It has following properties.

Table 1: Material Property of Mild Steel (Mehreganian et al, 2018)

Property	Value
Density	7830 Kg/m^3
Young's modulus	200 GPa
Poisson's ratio	0.3
Cowper Symond parameter (c)	$40s^{-1}$
Cowper Symond parameter (p)	5

3.2.4 Boundary conditions

Boundary conditions are a set of rules that specify the behavior of a physical system at its boundaries. They are used to solve differential equations and are essential for modeling many physical phenomena.

The boundary in this case consists of impactor and rigid wall. One side of the crash box has the rigid wall and the other side has impactor with mass of 250 kg. It approaches to rigid wall with velocity 15 mm/ms.

Table 2: Boundary Condition

Boundary	Boundary condition
Rigid wall 1	Stationary
Rigid wall 2	Velocity (15 mm/ms)

3.3 Optimization aspects

Namely, the optimization objective, optimization bounds (constraints) and design variables are the aspects of optimization. These aspects work in tandem to ensure that optimization algorithms can navigate intricate search spaces and converge on the best possible outcomes.

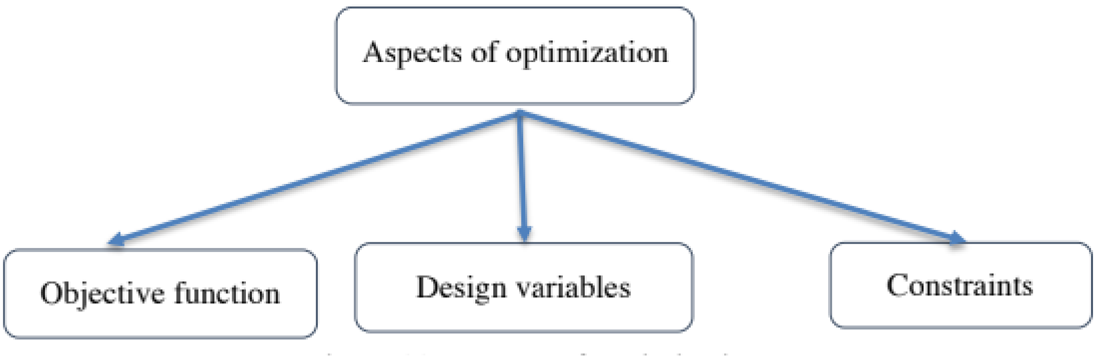

Figure 3-7: Aspects of optimization

3.3.1 Objective Function

Specific Energy Absorption (SEA) is a measure of a material's ability to absorb energy during deformation or impact. It is commonly used in crashworthiness analysis to evaluate the performance of protective materials and structures. A higher SEA value indicates better energy absorption, which can reduce the severity of injuries or damage in collisions. SEA is often used in conjunction with other crashworthiness metrics for a comprehensive evaluation.

Specific energy absorption is single objective of this optimization.

3.3.2 Design variables

Design variables are the parameters that can be manipulated to optimize a system or process. They are the key decision points that an engineer or designer has control over. In the context of optimization, design variables are the inputs to an optimization algorithm that it can change to find the best possible solution.

Height, width, intrusion in x-direction, intrusion in y-direction and thickness are the design variables in this case. They are also called geometric parameters of star crash box geometry.

3.3.3 Constraints

Constraints in optimization refer to the limitations or restrictions that are placed on the decision variables in an optimization problem. These constraints can represent real-world limitations, such as resource availability, physical limitations, or regulatory requirements. In this case, physical limitations is reason for constraints.

Table 3: Design parameter and their constraints

Design Parameter	Symbol	constraints
Height	a	[60, 120] mm
Width	b	[60, 120] mm
Intrusion in x-direction	u	[0, 30] mm
Intrusion in y-direction	v	[0, 30] mm
Thickness	t	[0.7,3] mm

CHAPTER FOUR: RESULTS AND DISCUSSION

The result of the research is segregated in to result of Particle Swarm Optimization, Bayesian optimization and their comparison.

4.1 Particle Swarm Optimization

The optimization study is first performed using particle swarm optimization. Initially the plot of specific energy absorption vs no. of iteration is done. In the PSO, the function given is the calculation of SEA from LS dyna result. The dimension is 5 due to 5 input variables namely, a, b, u, v and t. The maximum iteration is put 480 simulations due to computational resource constraints. The lower bound and upper bound is put as in the constraints of the design variables. The W is positive constant called inertia factor and c_1 and c_2 are non-negative constant called cognitive learning rate. The values are given in the table.

Table 4: PSO input parameters

PSO Function parameter	symbol	Values
Objective function	func	SEA from LS Dyna
Dimension	n_{dim}	5
Population size	pop	10
Maximum iteration	max_{iter}	480
Lower bound	lb	[60,60,0,0,1.7]
Upper bound	ub	[120,120,30,30,3]

4.1.1 Specific Energy Absorption

The geometric parameter input values, energy, mass is written in a file. The energy is taken from binout file produced in the directory folder. Similarly for the mass of the crash box the massout file is produced. Since, the star geometry is regular it can is compared with analytical value. The value of mass is given by following expression

$$m=\left(\sqrt{\frac{h^2}{4}+u^2}+\sqrt{\frac{w^2}{4}+v^2}\right)4\,t\,h_z\,\rho \tag{8}$$

h_z is the height of the crash box = 120 mm.

Then, after simulation is run, the python file is created for visualization. The matplotlib function of python is used for the plot. The plot shows variation of Specific energy absorption with the no. of iteration. The simulation is noisy but in increasing trend. The simulation is not converged even after 480 simulations.

This simulation takes around 5 days to complete in computer with DDR4 RAM 16 GB with 4 cores Intel processor customized for simulation. The PSO doesn't necessarily give the optimized value and converge to global maxima, rather it can be used as the search process to find the global maximum.

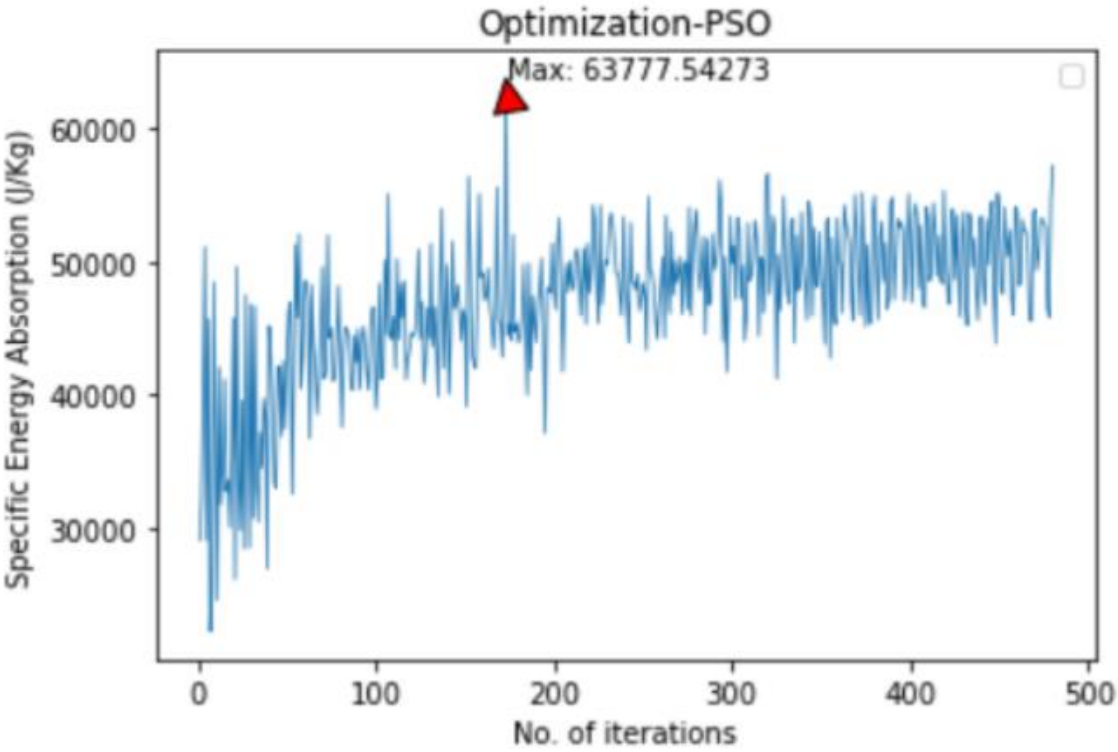

Figure 4-1: SEA vs No. of iteration (PSO)

In this case, the maximum value of 63.77 KJ/Kg of specific energy absorption is found. It is obtained at no. of iteration of 189. The plot is plotted in the figure 4-1.

The numerical simulation of crash box is done in LS dyna without optimization with baseline values. The values of geometric parameters are a= 90 mm, b = 90 mm, u = 15 mm, v = 15 mm and t = 1.85. These are the middle values of extreme constraints of design parameters. From the simulation result, the SEA of 37.94 KJ/Kg is obtained.

4.1.2 Geometric Parameters

Geometric parameters are measurable characteristics that define the shape, size, and position of an object. Geometric parameters play a crucial role in designing, analyzing, and understanding objects and systems across various domains.

Geometric parameters define the cross section of the star crash box. It influences both the energy absorption and mass of the object.

For the optimized geometry using particle swarm optimization, the maximum specific energy absorption of 63.77 J/Kg is obtained at the values a = 60 mm, b = 112.420 mm, u = 13.876 mm, v = 0 mm and t = 0.987 mm. The cross section of star crash box in both cases is plotted in figure 4-2.

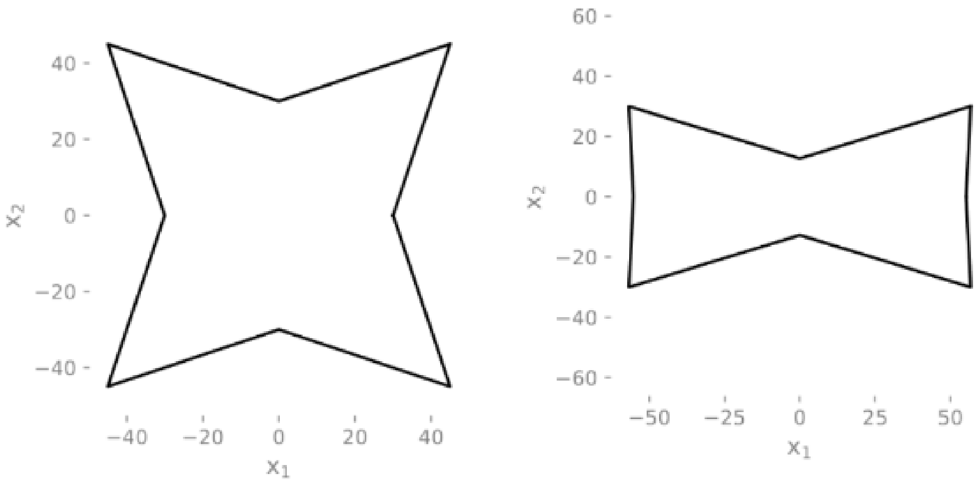

Figure 4-2: Baseline geometry (left) and PSO optimized geometry (right)

From the baseline geometry, the value of height remains constant. The width is increased in particle geometry optimized using particle swarm optimization. The intrusion in x-direction, intrusion in y-intrusion and thickness of the cross section values are decreased in optimized geometry using particle swarm optimization method.

