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MULTI-OBJECTIVE OPTIMIZATION OF COMPOSITE SANDWICH STRUCTURES BY USING ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM

PH.D. THESES

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CONTENTS

LIST OF SYMBOLS AND ABBREVIATIONS

GREEK LETTERS

δ	Deflection of the sandwich structure	mm
δ_{Req}	Requested deflection	mm
δ_{analy}	Analytical deflection	mm
δ_{max}	Maximum deflection	mm
σ_{xt}	Longitudinal tensile strength of the layer in the face sheets	MPa
σ_{xc}	Longitudinal compressive strength of the layer in the face sheets	MPa
σ_{yt}	Transverse tensile strength of the layer in the face sheets	MPa
σ_{yc}	Transverse compressive strength of the layer in the face sheets	MPa
σ_{xy}	In-plane shear strength of the layer in the face sheets	MPa
σ_{xz}	Core strength in plane *x*-*z*	MPa
σ_{yz}	Core strength in plane *y*-*z*	MPa
σ_{zz}	Core strength in plane *z*-*z*	MPa
$\sigma_{wr,x}$	Face sheets wrinkling critical stress	MPa
$\sigma_{in,cr}$	Face sheets Intra-cell buckling critical stress	MPa
τ_c	Core shear stress	MPa
ρ_l	Density of the layer's materials in the face sheets	kg/m^3
ρ_c	Core density	kg/m^3
ν_{xy}	Poisson's ratio of the composite layers	N/A
θ_{FRP}	Fiber orientation angle	degree
λ_1	Upper limit of normalized parameters	N/A
λ_2	Lower limit of normalized parameters	N/A

LATIN LETTERS

l	Length of the sandwich structure	mm
b	Width of the sandwich structure	mm
t_{sw}	Total thickness of the sandwich structure	mm
t_f	Face sheet thickness	mm
t_c	Core thickness	mm
N_l	Number of layers in the face sheets	piece
t_l	Layer thickness	mm
P	Applied load	N
p	Distributed load	MPa
W_t	Total weight of the sandwich structure	kg
W_f	Face sheets weight	kg
W_c	Core weight	kg
C_t	Total materials cost	Unit price
C_f	Cost of the face sheets	Unit price
C_c	Cost of the core	Unit price
D_{min}	Minimum distance between normalized weight and cost objectives	N/A
D	Flexure stiffness of a composite sandwich structure	N/m
S	Shear stiffness of a composite sandwich structure	N/m
K_b	Bending deflection coefficient	N/A
K_s	Shear stiffness of a composite sandwich structure	N/A
d	Distance between face sheets center lines	mm
G_c	Core shear modulus	GPa
G_{xz}	Core shear modulus in x-z plane	GPa
G_{yz}	Core shear modulus in y-z plane	GPa
M	Maximum bending moment	N.m
F	Maximum shear force	N
$E_{f,x}$	Young's modulus elasticity of composite face-sheet in x-direction	GPa
$E_{f,y}$	Young's modulus elasticity of composite face-sheet in y-direction	GPa
E_{zz}	Young's modulus elasticity of the core	GPa
net_j	Summation of the weights vector in the neuron	N/A
w	The weight vector in the neuron	N/A
b_j	The bias value of (j) neuron in the hidden layer,	N/A
Out_j	The output of the (j) neuron.	Unit depend on the output parameters
x_i	The normalized value of certain parameter	N/A
z_i	Original data of certain parameters	Depends on the specific parameter
R^2	The coefficient of determination	N/A
MSE	Mean Square Error	Depends on the specific parameter
$x_{pred,i}$	Predicted value of the ANN network	Depends on the specific parameter
$x_{act,i}$	Actual value of the training ANN data	Depends on the specific parameter

x_{avg}	Average value of the ANN data	Depends on the specific parameter
l/b	Length to width ratio	N/A
C_δ	Maximum deflection limit	N/A

SUBSCRIPTS

sw	Sandwich structure	N/A
$Anal$	Analytical	N/A
Req	Requested	N/A
max	Maximum	N/A
min	Minimum	N/A
x, y, z	Property refers to a Cartesian direction	N/A
c	Property refers to the core	N/A
f	Property refers to the face sheet	N/A
wr	Wrinkling	N/A
in	Intra-cell	N/A
l	Property refers to the layer	N/A

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION TO SANDWICH STRUCTURES AND AIMS OF THE RESEARCH

In recent years, sandwich structures have gained attention due to their exceptional properties, including high bending resistance, superior stiffness, low weight and excellent design flexibility aligned with engineering applications. Sandwich structures consist of 1) a pair of thin and strong face sheets 2) a thick lightweight core to separate the face sheets and carry applied loads from one face sheet to the other and 3) a bonding material between the face sheets and the core that transmits the shear and axial loads to and from the core. The separation of the face sheets by the core increases the moment of inertia of the structure with little increase in weight, producing an efficient structure that resists bending and buckling loads. The face sheet materials can be metal alloys, Fiber Reinforced Plastic (FRP) composites, or hybrid materials (combined metal and composite materials). The cores can be in different forms, such as honeycomb or foam. The face sheets and core are bonded together by using an appropriate technique [1-3].

Honeycomb sandwich structures are widely used in weight-sensitive and damping structures where high flexural rigidity is required in many engineering fields. Research on them began at the beginning of the 20th century. By varying the core density, core thickness and material of the face sheet, various properties and desired performance, particularly a high strength-to-weight ratio, can be obtained. From this perspective, honeycomb sandwich structures are important structural materials [4-6].

1.1 Laminated FRP composite materials and their structural designs

The use of composite materials for industrial purposes is steadily increasing due to their outstanding and potential properties that have not yet been fully explored. Composite materials consist of two or more distinct materials, usually referred to as matrix and reinforcement phases. Constituents' phases support each other, and the overall achieved performance is superior to that of a single material. The reinforcing phase provides the resulting composite with strength and stiffness properties. The reinforcing phase appears in various forms, including short fibers, particles in different scales, or chopped fibers, while the matrix phase can be a polymer (plastic), metal, or ceramic [7-8].

