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Data-Driven Multi-Objective Topology Optimization of Electric Vehicle Body-in-White under Real Crashworthiness and Battery Protection Constraints Using Euro NCAP and NHTSA Datasets

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Abstract

The increasing structural complexity of modern electric vehicles has introduced substantial challenges in achieving simultaneous lightweight performance, crashworthiness enhancement, and battery safety protection. Unlike conventional internal combustion vehicles, electric vehicle body-in-white (BIW) structures must withstand severe multi-directional crash loads while minimizing deformation transfer to battery enclosures and preserving occupant survivability. Existing optimization approaches often focus on either lightweighting or crash energy absorption independently and rarely integrate real-world crash datasets with multi-objective topology optimization frameworks. This limitation reduces the practical applicability of many current structural optimization methodologies in industrial electric vehicle development. This study proposes a data-driven multi-objective topology optimization framework for electric vehicle BIW structures using real crashworthiness constraints extracted from Euro NCAP and NHTSA datasets. The proposed methodology integrates finite element crash simulations, machine learning-based surrogate modeling, and non-dominated sorting genetic algorithm II (NSGA-II) optimization to simultaneously minimize structural mass and peak battery intrusion while maximizing crash energy absorption performance. Frontal offset impact, side pole impact, and progressive deformable barrier crash scenarios were incorporated into the optimization process to represent realistic multi-load operating conditions. The topology optimization domain was defined around critical BIW load paths, including rocker panels, side members, cross beams, and battery-supporting substructures. A hybrid surrogate-assisted optimization architecture was developed to reduce computational cost while maintaining high prediction accuracy for crash responses. Multiple crash indicators, including intrusion displacement, specific energy absorption, peak deceleration, and structural stiffness, were considered as objective functions and constraints. The optimized BIW configuration demonstrated substantial improvements in crashworthiness behavior compared with the baseline structure. Numerical analyses indicated reductions in battery intrusion and structural mass while preserving compliance with Euro NCAP side-impact safety thresholds. The obtained Pareto-optimal solutions revealed strong nonlinear relationships between lightweight design strategies and crash energy management mechanisms. The results further demonstrated that integrating data-driven surrogate models with topology optimization significantly improves optimization efficiency under multi-load crash conditions. The proposed framework provides a scalable methodology for next-generation electric vehicle structural design and offers practical implications for safety-oriented lightweight vehicle development under increasingly stringent international crash regulations.

Keywords: Electric Vehicle; Topology Optimization; Crashworthiness; Battery Protection; Data-Driven Design

1- Introduction

The rapid global transition toward electrified transportation systems has significantly transformed the structural design philosophy of modern passenger vehicles. In recent years, electric vehicles (EVs) have become a dominant research and industrial focus due to increasingly strict environmental regulations, carbon neutrality targets, and advancements in battery technologies. Despite these developments, the integration of large battery systems within vehicle platforms has introduced major engineering challenges associated with structural safety, crash energy management, and lightweight design optimization. Compared with conventional internal combustion engine vehicles, electric vehicles exhibit substantially different load transfer mechanisms because of battery pack positioning, altered mass distribution, and reinforced underbody architectures [1].

One of the most critical structural components in electric vehicles is the Body-in-White (BIW), which acts as the primary load-bearing framework responsible for maintaining occupant safety during collision events. The BIW structure must simultaneously provide sufficient torsional rigidity, impact resistance, fatigue durability, and lightweight characteristics while protecting high-voltage battery systems from mechanical intrusion during severe crashes. The conflicting nature of these requirements has made multi-objective structural optimization an essential research topic in electric vehicle engineering [2].

Recent developments in automotive lightweighting strategies have intensified the need for advanced optimization techniques capable of balancing crashworthiness and mass reduction objectives. Traditional sizing optimization approaches are often insufficient for handling the increasing geometric and functional complexity of EV structures. Consequently, topology optimization has emerged as an effective computational framework for identifying optimal material distributions under multiple loading conditions. Unlike conventional parameter tuning methods, topology optimization enables the discovery of entirely new structural load paths that significantly improve energy absorption efficiency and stiffness-to-weight ratios [3].

In electric vehicle applications, crashworthiness optimization cannot be separated from battery protection considerations. During frontal, side, or pole impacts, excessive deformation in the underbody or side sill regions may directly compromise battery enclosure integrity, potentially leading to thermal runaway, electrical short circuits, or post-crash fire hazards. Therefore, modern EV structural design increasingly requires simultaneous consideration of occupant injury reduction and battery intrusion prevention [4]. This dual safety requirement has motivated researchers to integrate crash energy absorption mechanisms with battery protection-oriented structural reinforcement strategies [5].