The intrusion in y direction is equal to zero. The vertical lines become parallel. Hence, it produces degenerated shape of star geometry shown in figure 4.2.

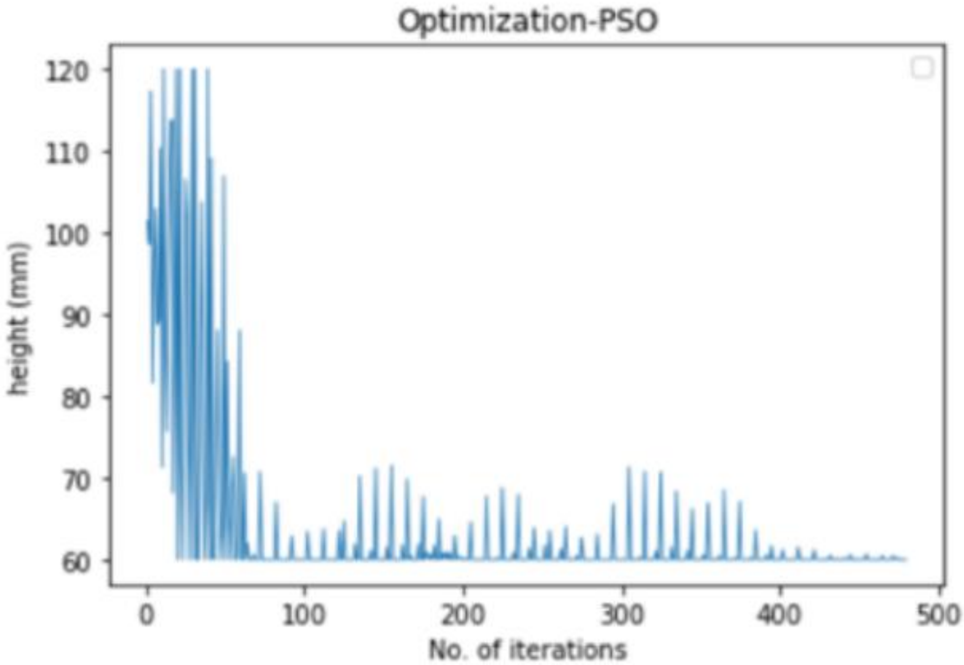

Figure 4-3: Height (a) vs No. of iteration (PSO)

The value of height is plotted against no. of iteration in figure 4-3. Initially, the result is fluctuating but with time with up to 81 iterations. The fluctuation is in whole design space. But after that, the fluctuation is from 60 mm to 70 mm. Also the fluctuation is less compared to initial fluctuations. Finally, after 400 iterations, the height keeps also constant of 60 mm.

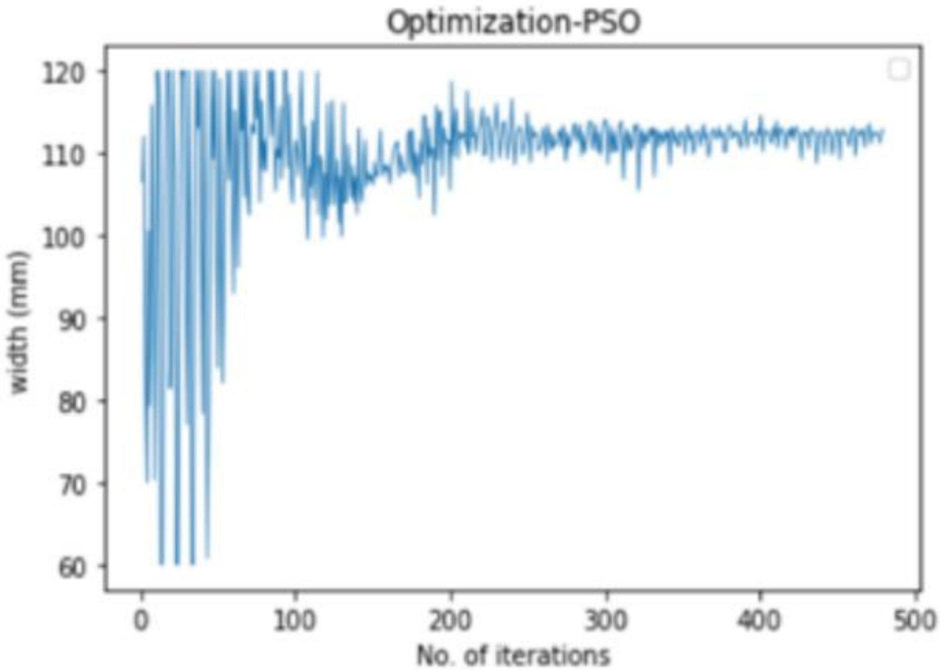

Figure 4-4: Width (b) vs No. of iteration (PSO)

The value of width is plotted against no. of iteration in figure 4-4. Initially, the result is fluctuating from 60 to 120mm up to 81 simulations. But with time, the width is less fluctuating and finally converging to the 112.42 mm.

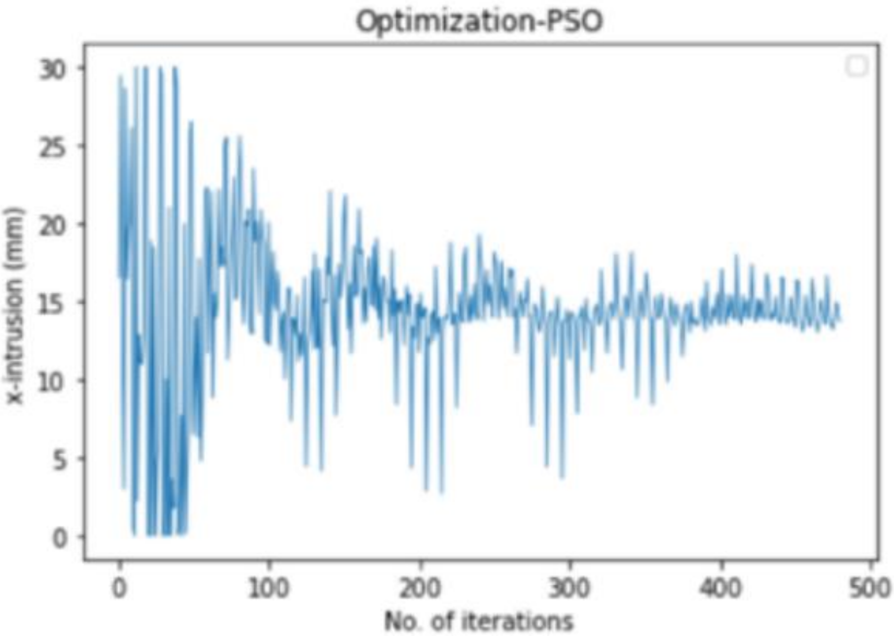

Figure 4-5: x-intrusion vs No. of iterations (PSO)

The value of intrusion in x-direction is plotted against no. of iteration in figure 4-5. The value keeps fluctuating till 480 simulations.

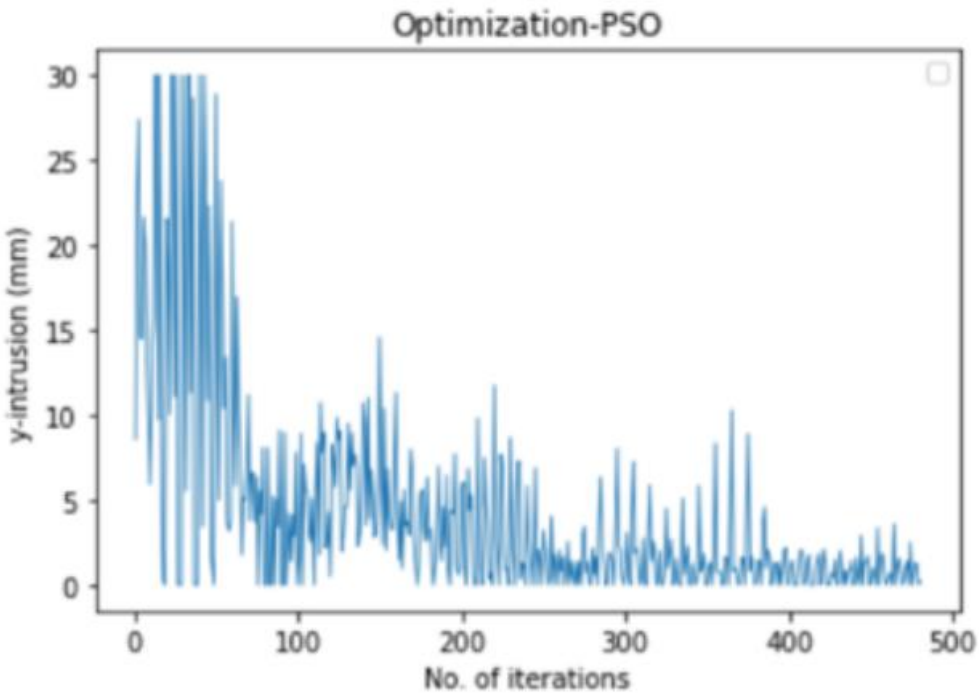

Figure 4-6: y-intrusion vs No. of iterations (PSO)

The value of intrusion in y-direction is plotted against no. of iteration in figure 4-6. The value keeps fluctuating till 480 simulations through the fluctuation range becomes smaller with time.

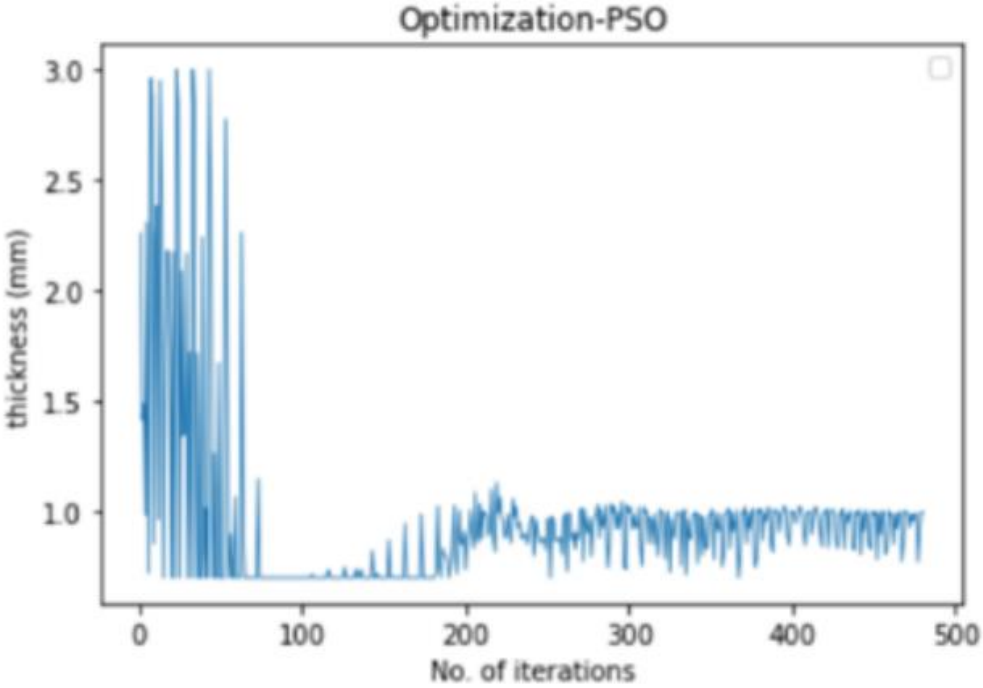

Figure 4-7: Thickness vs No. of iterations (PSO)

The value of intrusion in thickness is plotted against no. of iteration. The value keeps fluctuating till 480 simulations and doesn't converge to one value.