FRP composite materials are the most common class of composite materials which used widely in different engineering applications. The high strength-to-weight and stiffness-to-weight ratios make FRP composites ideal for various applications where mechanical behavior and weight reduction are critical, such as aerospace, marine, automotive and construction [9-11].

In the real world, composites take a multilayered form in applications requiring structural flexural, high tensile, high compressive, torsional strengths and stiffnesses. The properties of these composites depend not only on the properties of the constituent materials but also on the geometrical design of the structural elements. Laminated composites are the most common structural mode.

Lamina, or ply, is a plane (or curved) layer of unidirectional fibers or woven fabric in a matrix. In the case of unidirectional fibers, it is also referred to as unidirectional lamina. The lamina is a composite material with principal mechanical material properties in the direction of the fibers.

Laminate is made up of two or more laminae or plies stacked together at various orientations as illustrated in Figure 1.1. The laminae (or plies, or layers) can be of various thicknesses and consist of different materials [12-13].

Composite laminates containing plies of two or more different types of materials are called hybrid composites and more specifically for example, a composite laminate may be made up of unidirectional glass/epoxy, carbon/epoxy and aramid/epoxy layers stacked together in a specified sequence.

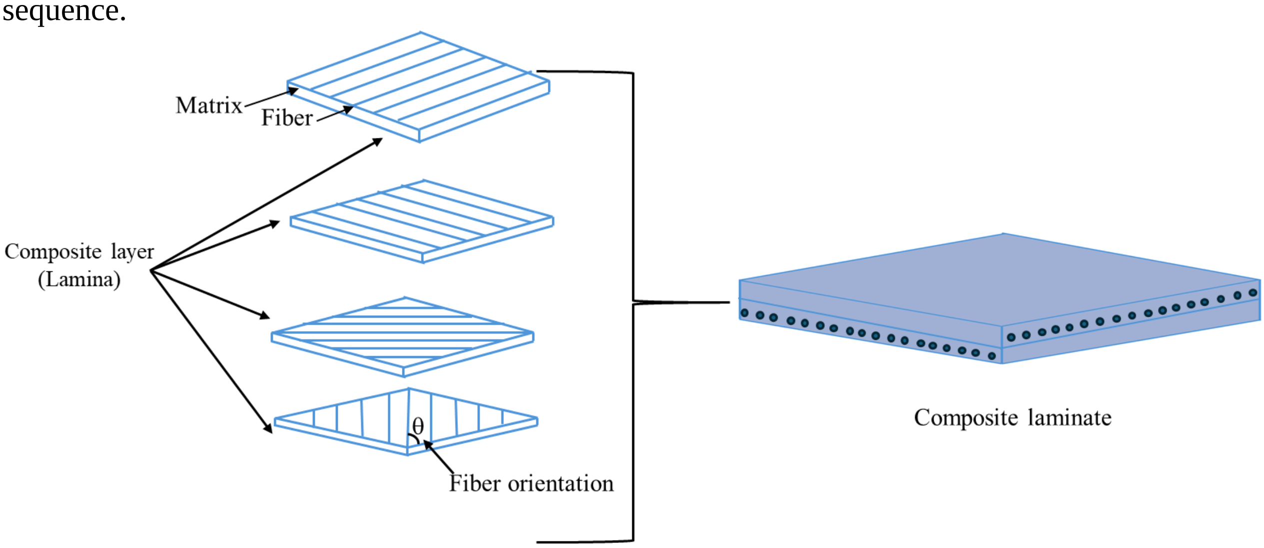


Figure 1.1. Basic concept of composite laminate structure

The FRP materials are characterized as orthotropic materials, which means the properties of the single ply in the transverse direction are significantly weaker than in the longitudinal direction. Therefore in practical applications, FRP structures consist of multiple layers in specific sequence. By stacking several layers with different fiber orientations, it is possible to ensure that the reinforcing layers is effective in the organized loading directions.

Theoretically, an unlimited number of layer arrangements can be composed, depending on the layer's mechanical properties, thickness, orientation angle of the lamina, type, stacking order and number of layers. The most commonly used laminates can be categorized into three main types: symmetric, antisymmetric and asymmetric structures.

A laminate is considered symmetric if the upper and the lower halves are same in both layer properties and stacking order relative to the mid-plane of the final laminate. A symmetric laminate can be composed of unidirectional or multidirectional layers. A structure made from unidirectional fiber layers is called a Single Orientation Ply Laminate (SOPL), while one made from multidirectional fiber layers is called a Multi-Orientation Ply Laminate (MOPL).

A symmetric SOPL may consist of isotropic or orthotropic plates. An isotropic layer can be formed as a thin slice of isotropic materials. The fiber composite layers constitute the group of orthotropic materials.

We call a laminate structure antisymmetric when the specific layer composition (layer properties and thicknesses) is the same in both the lower and upper halves with respect the middle surface of the laminate, but the fiber orientation of the layers is different. An antisymmetric structure can consist only of orthotropic layers.

The third type is asymmetric laminates. This category includes structures that are neither symmetric nor antisymmetric. This type consists of multidirectional layers, which can include isotropic layers (at least two different isotropic materials) and orthotropic layers [14]. Schematic for main composite materials layup is illustrated in the Figure 1.2.