Recent studies have demonstrated that side-impact loading conditions represent one of the most severe threats to battery safety in electric vehicles. Under lateral collision scenarios, deformation propagation through rocker panels and floor cross-members may induce localized stress concentrations around battery modules. Liu et al. [6] showed that battery intrusion constraints substantially alter optimal load transfer paths in electric vehicle side structures. Their findings indicated that conventional lightweighting strategies may unintentionally increase deformation sensitivity near battery compartments if battery-specific crash constraints are neglected during optimization procedures.

Alongside structural optimization advancements, the increasing availability of crash databases and high-fidelity simulation technologies has accelerated the adoption of data-driven design methodologies in automotive engineering. Traditional finite element crash simulations require extremely high computational resources, particularly when integrated with iterative optimization algorithms involving hundreds or thousands of design evaluations. To address this limitation, surrogate modeling and machine learning-assisted crash prediction methods have gained significant attention in recent years [7].

Data-driven surrogate models can establish nonlinear relationships between structural design variables and crash responses while substantially reducing computational cost. These models enable efficient exploration of high-dimensional design spaces without requiring excessive full-scale finite element analyses. Zhao et al. [8] demonstrated that surrogate-assisted optimization frameworks significantly improve convergence efficiency in vehicle crashworthiness design problems involving multiple conflicting objectives. Similarly, recent machine learning-assisted topology optimization frameworks have shown promising capabilities in accelerating lightweight structural development while preserving prediction accuracy [9].

Another important challenge in electric vehicle crashworthiness design arises from the presence of multiple real-world crash loading conditions. Regulatory organizations such as Euro NCAP and the National Highway Traffic Safety Administration (NHTSA) have introduced increasingly stringent crash evaluation protocols involving frontal offset impacts, side pole collisions, progressive deformable barrier tests, and far-side occupant protection scenarios. Optimizing EV structures under only a single crash condition often produces solutions that are highly load-case dependent and unsuitable for practical implementation [10]. Therefore, multi-load-case optimization frameworks are necessary to ensure robust structural performance under realistic accident scenarios.

In addition to deterministic optimization approaches, uncertainty-aware and robust optimization methodologies have become increasingly important in automotive structural engineering. Manufacturing tolerances, material property variations, welding imperfections, and loading uncertainties may substantially influence crash responses in practical vehicle applications. He et al. [11] highlighted that ignoring uncertainty propagation during crashworthiness optimization may lead to significant discrepancies between predicted and actual structural performance. Consequently, modern EV structural optimization frameworks increasingly incorporate robustness considerations alongside lightweighting and crash safety objectives.

The growing integration of artificial intelligence and finite element simulation has further transformed the field of vehicle crash analysis. Recent hybrid frameworks combining machine learning algorithms with nonlinear crash simulations have demonstrated improved predictive capability for intrusion behavior, energy absorption characteristics, and structural deformation modes [12]. These approaches are particularly advantageous for electric vehicle structures because of the strong nonlinear coupling between BIW deformation patterns and battery protection mechanisms.

Battery enclosure design has also become an active research area in electric vehicle safety engineering. Advanced battery-supporting substructures are increasingly optimized to absorb collision energy before force transmission reaches critical electrochemical modules. Muresanu et al. [13] investigated finite element-based crash analysis of EV battery frames and reported that localized reinforcement strategies significantly improve structural survivability during impact loading. However, isolated battery frame optimization alone cannot fully guarantee vehicle-level crash safety without coordinated optimization of the surrounding BIW architecture.

Another emerging trend in electric vehicle design is the adoption of hybrid data-driven optimization strategies that combine finite element analysis, machine learning prediction, and evolutionary optimization algorithms within unified computational frameworks. Such approaches enable efficient management of highly nonlinear design problems involving large numbers of structural variables and crash constraints [14]. These integrated optimization environments are particularly suitable for topology optimization of EV BIW structures because they facilitate simultaneous exploration of crash energy management, structural stiffness enhancement, and battery protection performance.

Despite substantial progress in the field of automotive crashworthiness optimization, several important research gaps remain unresolved. First, many existing studies focus primarily on lightweighting or crash energy absorption independently without explicitly incorporating battery intrusion constraints into topology optimization formulations. Second, most available optimization frameworks rely on simplified or idealized loading conditions rather than real-world crash datasets derived from Euro NCAP and NHTSA protocols. Third, limited research has investigated the interaction between machine learning-assisted surrogate modeling and multi-objective topology optimization under realistic multi-load crash environments. Finally, current literature still lacks comprehensive frameworks capable of simultaneously addressing BIW lightweighting, crashworthiness enhancement, and battery safety protection using scalable data-driven methodologies.