4.1.3 Deformation Pattern

Progressive buckling is a type of structural failure that occurs when a material or structure is subjected to a compressive load that exceeds its buckling load. Unlike elastic buckling, where the structure suddenly deforms without significant loss of load-carrying capacity, progressive buckling involves a gradual and continuous deformation of the structure, accompanied by a decrease in its load-carrying capacity.

The process of energy absorption depends upon the progressive buckling. The number of buckling and time taken determines the energy absorbed by the crash box.

Also the energy absorption depends upon the failure pattern. The geometry may buckle inward or outward depending on geometry. The inward buckling of the geometry absorbs less energy than outward buckling. So, outward buckling is preferred.

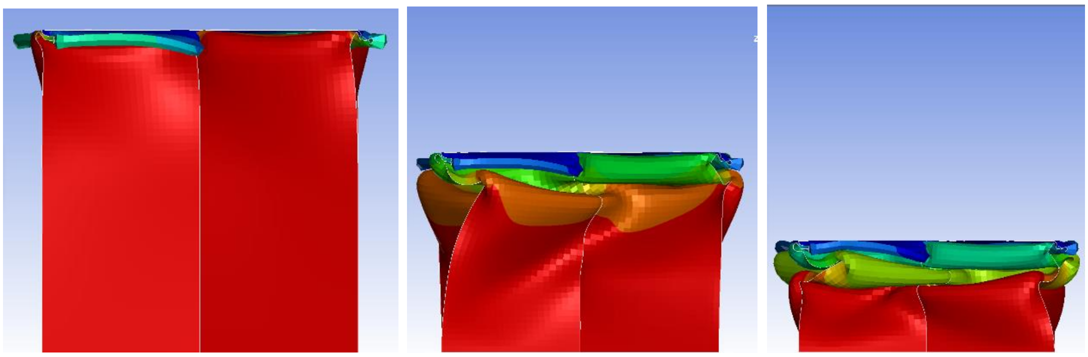

Figure 4-8: Baseline geometry at showing progressive buckling

Figure 4-8 shows the deformation pattern of the star crash box from front direction. The representative three states are shown in it. The left figure is at 2 ms, the middle is at 4 ms and right is at 6 ms. The buckling starts at triggered layers and next buckling occurs in 6 ms.

There is delayed deformation in the baseline geometry. In 2 ms, the deflection is in the part joined with the impactor. The deformation is still not significant in the 4 ms. In 6 ms, the deformation is significant showing first fold.

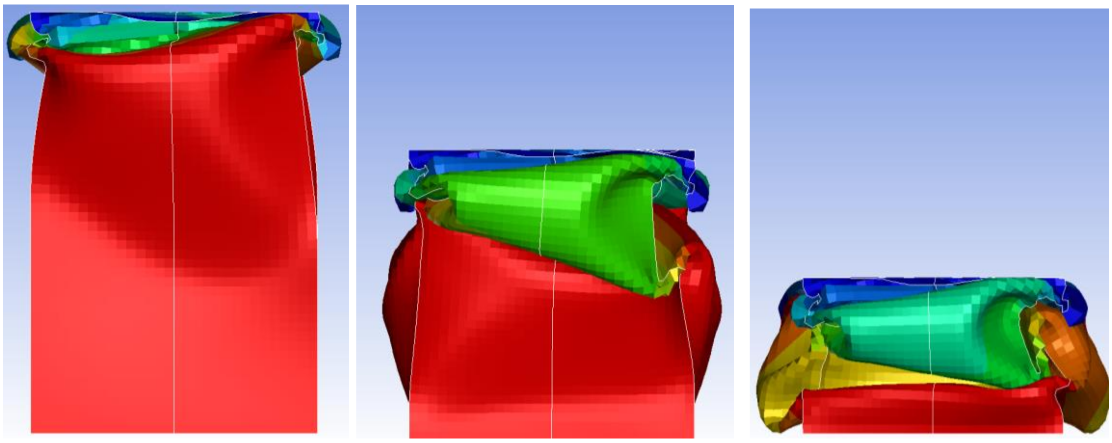

Figure 4-9: PSO optimized geometry showing progressive buckling

Figure 4-9 shows the deformation pattern of the star crash box from front direction.

The deformation starts early in case of optimized geometry using particle swarm optimization. More the deformation, more the energy absorbed by the crash box.

The number fold in PSO optimized geometry is more than that in baseline geometry. Also, the deformation pattern shows the buckling is inward in PSO optimized case.

4.1.4 Other crashworthiness parameters

A variety of metrics are utilized to assess the crashworthiness of energy-absorbing structures. These include measures such as energy absorption (EA), specific energy absorption (SEA), peak crush force (PCF), mean crash force (MCF), and crush force efficiency (CFE). In this study, we have studied peak crush force. It is imperative to restrict and maintain PCF (Peak Crush Force) at an acceptable level in crashworthiness design, prioritizing the safety of the survival space.

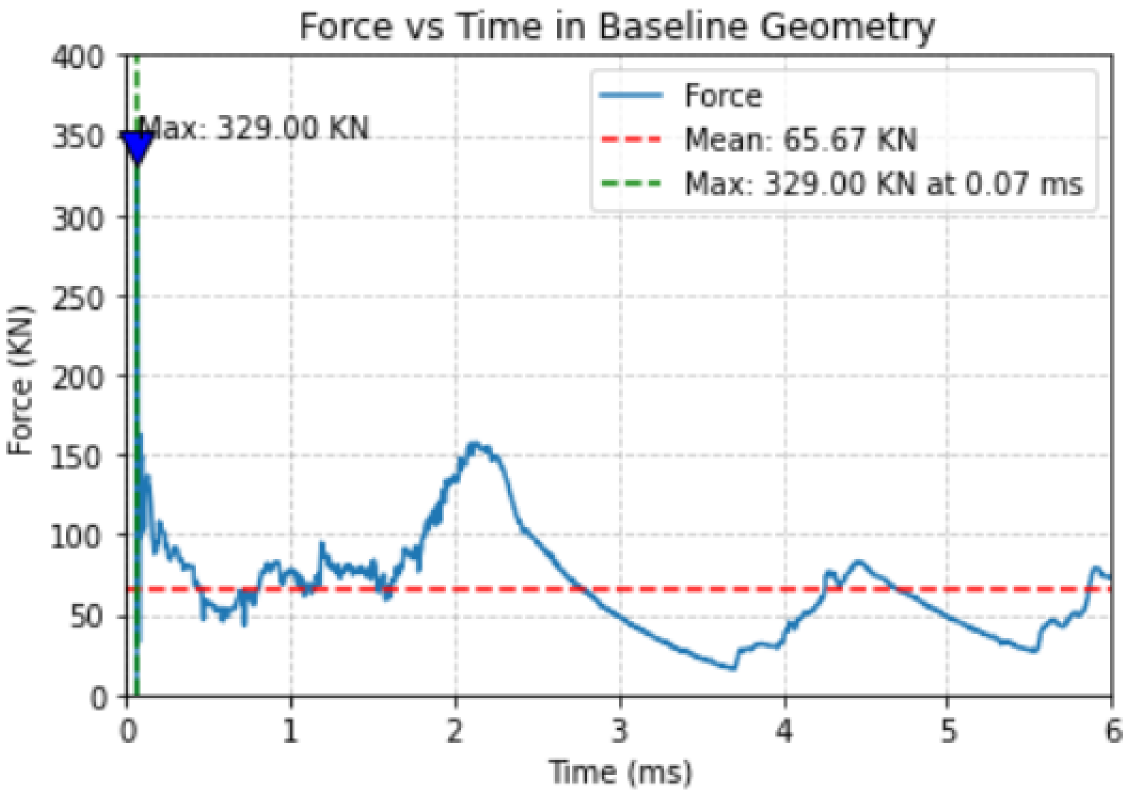

Figure 4-10: Force vs time (baseline)

The force vs time graph for baseline geometry is plotted in figure 4-10. The peak crushing force is 329 KN at 0.07 ms. The mean line is created using python script. The mean crushing force is 65.67 KN.

$$CFE = \frac{MCF}{PCF} \times 100\% = \frac{65.67}{329} \times 100\% = 19.96\ \%$$

Hence, the crushing force efficiency is equal to 19.96%.

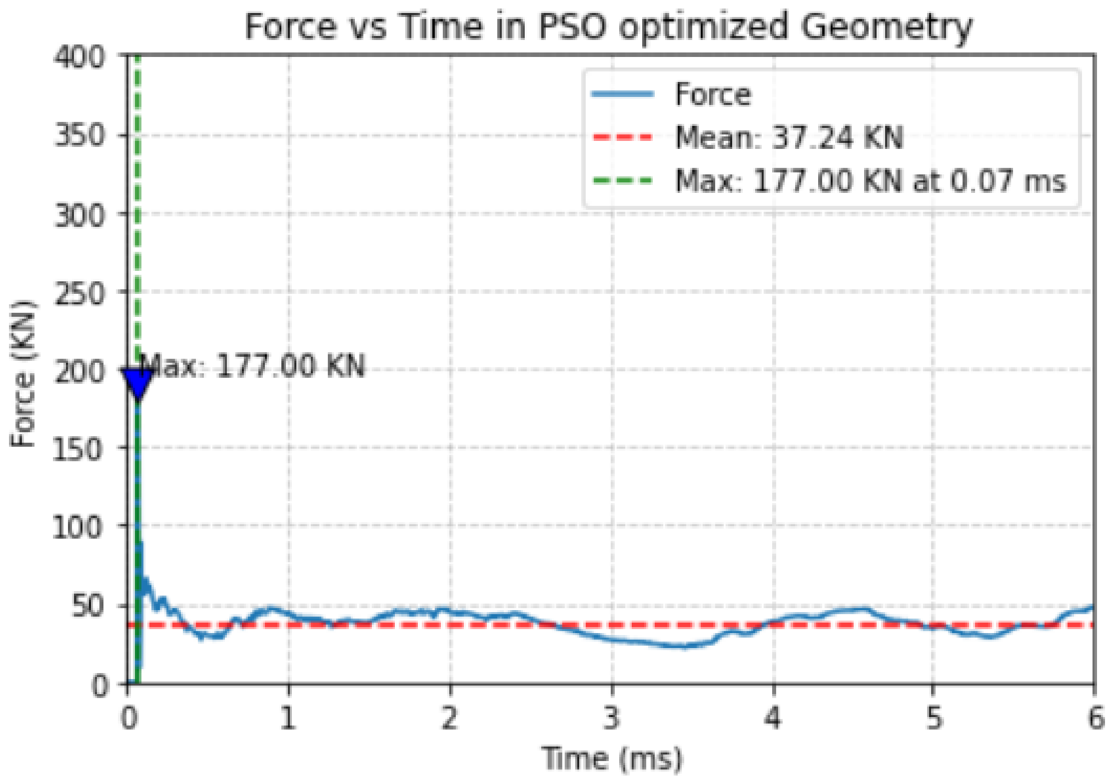

Figure 4-11: Force vs time (PSO)

The force vs time graph for PSO optimized geometry is plotted in figure 4-11. The peak crushing force is 177 KN at 0.07 ms.