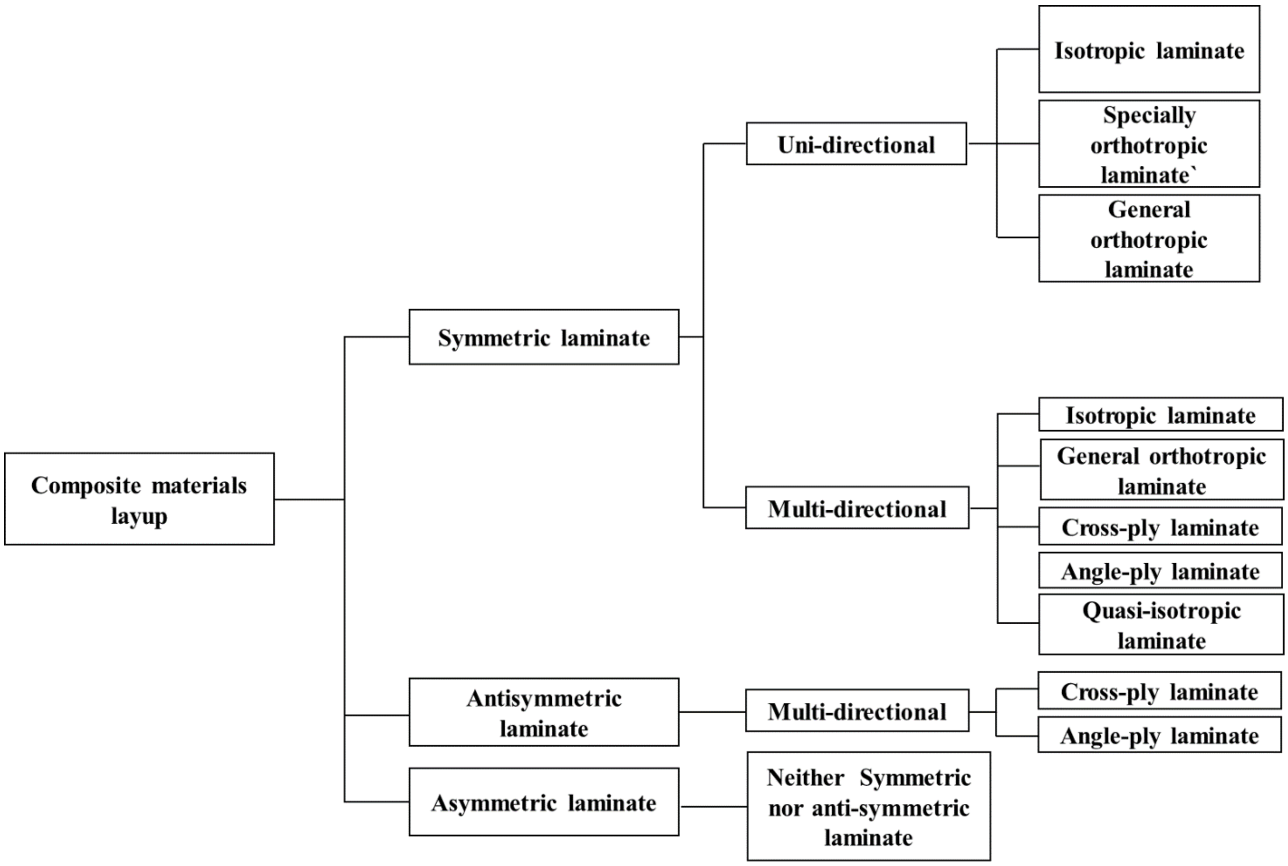


Figure 1.2. Possible laminate layup

Totally FRP laminates are composite structures composed entirely of FRP layers. These laminates can be made from unidirectional plies, such as Glass Fiber Reinforced Plastic (GFRP) and Carbon Fiber Reinforced Plastic (CFRP), or woven plies, such as Woven Carbon Fiber Reinforced Plastic (WCFRP) and Woven Glass Fiber Reinforced Plastic (WGFRP). The fibers within these laminates may be oriented in various directions, depending on the required strength and performance characteristics of the structure. Fully FRP laminates are distinguished by their exclusive use of fiber reinforced plastic materials throughout the entire laminate, without the inclusion of metal or other non-FRP layers.

Fiber Metal Laminate (FML) is a particular class of hybrid composite materials that merges the benefits of both metallic and composite constituents through a combined laminate approach. The FMLs are made up of alternating layers of FRP composites and metals. The performance of the final FML is characterized by the composite layer structure, metal volume fraction and interlaminar adhesion strength [15]. The general configuration of an FML laminate is illustrated in Figure 1.3.