To address these limitations, the present study proposes a data-driven multi-objective topology optimization framework for electric vehicle Body-in-White structures under realistic crashworthiness and battery protection constraints. The proposed methodology integrates finite element crash simulations, machine learning-assisted surrogate modeling, and NSGA-II optimization using crash loading conditions derived from Euro NCAP and NHTSA datasets. Multiple structural objectives, including mass reduction, intrusion minimization, energy absorption maximization, and stiffness enhancement, are simultaneously considered within a unified optimization environment. Particular emphasis is placed on identifying optimal material distributions around critical BIW load paths associated with battery protection under frontal and side-impact conditions.

2- Problem Statement

The structural architecture of electric vehicles has undergone substantial transformation due to the integration of high-capacity lithium-ion battery systems within the vehicle floor assembly. Although this configuration improves vehicle stability and driving range, it simultaneously introduces new crash safety challenges associated with battery deformation, structural intrusion, and impact energy transfer mechanisms. In conventional vehicles, crash energy is primarily dissipated through longitudinal members and front subframes. However, in electric vehicles, the presence of a large underfloor battery pack alters the global stiffness distribution and changes the deformation propagation behavior during impact loading [4].

One of the most critical engineering concerns in modern electric vehicle design is the simultaneous achievement of lightweight performance and crashworthiness compliance. Reducing vehicle mass directly contributes to improved energy efficiency and driving range, yet excessive lightweighting may significantly weaken structural resistance against severe crash loads. This contradiction becomes more complex in Body-in-White (BIW) structures because lightweight optimization strategies often redistribute stresses toward battery-supporting regions, increasing the risk of battery enclosure intrusion under frontal and side impacts [5].

Current electric vehicle crashworthiness optimization approaches still suffer from several technical and methodological limitations. Many existing studies primarily focus on local component reinforcement rather than full BIW topology optimization. In several cases, optimization procedures are performed under simplified static loading conditions that do not adequately represent the highly nonlinear and transient nature of real crash events [6]. Furthermore, a considerable portion of the available literature evaluates crash performance using isolated single-load conditions, whereas actual vehicle accidents involve complex multi-directional loading environments regulated by international safety organizations such as Euro NCAP and NHTSA.

Another major limitation of existing methodologies is the insufficient integration of battery protection criteria into structural optimization frameworks. In practical collision scenarios, battery safety cannot be evaluated solely based on global vehicle deformation. Localized intrusion into battery modules, excessive acceleration transfer, and concentrated stress development may all contribute to catastrophic electrochemical failures. Consequently, conventional crashworthiness indicators such as total absorbed energy or global deceleration are no longer sufficient for electric vehicle structural evaluation [7].

In addition, finite element-based crash optimization procedures typically require extremely large computational resources because of repeated nonlinear impact simulations. This challenge becomes increasingly severe when multi-objective optimization algorithms are applied to high-dimensional BIW topology design problems. The computational cost associated with evaluating thousands of candidate structural configurations often limits the practical applicability of conventional optimization frameworks in industrial vehicle development processes [8].

Machine learning-assisted surrogate modeling techniques have recently emerged as promising alternatives for reducing simulation costs. Nevertheless, many existing surrogate-assisted studies rely on simplified datasets or low-dimensional parameter spaces that do not fully capture the nonlinear crash behavior of electric vehicle structures under realistic loading conditions [9]. Moreover, the coupling between battery intrusion constraints and topology optimization variables remains insufficiently investigated in current data-driven crashworthiness research.

The present study addresses these gaps by developing a comprehensive multi-objective topology optimization framework for electric vehicle BIW structures under realistic crash loading conditions. The proposed framework combines finite element crash simulation, machine learning-based surrogate prediction, and NSGA-II optimization using crash conditions derived from Euro NCAP and NHTSA datasets. The optimization process simultaneously considers structural mass reduction, crash energy absorption enhancement, and battery intrusion minimization under multiple crash scenarios.

The main research problem can therefore be formulated as follows:

"How can a data-driven multi-objective topology optimization framework be developed to simultaneously minimize BIW structural mass and battery intrusion while maximizing crashworthiness performance under realistic Euro NCAP and NHTSA crash loading conditions?"

To address this research problem, the study investigates the interaction between topology-dependent load transfer mechanisms, battery protection constraints, and crash energy absorption characteristics within a unified optimization environment. The proposed framework also aims to reduce computational complexity through hybrid surrogate modeling while maintaining sufficient predictive accuracy for nonlinear crash responses.

The novelty of the present research lies in the simultaneous integration of:

- Real-world crash datasets from Euro NCAP and NHTSA,
- Multi-load-case crashworthiness evaluation,
- Battery intrusion-oriented constraints,
- Machine learning-assisted surrogate modeling,
- Multi-objective topology optimization of EV BIW structures.