The mean line is created using python script. The area under force time graph is calculated. Then this value is divided with the total time to obtain mean crushing force. The mean crushing force is 37.24 KN.

$$\text{CFE} = \frac{\text{MCF}}{\text{PCF}} \times 100\% = \frac{37.24}{177} \times 100\% = 21.11\ \%$$

Hence, the crushing force efficiency is equal to 21.11%.

The peak crushing force is more in case of baseline geometry. Also, the crushing force efficiency is less in it. This shows that the energy is dissipated to other parts of the automobile and hence can cause severe injury to the occupants. And, in case of PSO optimized geometry most of the energy is absorbed by the crash box leaving less amount of energy passing without absorption.

The force reaches to peak crushing force in short time. It is during impactor impacting in the crash box. The force time graph shows significant variation in baseline geometry whereas the variation is small in case of PSO optimized geometry.

4.2 Bayesian Optimization

The optimization study is then performed using Bayesian optimization. Initially the plot of specific energy absorption vs no. of iteration is done. The function parameters are given below.

Table 5: Function parameters of Bayesian Optimization

Function parameter	symbol	Values
Objective function	f	SEA from LS Dyna
Constraints	bound	[60,120],[60,120],[0,30],[0,30],[1.7,3]
Acquisition function	acq_func	Expected Improvement (EI)
No. of random initialization	n _calls	5
No of evaluation of f	n_random_calls	5
Random seed	random_state	1234

4.2.1 Specific Energy Absorption

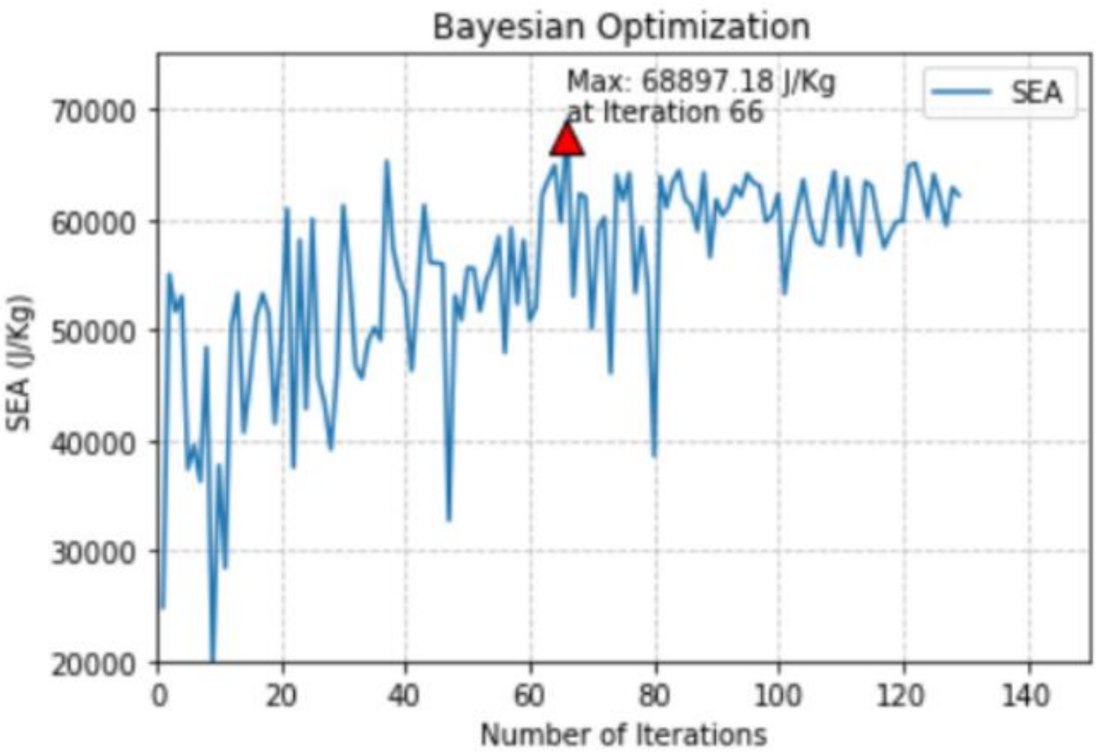

Figure 4-12: SEA vs No. of iteration (PSO)

In this case, the maximum value of 68.89 KJ/Kg of specific energy absorption is the maximum value. It is obtained at no. of iteration of 66. The plot is plotted in the figure 4-12.

4.2.2 Geometric Parameters

For the optimized geometry using Bayesian the maximum SEA of 68.89 KJ/Kg is obtained at geometric parameter values of a= 72.291 mm, b=75.314 mm, u = 20.162 mm, v = 4.978 mm and t = 0.985 mm.

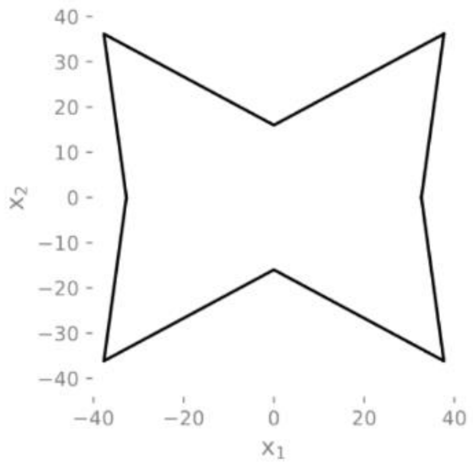

Figure 4-13: Optimized geometry using Bayesian optimization

From the baseline geometry, the value of height, width, y-intrusion and thickness are decreases and the value of x-intrusion is increased.

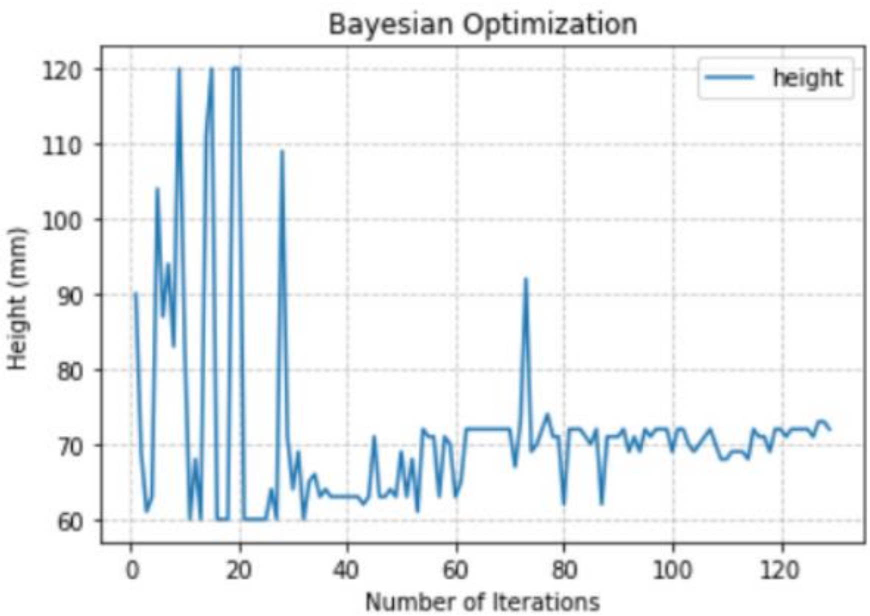

Figure 4-14: Height vs No. of iterations (Bayesian)

In the plot of height vs no. of iteration, the simulation is converged in about 122 simulations in value of height = 72 mm.

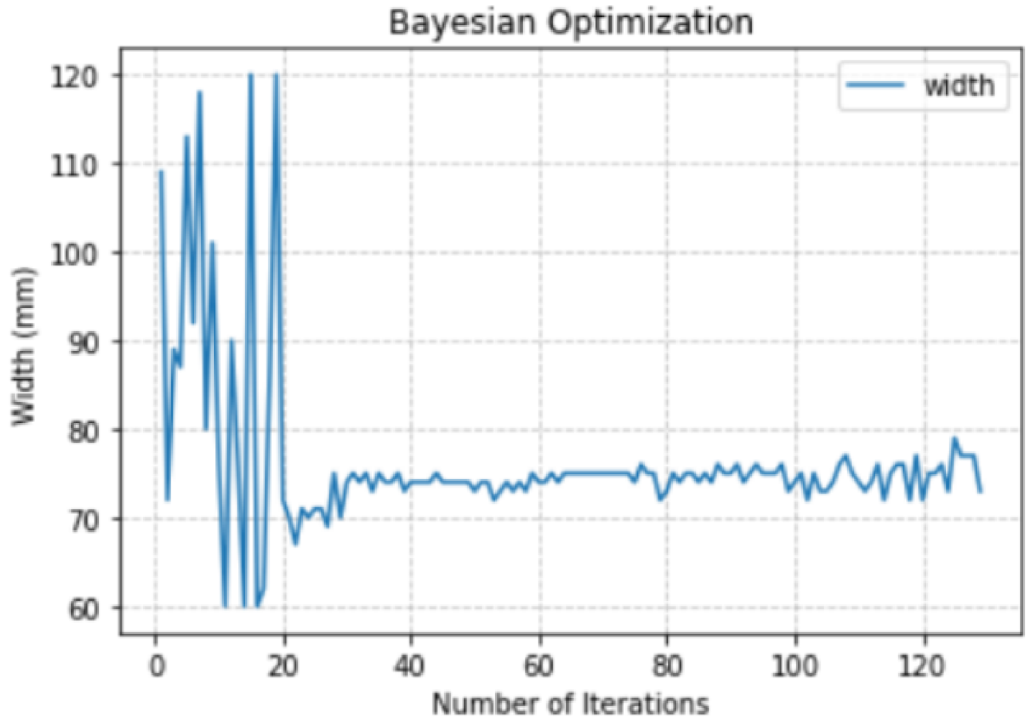

Figure 4-15: Width vs No. of iterations (Bayesian)

In the plot of width vs No. of iterations, there is initial fluctuation in values upto 4 set of random calls but after that simulation somewhat converged.