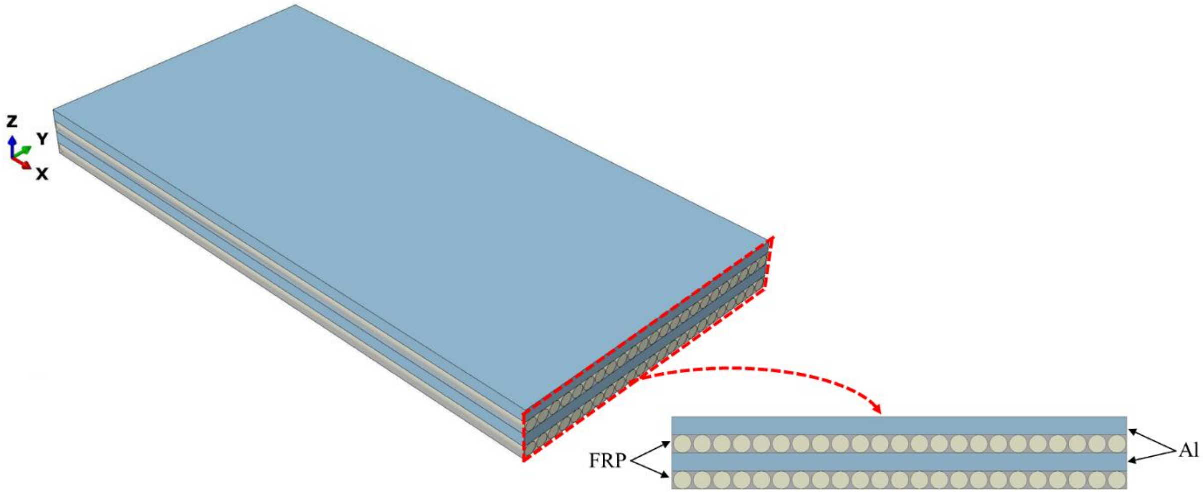


Figure 1.3. FML materials structure concept

1.2 Overview of honeycomb core in sandwich structure

Honeycomb core is a structural design inspired by biomimicry of a beehive. The honeycomb core structure is a thin-walled hollow shell material developed by assembling hollow cells. Honeycombs are manufactured by designated cell shapes, sizes and configurations. The honeycomb characteristics depend on the size of the cells, thickness and strength of the base material. Because of the design method, the honeycomb core is anisotropic with respect to out of plane shear stifnesses and strength. Lightweight honeycomb core would be made from different materials namely, kraft paper, thermoplastics, aluminum, carbon, steel, fiberglass, Nomex, plastic and aramid fiber. The honeycomb sandwich structure effectively couples the lightweight and superior strength; therefore, its applications are extensively applied in many fields, including but not limited to [16]:

- **Aerospace**: Used in aircraft and spacecraft components like wings, fuselage panels and interior structures to reduce weight while maintaining strength.
- **Automotive**: Employed in car body panels, floors and crash structures to enhance safety and fuel efficiency.
- **Construction**: Utilized in building panels, floors and roofs for lightweight and durable structures.
- **Marine**: Applied in boat hulls, decks and bulkheads for improved buoyancy and strength.

It is worth noting that although each component of the sandwich structure is relatively weak and flexible, they would provide a stiffer and more durable lightweight structure when combined in a sandwich panel. Figure 1.4 illustrates the typical configuration of the honeycomb core of the sandwich structure.

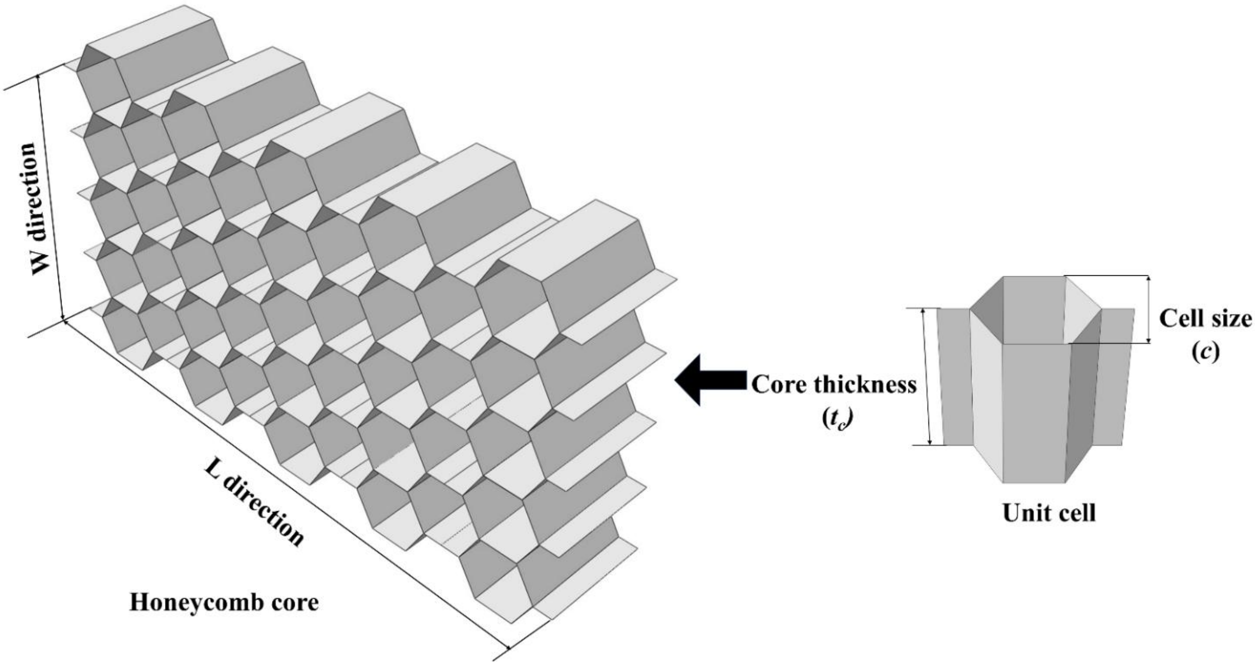


Figure 1.4. Illustration of the schematic representation of a typical honeycomb core

1.3 The sandwich structure includes laminated face sheets with a honeycomb core

Aiming to achieve minimal weight with maximum stiffness, sandwich structures have been utilized across a wide range of engineering applications. Tracing back through history, the concept of arranging two cooperating thin faces separated by a certain distance is an early recognition of the sandwich structure principle [17]. The need for materials with high strength, low weight and higher damage tolerance arose from advancements in industrial demands. For many applications, including structural components, sandwich structures that met these needs quickly became the preferred option. These days, their structural applications have spread to ground transport and marine vessels [18].

A sandwich structure is defined as a multi-layered structure with facing materials consisting of one or more rigid layers bonded to flexible low-density layers (core) [19]. The purpose of the face sheets is to carry the load, while the lightweight core transfers the load between the connected layers. The cores generally involve low-density solid materials (e.g. solid foam), cellular shapes (e.g. honeycomb) and corrugated shapes (e.g. truss) [20-21].

Many variations of this definition are available, but the key factor in making this type of structure remains the lightweight core, which reduces the overall density of the material and stiff face sheets, which provide strength. The structure of sandwich composites is shown in Figure 1.5. Integral bonding between face sheets and core prevents interfacial failure under the applied load, enhancing the flexural properties of sandwich structures.