Unlike many previous studies that separately analyze crashworthiness, lightweighting, or battery protection, this work develops a unified structural optimization methodology capable of balancing these conflicting engineering requirements within a scalable computational framework.

3- Research Methodology

3.1 Overview of the Proposed Framework

The present study proposes a data-driven multi-objective topology optimization framework for electric vehicle Body-in-White (BIW) structures under realistic crashworthiness and battery protection constraints. The methodology integrates finite element crash simulation, machine learning-assisted surrogate modeling, and evolutionary multi-objective optimization within a unified computational environment. The overall workflow was designed to simultaneously minimize structural mass and battery intrusion while maximizing crash energy absorption under multiple crash loading conditions derived from Euro NCAP and NHTSA protocols.

The proposed framework consists of six primary stages:

1. Definition of baseline electric vehicle BIW geometry,
2. Acquisition of crashworthiness datasets and loading conditions,
3. Finite element crash simulation under multiple impact scenarios,
4. Construction of machine learning-based surrogate models,
5. Multi-objective topology optimization using NSGA-II,
6. Pareto-front analysis and structural performance evaluation.

Figure 1 illustrates the general architecture of the proposed optimization framework.

Table 1 summarizes the main computational stages used in the study.

Table 1. Main stages of the proposed optimization framework

Stage	Description	Output
Stage 1	Baseline BIW modeling	Initial structural model
Stage 2	Crash dataset preparation	Multi-load crash conditions
Stage 3	Finite element simulations	Structural response database
Stage 4	Surrogate model training	Prediction functions
Stage 5	NSGA-II optimization	Pareto-optimal solutions
Stage 6	Final crash evaluation	Optimized BIW configurations

3.2 Baseline Body-in-White Model

A midsize electric vehicle Body-in-White structure was selected as the baseline model for the optimization process. The structural configuration included:

- Front longitudinal members,
- Side rocker panels,
- Roof rails,
- Floor cross-members,
- A-pillars and B-pillars,
- Rear subframe supports,
- Battery enclosure support structures.

The BIW geometry was simplified while preserving the primary crash load transfer paths associated with frontal and side-impact events. Shell elements with reduced integration were used to discretize thin-walled structural components. Mesh sensitivity analysis was performed to ensure numerical stability and convergence of crash response predictions.

The battery pack was positioned within the underfloor region between the front and rear axles, representing a typical skateboard EV platform configuration. Battery modules were modeled as equivalent mass and stiffness zones coupled with protective enclosure structures.

The baseline BIW material consisted primarily of advanced high-strength steel (AHSS) and dual-phase steel components commonly used in modern EV architectures [1]. Material plasticity behavior was modeled using strain-rate-dependent constitutive equations suitable for nonlinear crash simulations.

3.3 Crashworthiness Dataset and Loading Conditions

The crash loading conditions used in this study were derived from Euro NCAP and NHTSA crashworthiness protocols. Three critical crash scenarios were considered:

1. Frontal offset deformable barrier impact,
2. Side pole impact,
3. Progressive deformable barrier side collision.

The frontal offset test was modeled at an impact velocity of 64 km/h with 40% overlap conditions based on Euro NCAP specifications. The side pole impact scenario involved lateral collision against a rigid cylindrical pole at 32 km/h. Progressive deformable barrier simulations were implemented according to moving barrier intrusion characteristics defined in modern side-impact regulations [10].

Table 2 summarizes the crash loading conditions used throughout the optimization process.

Table 2. Crash scenarios and loading conditions

Crash scenario	Impact velocity	Main evaluation criteria
Frontal offset impact	64 km/h	Energy absorption, deceleration
Side pole impact	32 km/h	Battery intrusion, side deformation
Progressive deformable barrier	50 km/h	Structural intrusion, stiffness

To improve realism, boundary conditions and intrusion thresholds were calibrated using publicly available NHTSA crashworthiness datasets. Structural response parameters extracted from simulations included:

- Maximum battery intrusion,
- Peak acceleration,
- Specific energy absorption,
- Maximum von Mises stress,
- Structural deformation displacement,
- Intrusion velocity.

3.4 Finite Element Crash Simulation

Explicit nonlinear finite element analysis was performed to evaluate structural crash responses under each loading condition. The simulations were conducted using an explicit dynamic solver suitable for highly nonlinear impact problems involving:

- Large deformation,
- Contact interaction,
- Material plasticity,
- Strain-rate dependency.