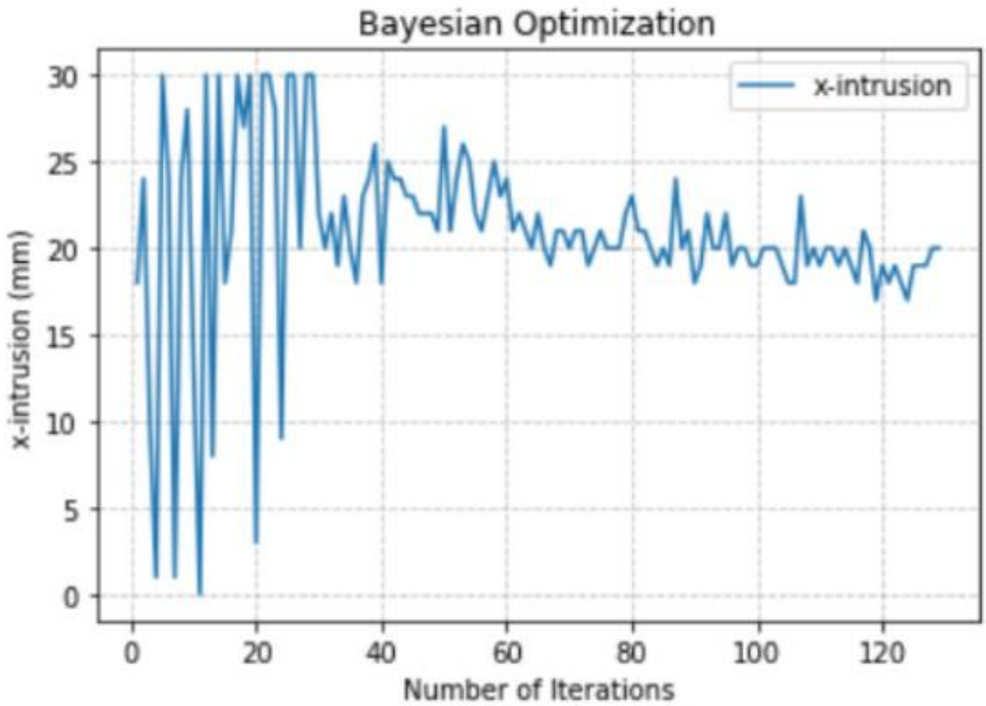

Figure 4-16: x-intrusion vs No. of iterations (Bayesian)

In the graph of x-intrusion vs no. of iterations, the simulation isn't converged properly but the range of values is near 20 mm.

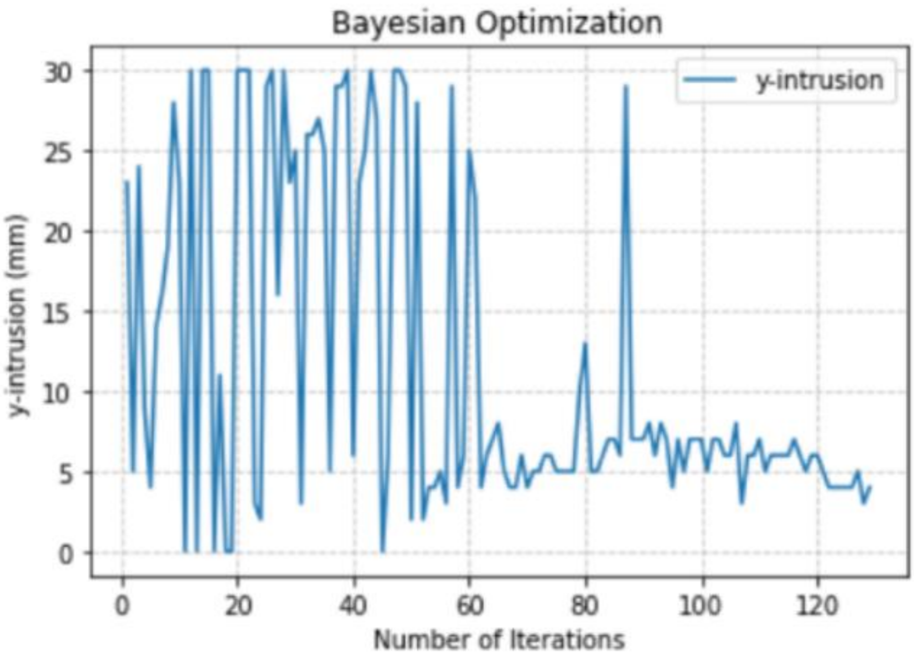

Figure 4-17: y-intrusion vs No. of iterations

In the graph of y-intrusion vs No. of iterations, there is noise up to 60 simulations, then the randomness decreases with exception of one peak. It converged near value of 5 mm.

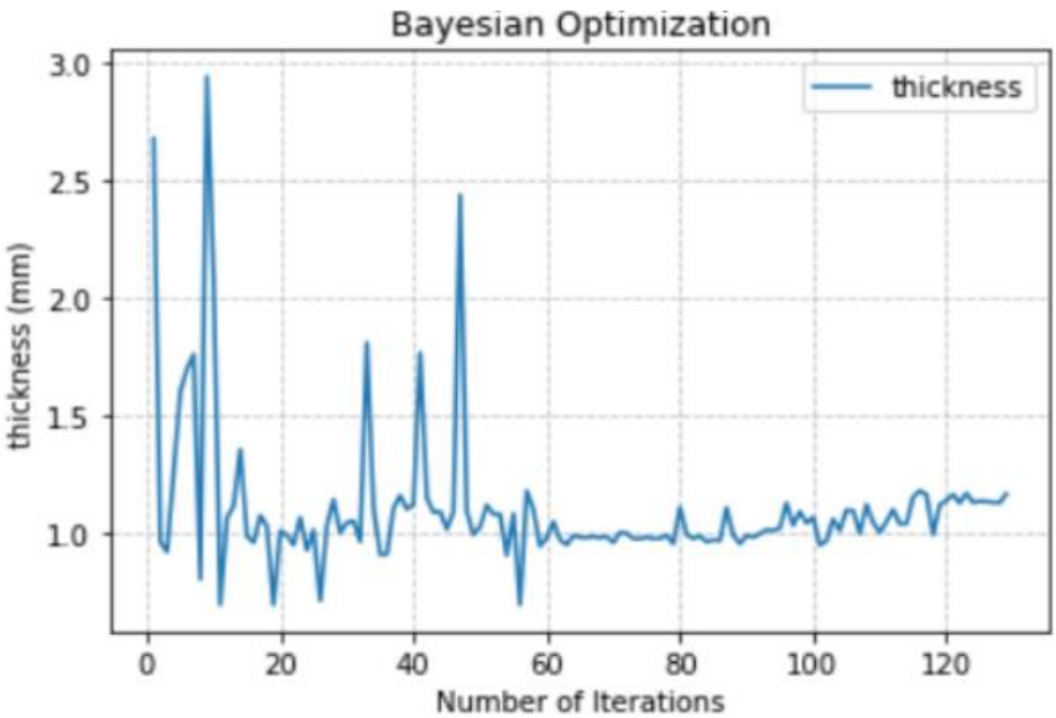

Figure 4-18: Thickness vs No. of iteration (Bayesian)

The value of thickness is not so fluctuating. It is finally converged near value 1 mm.

4.2.3 Deformation Pattern

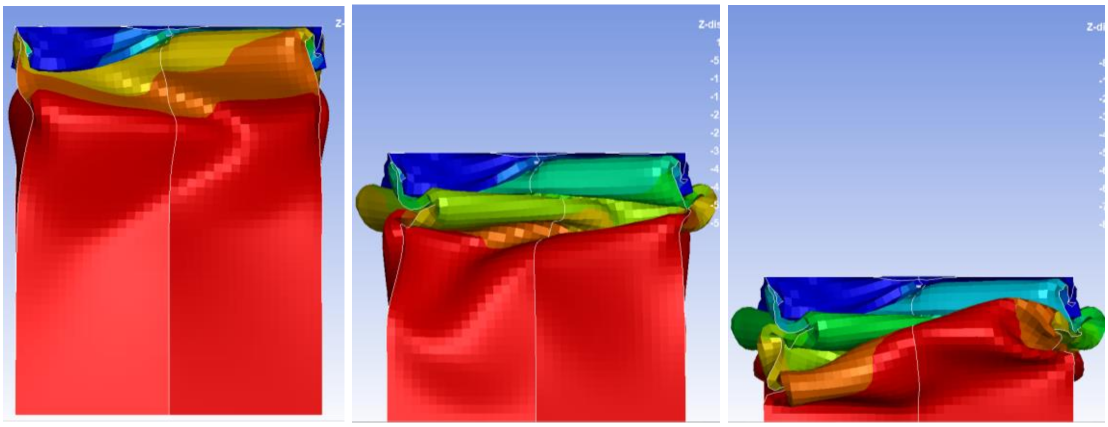

Figure 4-19: Bayesian optimized geometry showing progressive buckling

In the two second, the deformation is only in the part touching impactor. The deformation is more than that in baseline in 4s and in 6s, the complete fold appears in the simulation.