There is no general rule about the relationship between the thickness of the face sheet and the core. It depends on the application and required properties. A major advantage of sandwich structure is the possibility of tailoring properties by choosing appropriate constituting materials and their volume fractions. The same advantage also applies to sandwich structure composites. Proper choice of core and face sheets make sandwich composites adaptive to a large number of applications and environmental conditions. Some general characteristics of sandwich composites are described below:

1. Low density: the choice of lightweight core decreases the overall density of the sandwich composite. The volume of core is considerably higher in the sandwich composite compared to the volume of face sheets so any decrease in the density of the core material has a significant effect on the overall sandwich density.
2. High bending stiffness: This property comes from the skin part of the sandwich. Due to a higher specific stiffness sandwich composites result in lower lateral deformation, higher buckling resistance and higher natural frequencies compared to other structures.
3. Directional mechanical properties: The properties of the core control the *z*-direction (Figure 1.4) and the properties of the face sheets control the *x*- and *y*-directions.
4. Ease of fabrication: Sandwich composites structure can be manufactured using various methods and their structure allows for relatively simple fabrication processes, which can reduce production costs.

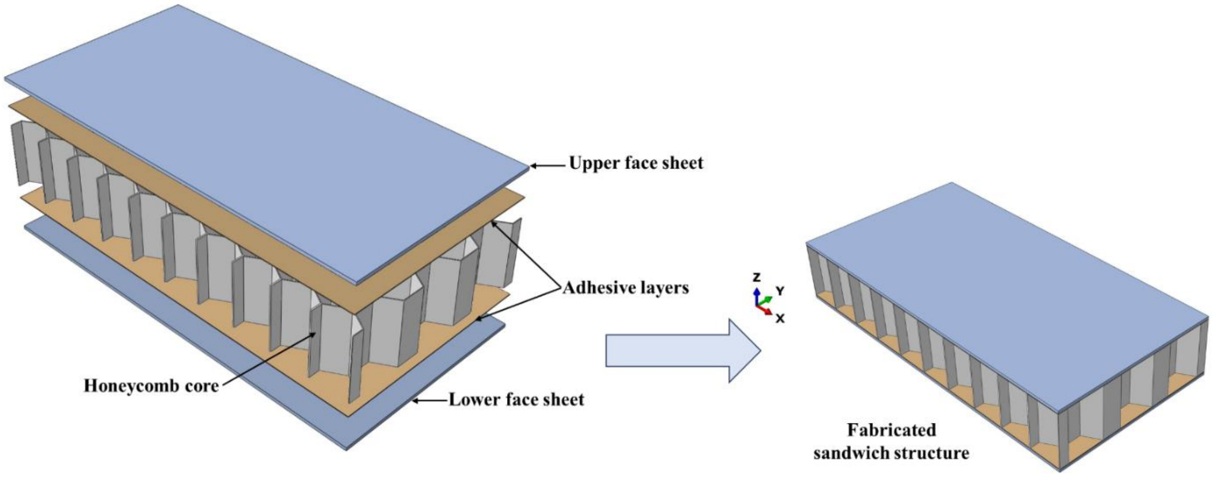


Figure 1.5. Schematic diagram showing the construction of a honeycomb core sandwich panel

1.4 Optimization of sandwich structures

Structural optimization has various definitions; one general definition is "improving the structural behavior to the best state it can be achieved". However, achieving the absolute theoretical best is not necessarily feasible due to real-world constraints. A more practical framework defines optimization as a process of searching for the best solution from a wide range of potential candidate solutions available within specified practical limitations [22].

An optimization problem is described as **single-objective optimization** when it deals with only one objective function. On the other hand, most practical problems involve optimizing two or more conflicting behavioral objectives simultaneously. These conflicting objectives are characterized by an improvement in one objective causing a deterioration in the other. Based on this, these kinds of problems are called **multi-objective optimization** problems. In these problems, because the objectives are in continuous competition, the solution is not a single, unique optimum but rather a set of optimal solutions [23].

In most multi-objective optimization scenarios, instead of obtaining a single solution, the outcome is a set of feasible solutions. The solutions that are non-dominated by others are called Pareto-optimal or non-dominated solutions. The plotted curve of the Pareto-optimal solutions is commonly called the Pareto front, which provides key insight into the solution space to attain the required balanced solution representing the tradeoff between the conflicting objectives [24]. Figure 1.6 illustrates the Pareto front concept.

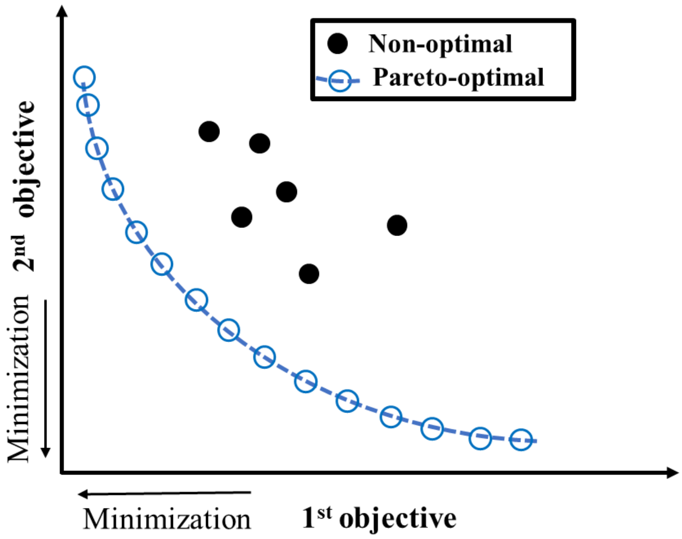


Figure 1.6. The principle of the Pareto line for the multi-objectives optimization

The optimization principle in sandwich structures means searching for the most suitable material combinations and structural parameters while ensuring that the final structure can provide the best performance against applied loads in the most efficient manner. The most efficient manner may take more aspects, however in general the optimization process involves selecting the best combination of core and face sheets configurations to achieve the desired objectives. This process must balance competing factors such as strength, stiffness and other mechanical properties.