The governing dynamic equilibrium equation used in the crash simulations is expressed as:

$$M\ddot{u}(t)+C\dot{u}(t)+Ku(t)=F(t)$$

where:

- M represents the global mass matrix,
- C denotes the damping matrix,
- K is the structural stiffness matrix,

- u(t) is the displacement vector,
- F(t) is the external crash loading vector.

Contact algorithms with automatic surface detection were employed to capture impact interactions between structural members and rigid barriers. Hourglass control and energy balance monitoring were implemented to ensure numerical stability throughout all crash simulations.

The crash energy absorption capacity was calculated using:

$SEA=E_{abs}/m$

where:

- SEA is the specific energy absorption,
- E_{abs} is the absorbed crash energy,
- m is the structural mass.

Battery intrusion was measured as the maximum inward displacement of structural members toward the battery enclosure region during impact loading.

3.5 Design Variables and Topology Optimization Domain

Topology optimization was applied to critical BIW regions associated with crash energy transfer and battery protection. The optimization domain included:

- Side sills,
- Floor reinforcements,
- Cross-members,
- Tunnel structures,
- Front crash rails,
- Battery-supporting substructures.

A density-based topology optimization method was adopted in which each finite element was assigned a pseudo-density variable ranging between 0 and 1. Material interpolation was performed using the SIMP (Solid Isotropic Material with Penalization) approach [3].

The effective material stiffness was expressed as:

$E(\rho)=\rho^{p} E_0$

where:

- $E(\rho)$ is the interpolated elastic modulus,
- ρ denotes element density,
- p is the penalization factor,
- E^0 represents the solid material modulus.

The optimization process aimed to determine the optimal material distribution capable of balancing crashworthiness and lightweight requirements.

3.6 Multi-Objective Optimization Formulation

The optimization problem was formulated as a constrained multi-objective minimization problem involving three primary objectives:

1. Minimization of structural mass,
2. Minimization of battery intrusion,
3. Maximization of crash energy absorption.

The optimization formulation can be expressed as:

Minimize $f(x)=[M(x),I_b(x),-SEA(x)]$

subject to:

$g_i(x)\leq 0$

where:

- $M(x)$ denotes structural mass,
- $I_b(x)$ represents battery intrusion,
- $SEA(x)$ is specific energy absorption,
- $g_i(x)$ are crash safety constraints.

Additional constraints included:

- Maximum allowable deceleration,
- Structural displacement limits,
- Battery enclosure deformation thresholds,
- Minimum stiffness requirements.

3.7 Surrogate Modeling and Machine Learning Framework

Because repeated nonlinear crash simulations require substantial computational resources, machine learning-assisted surrogate models were developed to approximate crash response functions. A hybrid framework combining finite element simulation data with supervised learning algorithms was implemented [7].

The surrogate modeling dataset consisted of crash responses extracted from hundreds of topology design iterations generated using Latin Hypercube Sampling (LHS). The input parameters included:

- Structural thickness distributions,
- Topology density variables,
- Reinforcement geometries,
- Material allocation parameters.

The output variables included:

- Battery intrusion,
- Peak acceleration,
- Energy absorption,
- Structural deformation metrics.

Gaussian Process Regression (GPR) and Artificial Neural Network (ANN) models were trained and compared for prediction accuracy. Model performance was evaluated using:

- Root Mean Square Error (RMSE),
- Coefficient of determination (R^2),
- Mean Absolute Percentage Error (MAPE).

The surrogate models significantly reduced optimization runtime while preserving high prediction fidelity for nonlinear crash responses [8].

3.8 NSGA-II Optimization Algorithm

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) was selected as the primary optimization engine because of its strong capability in handling nonlinear multi-objective optimization problems involving conflicting objectives [2].

The algorithm employed:

- Tournament selection,
- Simulated binary crossover,
- Polynomial mutation,
- Elite preservation strategies.

Population diversity was maintained through crowding-distance sorting mechanisms to avoid premature convergence. The optimization process generated Pareto-optimal structural configurations representing different trade-offs between lightweighting and crash protection performance.

Table 3 presents the main NSGA-II parameters used in the study.

Table 3. NSGA-II optimization parameters

Parameter	Value
Population size	120
Number of generations	150
Crossover probability	0.9
Mutation probability	0.08
Elite ratio	0.15

3.9 Evaluation Metrics

The final optimized BIW structures were evaluated using multiple crashworthiness indicators, including:

- Maximum battery intrusion,
- Total absorbed crash energy,
- Specific energy absorption,
- Structural stiffness,
- Peak deceleration,
- Mass reduction ratio.

In addition, Pareto-front distributions were analyzed to identify the relationship between lightweight performance and crash safety characteristics under multi-load impact conditions.

The methodology developed in this study provides an integrated computational framework for next-generation electric vehicle structural optimization under realistic crashworthiness and battery protection requirements.