4.2.4 Other Crashworthiness Parameters

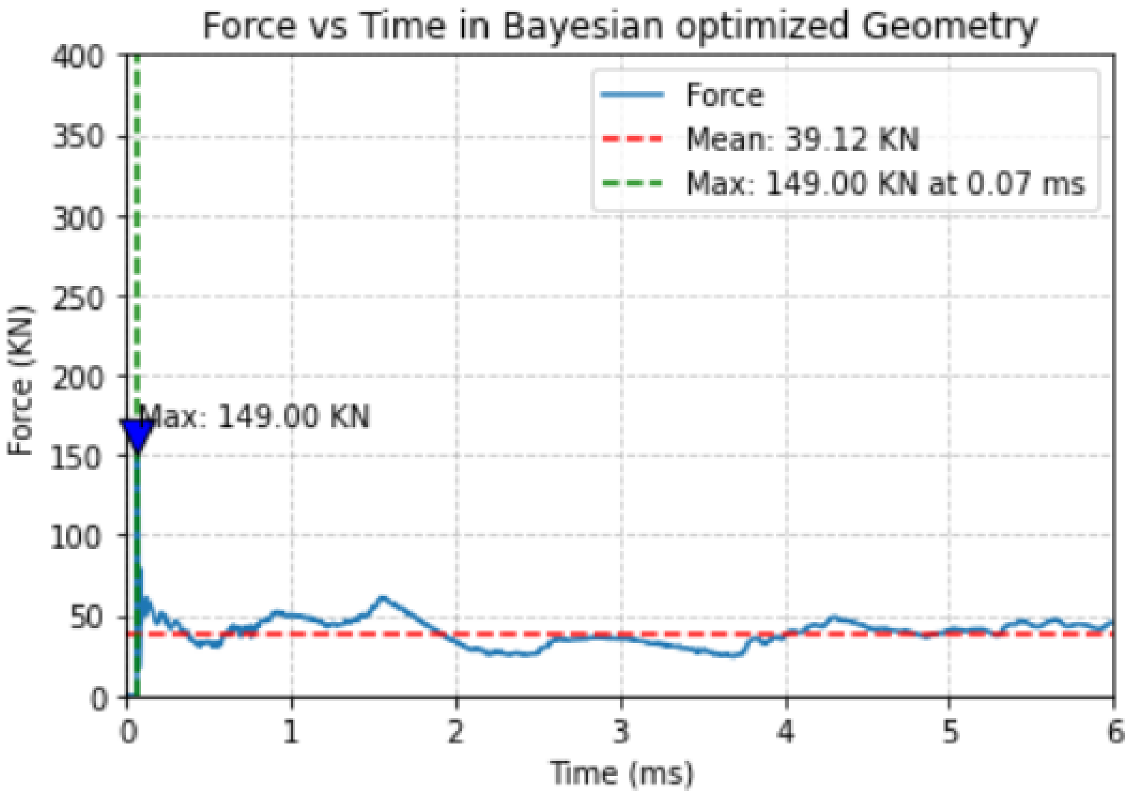

Figure 4-20: Force vs time (Bayesian)

The PCF is 149 N in the optimized geometry, the peak crushing force is less than that in baseline geometry. Hence, the optimized geometry enhances the crashworthiness.

The mean crushing force is calculated as 39.12 KN.

4.3 Comparison of Result from PSO and Bayesian optimization

The comparison of PSO and Bayesian optimization can be done in terms of crashworthiness parameters.

4.3.1 Specific Energy Absorption

Table 6: SEA Optimization using Bayesian and PSO

Optimization	a (mm)	b (mm)	u (mm)	v (mm)	t (mm)	SEA (KJ/Kg)
Baseline	90	90	15	15	1.85	37.948
PSO	60	112.42	13.876	0	0.987	63.777
Bayesian	72.291	75.314	20.162	4.978	0.985	68.897

The baseline geometry, representing an initial design point, was established using median values of design parameters. Both Bayesian and traditional optimization algorithms significantly improved SEA compared to the baseline. The Bayesian algorithm outperformed the traditional approach due to its efficient exploration of the design space and its probabilistic framework for identifying promising regions.

4.3.2 Convergence and computational time

When applying computational techniques, simulation time is a critical factor to consider. PSO required significantly more simulation time than Bayesian optimization. Bayesian optimization converged within 125 iterations, while PSO failed to converge within 480 simulations under the specified criteria.

This difference in efficiency can be attributed to the algorithms' inherent nature. PSO's population-based approach is computationally demanding, while Bayesian optimization's probabilistic approach and adaptive nature make it more efficient, particularly for complex problems.

4.3.3 Other Crashworthiness Parameters

PCF defines the crashworthiness behavior of the crash box. Less value of PCF is good for crashworthiness.

Table 7: Crashworthiness parameters from different optimization

Optimization	PCF(KN)	MCF (KN)	CFE (%)
Baseline	329	65.67	19.96
PSO	176.4	37.24	21.11
Bayesian	149.0	39.12	26.25

Bayesian optimization and Particle Swarm Optimization (PSO) in optimizing crash box design is compared. Bayesian optimization outperformed PSO in optimizing crushing force efficiency (CFE), achieving a 26.25% CFE compared to PSO's 21.11%. This indicates that Bayesian optimization can effectively design crash boxes that absorb more energy per unit mass, enhancing vehicle crashworthiness.

While Bayesian optimization resulted in a lower peak crushing force compared to PSO, this is not necessarily detrimental as the gradual and controlled deformation of a crash box is crucial for absorbing energy and preventing excessive occupant injuries. Both optimization algorithms effectively maintained the overall energy absorption capacity of the crash box.

Bayesian optimization emerges as a superior optimization technique for crashworthiness design, particularly in optimizing CFE. The study also highlights the effectiveness of population-based optimization techniques, such as PSO, in crash box design.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The study explored the optimization of geometric design parameters for a star crash box using particle swarm optimization (PSO) and Bayesian optimization. The goal was to maximize specific energy absorption (SEA) while maintaining a balance between lightweight design and effective energy absorption.

From our analysis, we come to the following conclusions:

- Particle Swarm Optimization (PSO) effectively optimized the geometric design of a star crash box, resulting in a significant improvement in specific energy absorption (SEA) from 37.94 KJ/Kg to 63.77 KJ/Kg. This enhanced energy absorption is attributed to the early deformation initiation and increased fold formation observed in the PSO-optimized geometry, indicating a more effective energy dissipation process. The optimized geometry also demonstrated superior force-time characteristics compared to the baseline geometry. The peak crushing force was reduced from 329 KN to 177 KN, and the crushing force efficiency increased from 19.96% to 21.11%. This suggests that the PSO-optimized crash box absorbs more energy and transmits less force to the vehicle structure, potentially reducing the risk of occupant injury.
- The Bayesian optimized crash box geometry exhibits enhanced crashworthiness performance, demonstrated by a maximum specific energy absorption (SEA) of 68.89 kJ/kg, a lower peak crushing force (PCF) of 149 N, and a mean crushing force (MCF) of 39.12 kN. The optimized geometry effectively absorbs impact energy, minimizing the force transmitted to the vehicle structure and reducing the risk of occupant injury. The observed deformation patterns indicate controlled and progressive energy dissipation, with complete fold formation occurring in 6 seconds of simulation time.
- Bayesian optimization and Particle Swarm Optimization (PSO) have emerged as effective techniques for optimizing crash box design, resulting in enhanced SEA, CFE, and overall crashworthiness performance. Bayesian optimization demonstrated superior performance in terms of both SEA and CFE, attributable to its efficient exploration of the design space, probabilistic framework, and computational efficiency. PSO, on the other hand, highlighted the potential of

population-based optimization techniques in crash box design. Both optimization algorithms effectively maintained the overall energy absorption capacity of the crash box, ensuring effective energy dissipation and occupant protection. However, Bayesian optimization emerged as the superior technique for crashworthiness design, particularly in optimizing CFE, a critical metric for crash box performance.

5.2 Recommendations

Following recommendations are recommended:

- Conduct experimental validation of the optimized geometry using your own setup to confirm the theoretical findings and verify the effectiveness of the PSO and Bayesian algorithm in real-world conditions.
- Expand the optimization framework to incorporate multi-objective optimization, considering factors such as material selection, safety performance, and specific energy absorption (SEA) simultaneously. This will provide a more comprehensive understanding of the trade-offs between different design objectives.
- Investigate model order reduction techniques to reduce the computational time and cost of the research. This will allow for more efficient optimization and evaluation of crash box designs, leading to faster and more cost-effective design iterations.

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APPENDIX: PSEUDO CODES

Pseudo code for PSO

Initialize population
for $t = 1$: maximum generation
  for $i = 1$: population size
    if $f\left(x_{i,d}(t)\right) < f\left(p_i(t)\right)$ **then** $p_i(t) = x_{i,d}(t)$
      $f\left(p_g(t)\right) = \min_i\left(f\left(p_i(t)\right)\right)$
    end
    for $d = 1$: dimension
      $v_{i,d}(t+1) = wv_{i,d}(t) + c_1 r_1\left(p_i - x_{i,d}(t)\right) + c_2 r_2\left(p_g - x_{i,d}(t)\right)$
      $x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t+1)$
      if $v_{i,d}(t+1) > v_{\max}$ **then** $v_{i,d}(t+1) = v_{\max}$
      else if $v_{i,d}(t+1) < v_{\min}$ **then** $v_{i,d}(t+1) = v_{\min}$
      end
      if $x_{i,d}(t+1) > x_{\max}$ **then** $x_{i,d}(t+1) = x_{\max}$
      else if $x_{i,d}(t+1) < x_{\min}$ **then** $x_{i,d}(t+1) = x_{\min}$
      end
    end
  end
end

Pseudocode for Bayesian Optimization

Input (hyper-parameter space Θ, Target score function $H(\boldsymbol{\theta})$, max n° of evaluation $\boldsymbol{n_{max}}$)

Select an initial configuration $\boldsymbol{\theta_0} \in \Theta$

Evaluate the initial score $y_0 = H(\boldsymbol{\theta_0})$

Set $\boldsymbol{\theta}^* = \boldsymbol{\theta_0}$, $\mathbf{y}^* = H(\boldsymbol{\theta_0})$, *and* $S_0 = \{\boldsymbol{\theta_0}, y_0\}$

For n=1,...,n_{max} **do**

Select a new hyper-parameter configuration $\boldsymbol{\theta_n} \in \Theta$ *by optimizing an acquisition function* U_n

$$\boldsymbol{\theta}_{\mathrm{n}} = \arg\max_{\boldsymbol{\theta}\in\Theta} U_n(\boldsymbol{\theta}; S_t),$$

Evaluate H *in* $\boldsymbol{\theta_n}$ *to obtain a new numeric score* $y_n = H(\boldsymbol{\theta_n})$

Augment the data $S_n = S_{n-1} \cup \{\boldsymbol{\theta_n}, y_n\}$

Update the surrogate model

If $y_n < F^*$

$\theta^* = \theta_n$ and $y^* = y_n$

End if

end for

Output: θ^* and y^*

Shape optimization by PSO and Bayesian optimization.pdf

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Particle Swarm Optimization of Star Crash Box

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ABSTRACT Crash box is energy-absorbing component to ensure the passive safety of vehicles during frontal crash. For crash-boxes - lightweight design, safety requirements absorbing energy are relevant. This research aims to determine the value of geometric design parameters in design space of star crash box optimizing specific energy absorption (SEA). The geometric modelling, meshing and finally input file for LS dyna is created using python scripting. Crash simulation is performed in LS Dyna. The energy absorption is taken from glstat of binout file and mass is taken from massout file. The particle swarm optimization is done using skopt python module. The geometric design parameters used are height (a), width (b), x-intrusion (u), y- intrusion (v) and thickness (t). For each simulation reference material Mild steel with density 7830 kg/m^3, Young's modulus 200 GPa and cowper-symond parameters c = 40s^{-1} and p = 5 is used. The impactor of 250 kg mass with speed of 15 mm/ms is used. After running simulations in batch mode, the maximum SEA of 63777.547 J/Kg is obtained at the values a = 60 mm, b = 112.420 mm, u = 13.876 mm, v = 0 mm and t = 0.987.