In the practical designs, whenever design improvements are attempted, the design techniques and analysis often become more complicated. For example, improving the mechanical properties of the sandwich structure with composite materials for the face sheets will increase the design variables, which include ply orientations, stacking sequence, materials properties for the face sheets, core thickness and core density for the core. Hence, the design and analysis of the sandwich structure will be more complicated than a traditional sandwich structure with isotropic face sheet materials. Thus, the efficient optimization process should find ways to deal with these complexities by developing proper techniques and methodologies.

The sandwich structure optimization in this research included single-objective optimization (weight optimization) and multi-objective optimization (weight and cost optimization). The single-objective optimization technique involved minimizing the sandwich structure weight by using different kinds of face sheets composite materials with a vast range of the plies orientations. The multi-objective optimization included e.g. cost and weight for specific sandwich structure designs. To conduct an effective optimization process, the face sheets are considered to be different kinds of totally FRP and FML laminates. The honeycomb cores are adopted in various densities and thicknesses to reach the final objectives. The isight software organizes the optimization process in interaction with Excel software which is used as a laminator tool for obtaining the effective properties of the composite face sheets. Moreover, the optimization methodology was linked to the ANN model which is used as a fitness function. The methodology is conducted under a Matlab environment as it will be explained in the next chapters.

1.5 Artificial Neural Network combining with optimization technique in case of sandwich structures

Artificial Neural Networks (ANNs) can be characterized as computational models based on parallel distributed processing with particular properties such as the ability to learn, generalize, classify and organize data. They are recognized as a sophisticated technique for modeling complex nonlinear relationships, especially when traditional models are difficult or impractical. Inspired by human brain, these networks simulate learning process in their computational modeling [25-26].

This approach does not require explicit knowledge of the physical phenomena under investigation but depends solely on the historic input-output dataset (example set) to learn the relationship between the data through training. ANN-based models provide multiple advantages, including an outstanding generalization ability, owing to which they can accurately predict outputs for a new input data set and the capability of dealing with noisy data and uncertainties [27-28].

Given the nonlinearities and challenges to existing modeling techniques of the sandwich structures, the problem appears well suited to the use of a machine learning technique, such as an Artificial Neural Networks. Therefore, several studies have explored using this modeling techinque in assessing sandwich structure panels [29-34]. With regard to the honeycomb core sandwich structure, the ANN modeling is utilized to establish a generalized prediction model that can capture the influence of each structural parameter (i.e. geometrical characteristics, core properties, face sheets configurations and the applied load).

The integration between ANN and optimization for the sandwich structures represents a promising design approach. The ANN predictive model that captures the structural performance of the sandwich structure under specific operational conditions would eliminate the need to establish a costly computational model for designing sandwich structure variations. Therefore, it can serve as a reliable predictor of the sandwich structure performance, while the integrated optimization algorithm enables exploration of the design space and identifies optimum designs. This, in turn, provides an effective framework to obtain a set of optimal solutions that represent the corresponding targeted objectives. The steps illustrated in Figure 1.7 represent the methodology that developed in this dissertation for using ANN in structural optimization. Starting from defining key structural parameters in Step 1, the process then involves the creation of an Artificial Neural Network model in Step 2, followed by configuring the optimization process in Step 3, where key design variables, objectives and constraints are set. Finally, Step 4 integrates the ANN with the optimization framework, providing a streamlined approach to achieve optimum structure performance. This detailed, step-by-step methodology that was developed to address the optimization of weight and cost for sandwich structures.

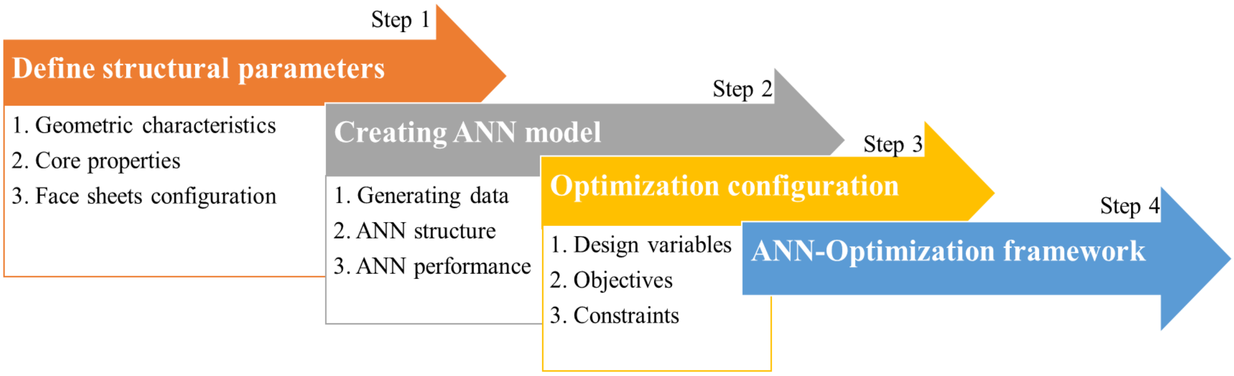


Figure 1.7. The main methodology steps in this research to develope an ANN-optimization framework for sandwich structure [Own compilation]

1.6 Goals of the research

The main aim of this research is to elaborate novel methodologies and approaches in modelling and optimizing sandwich structures for different kinds of applications. Consequently, the research purposes are following:

1. to develop an effective approach that can compute the final mechanical properties of stacking composite layers and provide accurate prediction for the strength limits of final laminates based on Classical Lamination Theory (CLT),
2. to create numerical and theoretical models to investigate the behavior of sandwich structures using laminated composites as face sheets,
3. to investigate using totally FRP and FML hybrid materials as face sheet materials in the honeycomb sandwich structure considering the design's alternatives,
4. to investigate the utilization of the different honeycomb cores and how they affect the overall behavior of the sandwich structure,
5. to develop an integrated platform between different modeling tools (i.e. theoretical or numerical) and related software that will provide a strong foundation to optimize the sandwich structure,
6. to define the optimization problems from the simplest concept, which includes single-objective optimization, to the complex concept, which includes multi-objective optimization of the investigated structures,
7. to use efficient methods to identify optimal solutions in terms of minimum weight and cost and provide the best tradeoff between the considered objectives in the case of multi-objective optimization,
8. to develop an ANN model for predicting objectives and constriants of the sandwich structure based on the provided design variables,
9. to develop an ANN model that can be integrated with an optimization algorithm to optimize structural weight and cost,
10. to carry out a series of experimental tests that provide deep insight into proposed sandwich structures and how the used techniques validated with the real test.

1.7 Added value of the research

1. Laminated face sheets and honycomb cores were investigated: The optimization methodologies utilized a wide range of materials for the face sheets and core.
2. Integrated optimization platform was developed: The research introduced a novel approach by integrating Excel with an optimization tool in the isight environment. This platform enabled advanced analysis and optimization of sandwich structures.
3. Single-objective and multi-objective optimization methods were elaborated: The research elaborated the single-objective optimization and multi-objective optimization for the honeycomb sandwich structure. The investigations provided a new scientific values for many optimization case studies.
4. Artificial Neural Networks model for the sandwich structure design was developed: The research explored the potential capability of ANN in modeling and optimizing sandwich structures. Consequently, a robust data-driven platform was provided for developing a predictive model that estimated structural performance, weight and cost.
5. Sandwich structure reverse design was elaborated by using ANN model: A novel reverse design methodology was developed using ANN to predict design variables based on structural response. This approach significantly differs from traditional design methods, accurately capturing structural behavior and validating the methodology against analytical solutions.
6. ANN with Genetic Algorithm based optimization was integrated: The research combined ANN with a Genetic algorithm optimization method to establish an efficient optimization model. This model was successfully applied to optimize the structural performance of honeycomb sandwich composites, including practical applications such as footbridge decks. The uniqueness of this integrated approach offers a flexible, time-efficient tool.
7. The analytical, FEM and ANN models were validated experimentally: The research included experimental tests to validate the behavior of sandwich structures under flexural loads. The comparison of experimental results with ANN, analytical and FEM models provided a strong foundation for the correctness of the developed methodologies, confirming the effectiveness of the integrated approaches.

1.8 Thesis outlines

After defining the engineering problem, this research reviews the literature studies for a better understanding of sandwich structure configurations and problems in Chapter 2. In Chapter 3, the optimization principles and methodologies used throughout this thesis are discussed in details, highlighting the properties of the utilized materials, objectives functions, design variables and design constraints for the optimization process. Chapter 4 deals with the elaboration of single objective optimization. In Chapter 5, the multi-objective optimization is elaborated for optimizing the floor panel for the high-speed train in terms of weight and cost. In Chapter 6, the Artificial Neural Network principles and modeling for sandwich structure are detailed. Chapter 7 investigates the reverse design of the sandwich structures by using ANN. Chapter 8 discusses the ANN modeling technique used for modeling sandwich structures and the integration of the ANN model with an optimization algorithm. In Chapter 9, the experimental results are investigated along with ANN modeling results and numerical modeling. Finally, in Chapter 10, the main contributions of the thesis are illustrated.

2. LITERATURE REVIEW RELATING TO THE SANDWICH STRUCTURES

2.1. Materials and modeling methods applied in the sandwich structures

Despite the literature review being focused on recent developments in sandwich structures, the earliest outlining sandwich structures theory and associated analysis methodologies were presented in the books by Plantema [35], Allen [36], Zenkert [37] and Vinson [38]. The main goal of the theoretical, numerical and experimental analyses in the sandwich structure area was to investigate these structures from various aspects [39]. Concerning the previous context, a combination of theoretical models such as strain energy analysis, equilibrium analysis and homogenization theory with the Finite Element (FE) model was adopted as a low-cost technique in designing sandwich structures [40-42].

Ruan et al. [43] modeled a hexagonal aluminum honeycomb by using FE simulations. The investigations covered the in-plane dynamic response of the proposed structure. The outcomes indicated that the core parameters and crushing speed influenced the deformation mode. Long et al. [44] conducted a failure analysis of foam sandwich structures under impact loading by a numerical model. The model effectively captured the changes in delamination shape and demonstrated its capability to simulate the impact response of sandwich structures. Wang et al. conducted an analytical model for different core geometries, such as triangular, square and hexagonal metal honeycombs. It was aimed to improve the sandwich structure in terms of in-plane stiffness and yield strength with various relative densities between 0.1 and 0.3 [45]. Aiming to expand honeycomb applications, Wei et al. developed analytical models to predict equivalent orthotropic properties of honeycombs with composite laminate cell walls. Detailed and homogenized finite element models agreed well with experimental tests, indicating good prediction capabilities [46].

In other research, Thomsen and Frostig [47] considered high-order sandwich panel theory for analytical modeling of sandwich beams with foam core under bending loads and compared the results with experimental work. Gibson [48] used analytical modeling for stiffness optimization in foam core sandwich composites and validated the results with experimental data using polyurethane foam core sandwich specimens. In another study by Qi et al. [49], numerical and theoretical methods were used to study the in-plane crushing response of chiral honeycomb under different load types (i.e. quasi-static and dynamic loads). Hadjiloizi et al. [50] studied an asymptotic homogenization approach that can analyze hexagonal honeycomb sandwich plates. The study suggested using a unit cell model to determine the effective elastic properties. The layer-wise third-order shear deformation theory was studied by Xiao et al. [51] to analyze delamination in sandwich panels subject to slamming loads. FEM formulation with reducing degrees of freedom was considered by Botshekanan et al. [52], where the authors proposed a layer-wise theory to analyze transverse stress in the composite face sheets. In another study by Fereidoon et al. [53], the effect of damping on the dynamic behavior of sandwich beams with an aluminum foam core was considered using Abaqus.