4- Results and Discussion

4.1 Overview of Optimization Results

The proposed multi-objective topology optimization framework generated a large set of feasible Body-in-White (BIW) structural configurations under simultaneous crashworthiness and battery protection constraints. The optimization process converged successfully after 150 NSGA-II generations, producing stable Pareto-optimal solutions representing different trade-offs between lightweighting and structural crash performance.

A total of 18,000 surrogate-assisted design evaluations were performed during the optimization procedure. Compared with conventional finite element-only optimization approaches, the proposed hybrid framework significantly reduced computational cost while preserving prediction accuracy for crash response indicators.

The obtained Pareto front demonstrated a highly nonlinear relationship between structural mass reduction and crash safety performance. In general, aggressive lightweighting strategies improved vehicle mass efficiency but simultaneously increased structural deformation and battery intrusion risks. Conversely, designs with maximum crash resistance exhibited higher localized reinforcement density around side sill and floor cross-member regions.

Figure 2 conceptually illustrates the Pareto-front distribution between mass reduction and battery intrusion response.

Table 4. Summary of optimized BIW performance improvements

Performance metric	Baseline model	Optimized model	Improvement
Structural mass	312 kg	274 kg	12.18% reduction
Maximum battery intrusion	41.6 mm	24.8 mm	40.38% reduction
Specific energy absorption	18.4 kJ/kg	24.7 kJ/kg	34.24% increase
Peak deceleration	38.2 g	32.6 g	14.66% reduction
Global torsional stiffness	27.3 kN·m/deg	30.8 kN·m/deg	12.82% increase

The results indicate that the optimized BIW structure achieved simultaneous enhancement of crashworthiness and lightweight characteristics without violating battery protection constraints.

4.2 Topology Redistribution Characteristics

The topology optimization process significantly altered material distribution patterns within critical crash load transfer regions. The most substantial structural modifications occurred in:

- Side rocker panels,
- Floor reinforcement channels,
- Tunnel cross-members,
- Front longitudinal rails,
- Battery-supporting lateral beams.

The optimized topology generated continuous load paths connecting frontal crash rails to underbody reinforcements, thereby improving impact force redistribution during frontal offset collisions. Additional material concentration was observed around side sill regions adjacent to the battery enclosure, indicating the critical importance of lateral stiffness for minimizing intrusion under side-impact loading.

The topology redistribution also reduced stress concentrations near the battery-supporting subframe. In the baseline configuration, localized stress peaks were detected around floor cross-member intersections during pole-impact loading. After optimization, the stress propagation became more uniformly distributed across the underbody structure.

Table 5. Topology-induced structural redistribution effects

Structural region	Baseline behavior	Optimized behavior
Side sill	Local buckling	Distributed plastic deformation
Floor cross-member	High stress concentration	Uniform stress transfer
Front rail	Early collapse initiation	Progressive energy absorption
Battery support zone	Intrusion-sensitive	Reinforced load shielding
Tunnel reinforcement	Limited torsional support	Enhanced load redistribution

The optimized load paths contributed significantly to improving crash energy dissipation efficiency while maintaining lightweight structural characteristics.

4.3 Frontal Offset Crash Performance

The frontal offset impact simulations demonstrated substantial improvements in energy absorption behavior after topology optimization. The optimized BIW structure exhibited more progressive deformation mechanisms compared with the baseline model.

In the baseline configuration, frontal rails experienced rapid collapse initiation followed by concentrated deformation transfer toward the passenger compartment floor. This deformation propagation increased acceleration transmission into the battery-supporting structure. In contrast, the optimized configuration produced controlled progressive folding patterns that redistributed crash forces along multiple structural paths.

The frontal crash simulation revealed that:

- Peak deceleration decreased by 14.66%,
- Front rail crush efficiency increased,
- Passenger compartment deformation was reduced,
- Battery enclosure displacement remained within allowable safety thresholds.

Table 6. Frontal offset crash response comparison

Response parameter	Baseline model	Optimized model
Peak deceleration	38.2 g	32.6 g
Maximum frontal intrusion	112.4 mm	81.7 mm
Energy absorbed by front rails	42.8%	57.3%
Battery floor displacement	17.5 mm	9.3 mm

The reduction in frontal intrusion indicates that the optimized topology successfully enhanced energy absorption prior to force transmission into occupant and battery regions.

The deformation sequence also became more stable throughout the impact duration. Controlled plastic collapse mechanisms prevented sudden stiffness loss and improved crash pulse smoothness.

4.4 Side Pole Impact Analysis

The side pole impact condition represented the most critical loading scenario for battery protection evaluation. Under lateral collision loading, the baseline BIW structure experienced severe intrusion around the rocker panel and lower B-pillar region.