INDEX TERMS crash box, specific energy absorption, crash simulation, particle swarm optimization, progressive buckling, failure-mode

1. INTRODUCTION

With the increase in population, the number of automobiles is also increasing. Road traffic crashes result in the deaths of approximately 1.3 million people per year and about 93% of this case comes from middle income and low-income countries like Nepal [1]. The number of frontal collisions is significantly more than side collisions. This has increased the need of enhancing safety of the vehicle and its occupants. Crash box is important component of vehicle for passive safety of vehicle and its occupants during frontal crash. It serves as a kinetic energy absorber during collision. It is a tube shape thin-walled structure, which is located between bumper and chassis. During collision, it undergoes progressive buckling plastic deformation thereby absorbing most of the energy prior to the transfer the main cabin of a vehicle. The specific modes of deformation observed in crash box design and collapse behavior are concertina mode and diamond mode.

Concertina mode is a deformation pattern characterized by a series of accordion-like folds or wrinkles along the length of a structure, resembling the folds of a concertina musical instrument. Diamond-shaped deformation occurs when a thin-walled structure undergoes a collapse, and the resulting folds or distortions take on a pattern resembling diamond shapes. The failure of the crash box should ensure crashworthiness.

The crashworthiness of a structure refers to its ability to shield its occupants during collisions. The ultimate objective is to enhance the crash response of the structure, thus safeguarding the occupants. Crashworthiness evaluates a structure's capacity to shield occupants during impact and must meet two fundamental requirements i) It must absorb high levels of energy via controlled plastic deformation and ii) it must maintain a minimum survival space to avoid injury [2]. Along with it, lightweight and economical are the requirement of automotive industries. Hence, specific energy absorption, the ratio of energy absorbed by the structure to the mass of the structure measures the crashworthiness of crash box. Different optimization algorithms can be used for the optimized value of the design parameters in design space. Optimization is the process of finding the best solution for a given problem within a defined set of possible solutions. the crash behavior is highly nonlinear, making it complex to find an optimized design that maximizes energy absorption. Population-based optimization is a type of optimization strategy that involves maintaining a population of candidate solutions and iteratively evolving this population to improve the overall performance with respect to an objective function. This approach is particularly useful for complex and nonlinear optimization problems like crash behavior of crash box.

2. LITERATURE REVIEW

Crash box design is based on energy absorption of thin-walled structure. The mechanics and analysis of thin-walled structures dates back to 1960s. Initially J.M. Alexander studied collapse of thin cylindrical shells under axial loading during concertina mode failure [3]. The more general case of failure is diamond shape. The crumpling of thin cylindrical column under diamond pattern of deformation is studied by A. Pugsley and M. Macaulay. The empirical relation of load required to crumpled is obtained by equating internal and external work. And the critical buckling load was much below from the classical theory based on small deflection [4]. The concertina mode of failure is in thick tubes and diamond mode of failure is in thin tubes. The transition is calculated at R/t value of 45 and the transition is due to post elastic behavior [5]. T Wierzbicki and W. Abramowicz showed that the zones of extensional deformations are restricted to even smaller fraction of the total area of the shell but they always contribute to as much as one-third of the total energy dissipated in the structure. The remaining two-thirds of the energy results in equal proportions from in extensional deformations at stationary and moving hinge lines. In all types of shell, the mean crushing force depends markedly on the thickness of the shell. At the same time the dependence on the linear dimension is much weaker [6]. They later gave mean crushing load for the design of metal honeycomb as energy absorbers [7]. In 1984, W Abramowicz modified alexander's theoretical solution. He considered effective crushing distance in static crushing and influence of material strain rate sensitivity is retained in case of dynamic crushing, the experimental validated the result [8]. Then, the specific energy absorption of the foam filled structures was analyzed [9,10]. The specific energy absorption somewhat increased in case of axial loading but in case of oblique loading result was opposite. In both cases the change from hollow wasn't significant [13,14]. Then, [11,12] studied the crashworthiness during oblique loading.

The material of the crash box is metal structure with light weight. But the number of researches has been in different materials. At first, thermoplastic composite was used as crash box material. The crash performance of the optimum composite crash box was compared with the optimum aluminum tube. The optimum composite crash box absorbed about 17% more energy than the optimum aluminum tube while it had about 26% less weight [26]. Number of researches were done during negative poison's ratio (NPR)[19], CFRP/aluminum hybrid material [2], auxetic core[25] as crash box material. Structural and material design was combined to improve specific energy absorption. Simulation results outline the great potential of a combining structural design and material design with a high total specific energy absorption of 27 kJ/kg. The tension parts, made of fully recrystallized HMnS, developed an outstanding specific energy absorption of 67 kJ/kg [23].

In the optimization of the crash box crashworthiness, the topology optimization was studied at first [17,18]. Different geometrical shapes like square section with diagonal welding line, square section with middle welding line, rectangle section, hexagon section, circular section, and octagon section was studied and the square section with diagonal welding line turned out to be best according to simulation result [22]. The use of optimization algorithm was limited to response surface approximation and radial basis functions [9,15,16] earlier. In recent trend, the use of metaheuristic optimization models is in use due to their global search approach, iterative method, simple heuristic and less computational time. Also, these can find optimal solution in difficult and complex optimization problems [19,21]. The objective function of the crashworthiness problem is used as specific energy absorption [23,21], energy absorption [9,10,15], area in between displacement curve [21,20], strain energies weighted at specified times [17] etc. Other objective functions suggested are internal energy, mass, maximum force, maximum acceleration and time for wall to stop [21]. The constraint can be volume [17] and maximum displacement [18]. The optimization objective of area between displacement curve and among meta heuristic optimization model, particle swarm optimization was suggested [21].

In reference to the literature, the star shape which can be made square, two honeycomb structure in its design space is selected for optimization. The PSO algorithm which works even works in the highly non-linear crushing of crash box is taken as optimization algorithm. The constraint is that the maximum displacement should be less than half of the length of the crash box. For the simplicity, the specific energy absorption is taken as the objective function.

3. METHODOLOGY

The initial design variables of the Finite element simulation are the cross-sectional dimension of the crash box. Based on the initial design variables, a LS dyna input file is created with proper meshing and simulation control in .k format. Now the simulation is run. The result of the LS Dyna file consists of binout file from where we can extract the energy absorbed and massout file from where we can extract the mass of crash box. Now in a different python file we call values of geometric parameter and we get result as energy/mass. Since we need maximum value instead of minimum, we return the negative value of specific energy absorption. Now, the PSO algorithm works and give new set of design variables which goes into FE simulation and the cycle runs till given number of iterations or the convergence criteria is met.

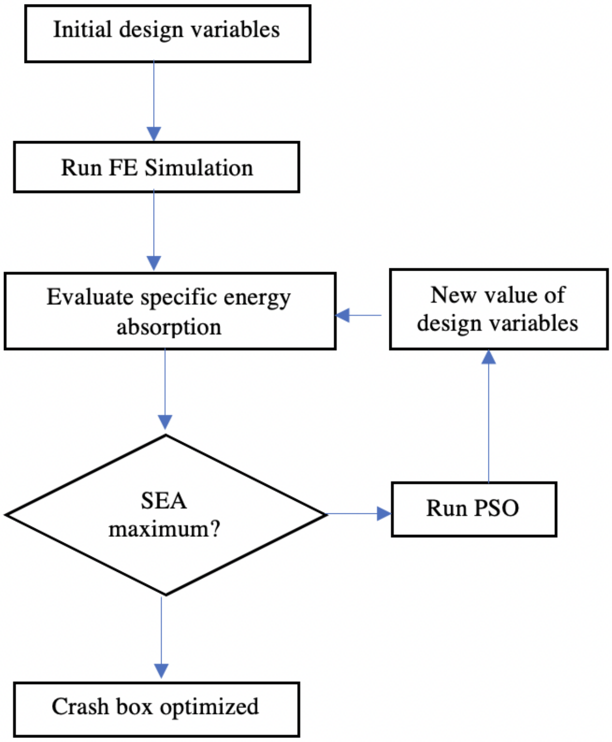

FIGURE 1. **Flow Chart**

4. NUMERICAL MODELLING

The numerical modelling step includes all the steps for numerical simulation. They are explained below.

4.1 Geometric Modelling

The cross-sectional geometry of the crash box is star shaped and it is extruded to the length with a one groove near the top place. But we only deal with the cross-sectional design parameters. They are height(a), width (b), x -intrusion(u), y-intrusion(v) and thickness(t) as shown in figure 2. The intrusion in x and y direction are symmetric in both sides.

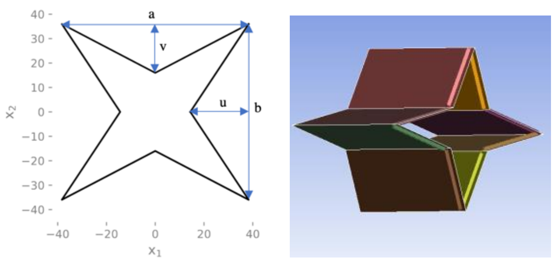

FIGURE 2. **Geometry with parameters(left) and in LS Dyna (right)**

The design space of the star crash box is a = [60,120], b = [60,120], u = [0.30], v = [0,30] and t= [0.7,3]. It is wide design space which includes degenerated shapes as shown in the figure 3.

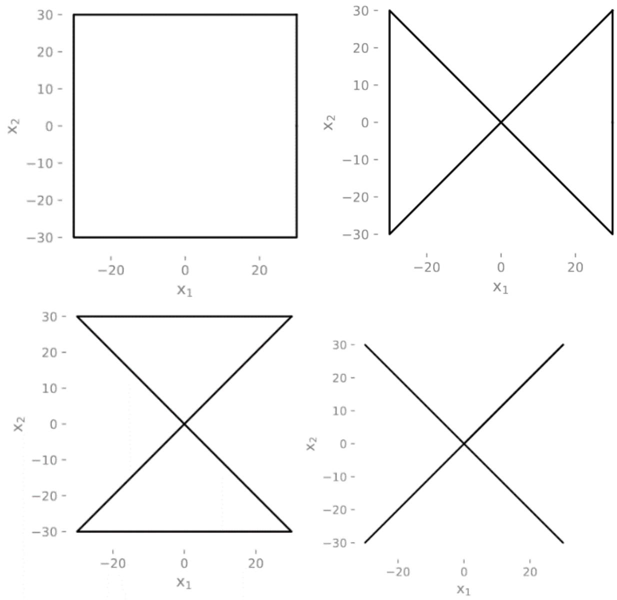

FIGURE 3. **Degenerated star shaped geometry**

The design space thus includes the square cross section, vertical and horizontal two triangular cross-sectional structure and part of honeycomb structure.

4.2 Meshing

The star crash box is meshed using Python script. Its simplified geometry allows for hex meshing on all surfaces, which reduces computational time and aids simulation convergence. The input for the mesh is the size of mesh in the code.

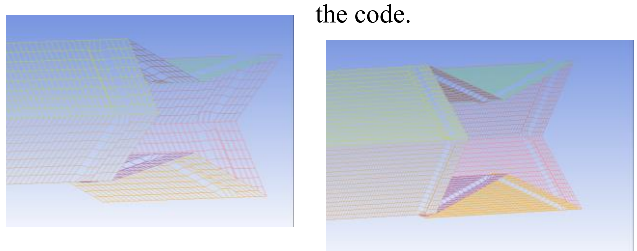

FIGURE 4. **Mesh with size 1 mm (right) and 4 mm (left)**

4.3 Material Properties

Conventionally, the steel and Aluminium are used as the material of the crash box. The mild steel is used due to high tensile strength and ductility. The optimize material for the crash box is out of scope of this research. Hence for simplicity, the mild steel is taken as reference material. It has following properties.