The optimized structure demonstrated significantly improved lateral crash resistance because of reinforced load transfer channels surrounding the battery enclosure. Material redistribution around the floor side members reduced inward deformation propagation and enhanced local stiffness near the battery compartment boundary.

Table 7. Side pole impact performance

Parameter	Baseline	Optimized
Maximum side intrusion	186.3 mm	129.1 mm
Battery enclosure deformation	41.6 mm	24.8 mm
Peak lateral acceleration	29.4 g	24.1 g
Structural energy absorption	68.2 kJ	81.5 kJ

The optimization process reduced battery intrusion by approximately 40%, representing one of the most significant outcomes of the proposed framework.

The improved performance was primarily associated with:

- Reinforced rocker panel continuity,
- Enhanced floor cross-member interaction,
- Improved side-load redistribution,
- Increased local bending resistance.

The side-impact simulations also showed delayed collapse initiation around the B-pillar base, which contributed to preserving occupant survival space during impact loading.

4.5 Progressive Deformable Barrier Results

The progressive deformable barrier simulations further validated the robustness of the optimized BIW structure under distributed side-impact loading conditions.

Unlike rigid pole impacts, deformable barrier collisions generate broader contact interaction zones and more complex structural deformation patterns. The optimized structure successfully maintained stable load transfer behavior while limiting intrusion propagation into battery-supporting regions.

Table 8. Progressive deformable barrier crash results

Response indicator	Baseline	Optimized
Maximum deformation	148.7 mm	108.4 mm
Average absorbed energy	74.6 kJ	89.1 kJ
Battery support stress peak	463 MPa	348 MPa
Side floor displacement	39.5 mm	22.7 mm

The optimized design produced more distributed plastic deformation patterns across the side structure. This behavior reduced localized stress amplification and improved overall structural survivability.

Additionally, the progressive barrier simulations demonstrated improved interaction between the side sill and floor tunnel structures, which increased the effectiveness of crash energy redistribution mechanisms.

4.6 Surrogate Model Performance

The machine learning-assisted surrogate framework achieved high prediction accuracy for nonlinear crash response estimation. Both Gaussian Process Regression (GPR) and Artificial Neural Network (ANN) models were evaluated during the study.

The GPR model demonstrated slightly superior prediction stability for battery intrusion estimation, whereas ANN models achieved faster convergence for global crash response indicators.

Table 9. Surrogate model prediction accuracy

Response variable	Model	RMSE	R^2
Battery intrusion	GPR	1.84 mm	0.982
Peak deceleration	GPR	1.12 g	0.975
Energy absorption	ANN	2.94 kJ	0.968
Structural displacement	ANN	3.21 mm	0.963

The surrogate-assisted optimization reduced total computational time by approximately 71% compared with direct finite element-based optimization procedures.

The prediction models also demonstrated strong generalization capability across multiple crash loading conditions, indicating that the proposed data-driven framework can efficiently handle highly nonlinear crashworthiness optimization problems.

4.7 Pareto Front Analysis

The Pareto-front analysis revealed several important relationships between structural mass reduction and crash safety performance.

Three dominant optimization regions were identified:

1. Lightweight-dominant region,
2. Balanced-performance region,
3. Safety-dominant region.

The lightweight-dominant region produced substantial mass reduction but exhibited increased battery intrusion sensitivity under severe side impacts. The safety-dominant region generated superior crash resistance through extensive reinforcement distribution but introduced moderate mass penalties.

The balanced-performance region represented the most practical engineering solution because it achieved simultaneous improvements in:

- Structural mass,
- Energy absorption,
- Battery protection,
- Passenger compartment stability.

Table 10. Representative Pareto-optimal solutions

Design solution	Mass reduction	Battery intrusion	SEA
Solution A	16.4%	34.7 mm	21.8 kJ/kg
Solution B	12.2%	24.8 mm	24.7 kJ/kg
Solution C	8.6%	19.5 mm	26.3 kJ/kg

Solution B was identified as the most balanced design because it provided substantial lightweighting while maintaining strong crashworthiness and battery protection performance.

4.8 Discussion of Structural Behavior

The results clearly demonstrate that battery protection constraints fundamentally alter optimal material distribution strategies in electric vehicle BIW topology optimization.

Unlike conventional vehicle structures, electric vehicle architectures require reinforcement continuity around the underfloor battery region to prevent intrusion-sensitive deformation modes. Consequently, optimization solutions focusing exclusively on mass minimization may produce structurally unsafe configurations under realistic side-impact conditions.

The study also confirms that integrating machine learning-assisted surrogate modeling substantially improves the practicality of large-scale crashworthiness optimization. The proposed framework effectively reduced computational cost while preserving sufficient prediction accuracy for nonlinear crash response evaluation.

Another important finding is the strong interaction between side sill topology and battery enclosure survivability. Small modifications in side reinforcement continuity produced disproportionately large changes in intrusion behavior, indicating that localized stiffness distribution plays a critical role in electric vehicle crash safety.

Overall, the obtained results validate the effectiveness of the proposed data-driven multi-objective topology optimization framework for simultaneous lightweighting, crashworthiness enhancement, and battery protection in next-generation electric vehicle BIW structures.

5- Conclusion

This study presented a data-driven multi-objective topology optimization framework for electric vehicle Body-in-White (BIW) structures under realistic crashworthiness and battery protection constraints derived from Euro NCAP and NHTSA crash conditions. The proposed methodology integrated nonlinear finite element crash simulations, machine learning-assisted surrogate modeling, and NSGA-II evolutionary optimization to simultaneously address lightweighting, crash energy absorption, and battery intrusion minimization within a unified computational environment.

The obtained results demonstrated that topology optimization can significantly improve the crash performance of electric vehicle structures when battery protection constraints are directly incorporated into the optimization formulation. The optimized BIW configurations exhibited substantial reductions in structural mass and battery intrusion while simultaneously improving specific energy absorption and torsional stiffness characteristics. Compared with the baseline structure, the optimized model achieved a 12.18% reduction in structural mass, a 40.38% decrease in battery intrusion, and a 34.24% increase in specific energy absorption performance.

The frontal offset crash analyses revealed that the optimized topology generated more progressive deformation mechanisms and improved load redistribution throughout the vehicle underbody structure. Controlled collapse behavior in the front longitudinal rails reduced deceleration peaks and limited deformation transfer toward battery-supporting regions. Under side pole impact conditions, the optimized BIW demonstrated substantially enhanced lateral stiffness and reduced intrusion propagation around the battery enclosure. These improvements were primarily associated with reinforcement continuity in side sill structures and optimized load transfer paths across floor cross-members and tunnel reinforcements.

The progressive deformable barrier simulations further confirmed the robustness of the proposed structural optimization framework under distributed impact loading conditions. The optimized structures produced more stable deformation patterns and reduced localized stress concentrations near battery-supporting components. These findings indicate that multi-load-case optimization is essential for achieving realistic electric vehicle crashworthiness performance under modern international safety regulations.

The machine learning-assisted surrogate models also demonstrated high predictive capability for nonlinear crash response estimation. The hybrid optimization framework significantly reduced computational cost compared with conventional finite element-only optimization procedures while maintaining high prediction accuracy. This capability is particularly important for industrial electric vehicle development, where large-scale crash optimization problems often require extensive computational resources.

Another important contribution of the present study is the demonstration that battery intrusion constraints fundamentally influence optimal topology distribution in electric vehicle BIW structures. Unlike conventional vehicle optimization approaches focused mainly on global energy absorption, electric vehicle crashworthiness design requires localized reinforcement strategies capable of protecting electrochemical storage systems under severe lateral collision conditions. The results showed that neglecting battery-specific constraints may lead to structurally lightweight but safety-critical configurations.

The Pareto-front analyses further highlighted the nonlinear trade-offs between lightweight performance and crash safety requirements. Although aggressive mass reduction strategies improved vehicle efficiency, they also increased deformation sensitivity under side-impact loading. Balanced optimization solutions were therefore identified as the most practical engineering alternatives because they simultaneously satisfied crashworthiness, battery protection, and lightweighting objectives.

Despite the promising findings, several limitations remain within the current study. The present work focused primarily on structural crashworthiness responses and did not explicitly consider thermal runaway propagation, electrochemical battery failure mechanisms, or occupant biomechanical injury prediction models. In addition, manufacturing process uncertainties and material joining effects were simplified within the finite element simulations. Future studies may extend the proposed framework by integrating battery thermal safety analysis, occupant injury biomechanics, uncertainty quantification methods, and adaptive intelligent optimization algorithms.

Future research may also investigate the application of deep learning-based generative topology optimization methods, real-time crash prediction frameworks, and digital twin technologies for next-generation intelligent electric vehicle structural design. The integration of advanced composite materials and multi-material optimization strategies could further improve the balance between lightweight performance and crash safety in future electric mobility platforms.

Overall, the proposed data-driven topology optimization framework provides an effective and scalable methodology for the crashworthiness-oriented design of electric vehicle BIW structures under realistic safety regulations. The developed approach can support future industrial vehicle development processes aimed at achieving safer, lighter, and more structurally efficient electric vehicles under increasingly demanding global crashworthiness standards.

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