TABLE I
MATERIAL PROPERTIES

Property	Value
Density (ρ)	7830 kg/m^3
Young's modulus (E)	200 GPa
Poisson's ratio (μ)	0.3
Cowper Symond Parameter (c)	40s^{-1}
Cowper Symond Parameter (p)	5

4.4 Boundary Conditions

The boundary consists of impactor and rigid wall. One side of the crash box has the rigid wall and impactor with mass of 250 kg approaches with velocity 15 mm/ms in the other side for crashing.

5. RESULTS AND DISCUSSIONS

The result of the research is segregated in to optimization result, simulation result and other crashworthiness results.

5.1 Optimization Results

The numerical simulation in LS dyna is combined with PSO optimization algorithm in python. After running 500 simulations in batch mode, the maximum SEA of 63777.547 J/Kg is obtained. at the values a = 72.291 mm, b = 75.314 mm, u = 20.162 mm, v = 4.978 mm and t = 0.985 mm.

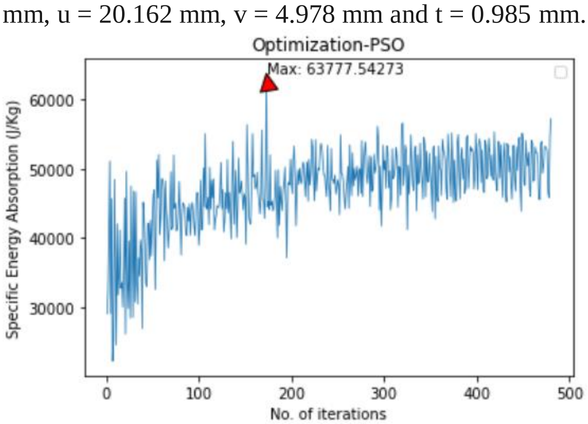

FIGURE 5. SEA vs No. of Iterations using PSO

The PSO algorithm don't necessarily converge for the best solution. In this case the value of SEA is about 100% more than that of baseline value. Graph of other geometric parameters vs no. of iteration is given in Figure 6.

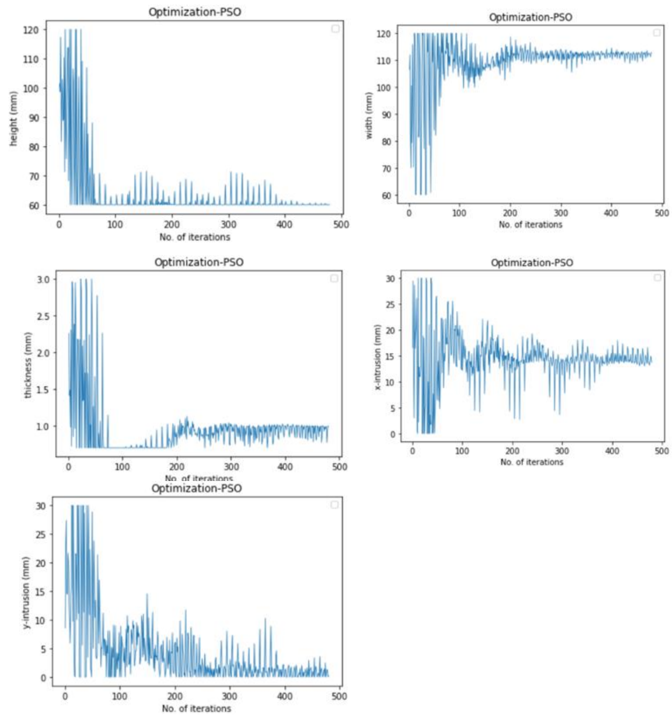

FIGURE 6. Geometric Parameters vs No. of iteration in PSO

5.2 Simulation Results

The numerical simulation of crash box is done in LS dyna without optimization with baseline values. The values of geometric parameters are a= 90 mm, b = 90 mm, u = 15 mm, v = 15 mm and t = 1.85. From the simulation result, the SEA of 37948.57 J/Kg is obtained. For the optimized geometry the maximum SEA of 63777.547 J/Kg is obtained at the values a = 60 mm, b = 112.420 mm, u = 13.876 mm, v = 0 mm and t = 0.987.

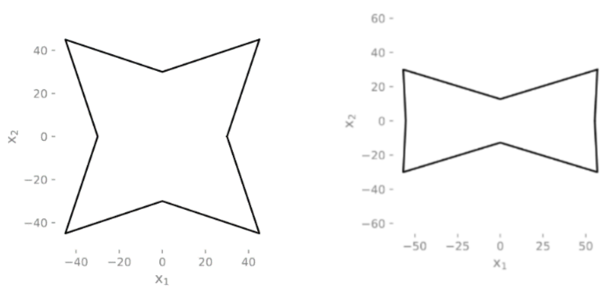

FIGURE 7. Baseline geometry (left) and optimized geometry (right)

This shows the population-based optimization technique can be exploited for the design of the crash box to significantly increase the specific energy absorption capacity hence increasing crashworthiness.

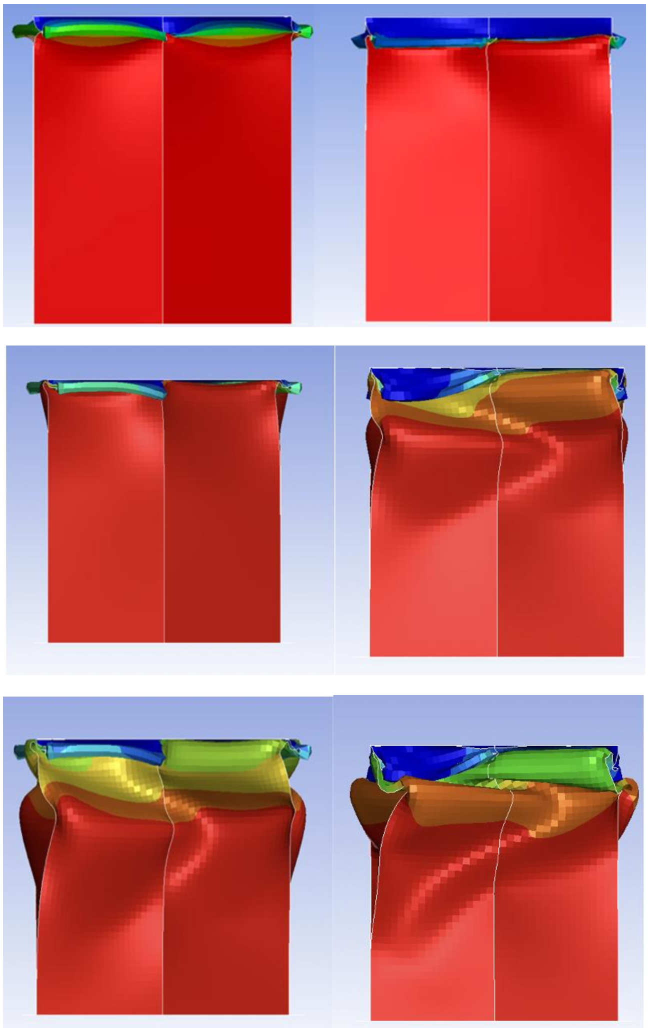

FIGURE 8. **Baseline (left) and optimized geometry (right) at 1s (top) 2s (middle) and 3s (bottom) showing progressive buckling**

The energy absorbed by the crashbox depends on the geometric parameters. The optimized geometry takes the high energy in short time than the baseline in this case. The progressive bucking starts early in it as shown in Figure. Hence it absorbs more energy than the baseline geometry.

5.3 Other Crashworthiness Parameters

A variety of metrics are utilized to assess the crashworthiness of energy-absorbing structures. These include measures such as energy absorption (EA), specific energy absorption (SEA), peak crush force (PCF), mean crash force (MCF), and crash force efficiency (CFE). In this study, we have studied peak crush force. It is imperative to restrict and maintain PCF (Peak Crush Force) at an acceptable level in crashworthiness design, prioritizing the safety of the survival space.

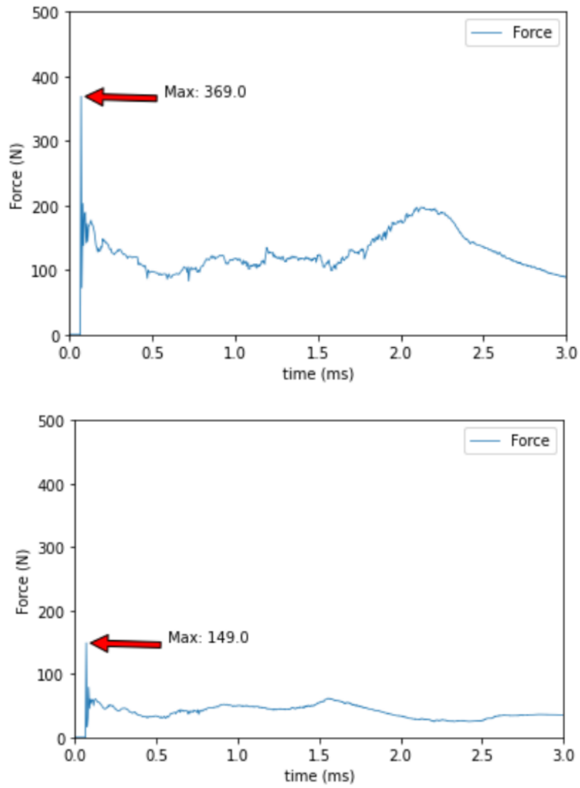

FIGURE 10. **Force vs time graph in Baseline (top) and optimized geometry (bottom).**

In the optimized geometry, the peak crushing force is less than that in baseline geometry. Hence, the optimized geometry enhances the crashworthiness.

6. CONCLUSIONS

In this paper, the optimization of the star crash box using PSO was done. The geometric design parameters had important effect in the crashworthiness of the crash box. The values of geometric parameters in baseline geometry of star crash box were a= 90 mm, b = 90 mm, u = 15 mm, v = 15 mm and t = 1.85. From the simulation result, the SEA of 37948.57 J/Kg was obtained. Using PSO optimization algorithm, 480 simulations was run in batch mode. The maximum SEA of 63777.547 J/Kg was obtained at the values a = 60 mm, b = 112.420 mm, u = 13.876 mm, v = 0 mm and t = 0.987. The progressive bucking started early in the optimized geometry than baseline absorbing more energy. In the optimized geometry, the peak crushing force was less than that in baseline geometry. Hence, the optimized geometry enhanced the crashworthiness. So, the population-based optimization technique can be instrumental for the design of crash box which shows highly non-linear crash behavior.

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