In the context of the core geometries, Yupu et al. [54] developed a Functionally Graded (FG) core with high stiffness-to-weight; the numerical examples demonstrated their superior stiffness, making FG plates promising for practical applications. Bartolozzi et al. [55] investigated the mechanical properties of the corrugation geometry core. Zhang et al. [56] introduced a comparative study to explore the sandwich structure's crashworthiness behavior for four core types: aluminum honeycomb, expanded polypropylene foam, plastic hollow balls and rubber foam balls. A deformation mechanism of the U-type corrugated core sandwich panel has been studied by Liu et al. [57]. The applied load was a lateral quasi-static compression. Experimental, numerical and analytical models revealed that the deformation was categorized into two distinct processes depending on whether or not the core was in contact during compression. The other study by Garrido et al. [58] focused on sandwich structure with a rigid polyurethane foam core and glass fiber reinforced plastic face sheets to investigate the creep behavior of sandwich structure. A composite core combined with the honeycomb and a regular grid were studied by Sun et al. [59]. The proposed combination represents a developed design with the potential to increase the strength and stiffness of sandwich structures. Melih et al. [60] studied a hexagonal honeycomb core considering composite wall cells. Flexure and torsional stiffnesses were improved compared with foam and traditional aluminum cores. Huang et al. [61] investigated enhancing the bending and crashworthiness of thin-walled aluminum tubes using a composite wrapping method with multi-cell sections. This study provided valuable insights for optimizing hybrid composite and cellular structures in bending and axial impact scenarios.

In the relevant structured cores, a truss core gained more attention recently; for instance, strength and failure modes under compression loads were studied by Hu et al. [62] for sandwich structures with lattice trusses made of composite material. In the other study, a numerical and experimental investigation was conducted by Wang et al. [63] to investigate the low-velocity impact of CFRP lattice core. The stacking sequences of the CFPR were found to affect crucially the structure behavior. On the other hand, Zhang et al. [64] proposed a thermal expansion mold to produce a CFRP lattice truss core; also, mechanical properties were investigated under flatwise compression and shear tests. In the same context, the torsional behavior of sandwich panels with pyramidal truss core was also studied by Li et al. [65].

As the exterior parts of sandwich structures, the face sheets are vital components directly influenced by external loads. Therefore, the proper choice of face sheet materials is a cornerstone in designing a structure that produces the desired performance in diverse engineering applications. The face sheet materials span a wide range of materials, from isotropic metals to advanced composite materials.

In this context, Takao et al. [66] collaborated to use aluminum (Al) face sheets with an aluminum foam core to investigate a developed method for attaching face sheets to the core. The friction stir welding was conducted to achieve metallurgical bonding between the foamable precursor and Al face sheets. Another study by Zhenyu et al. [67] involved a team effort to investigate using titanium as a base material for face sheets and core to produce multi-disciplinary lightweight structures. The structure was fabricated using a selective laser melting printing technique. A four-point bending experimental approach and analytical investigations were used to study the behavior of the structure. Mohan et al. [68] conducted a study to evaluate the low-velocity impact response of various face sheet materials, including stainless steel, aluminum and CFRP sheets with aluminum foam core. Utilized GFRP as face sheets was conducted by Mathieson and Fam [69]. The study involved experimental and analytical investigations for the failure response of sandwich structures fabricated from polyurethane foam with GFRP skins subject to axial force. Xiao et al. [70] studied the bending response of the aluminum honeycomb core with CFRP under a quasi-static bending load. The study concluded that the specific energy absorption and energy absorption were greatly enhanced with the ±30◦ fiber direction. As facing materials with milled glass fiber reinforced rigid polyurethane foam, a CFRP was used to fabricate composite sandwich structures for aircraft applications, as investigated by Harri et al. [71]. Wentao et al. [72] conducted a systematic study to explore the low-velocity impact and damage behavior of aluminum honeycomb sandwich structures with CFRP face sheets. The study revealed a significant influence of face sheet thickness on impact resistance.

Recently, FML has developed attractions to be used as a face sheet for sandwich structures due to its promising light weight and stiffness properties. Given this, Lu et al. [73] have investigated a two-material combination that included metal and CFRP's mechanical properties against loads in tensile and compressive modes. The study reported a significant influence of structural and material parameters on overall energy absorption and yield curve, providing valuable insights for future design considerations. Jianxun et al. [74] investigated the dynamic response of aluminum honeycomb plates with FML face sheets, consisting of glass fiber plies combined with aluminum layers. The study highlighted the influence of parameters like face sheet thickness and core stiffness on optimizing FML sandwich structures for projectile impact, offering practical guidance for structural optimization. A compressive strength assessment of FMLs post-impact was conducted by Patryk et al. [75]. The FML plate has configured glass fiber/titanium and carbon fiber/titanium to be subjected to impact energies. The study reported that delamination was the dominant damage type for different impact energies, a finding that can inform future material selection. The bending and impact performance of FMLs consisting of sisal fiber reinforced aluminum laminates was analyzed by Luciano et al. [76]. The study indicated that the proposed combination holds promising properties as a multifunctional FML, offering lightweight and sustainable characteristics for diverse applications, thereby broadening the scope of potential uses for FMLs. Hybrid material combined CFRP prepreg with aluminum alloy laminates was studied by Shiyi et al. [77]; an experimental test under three-point bending revealed that the bending properties enhanced with increasing CFRP volume, demonstrating the potential for CFRP to improve the mechanical properties of laminates.

2.2 Optimization of the investigated sandwich structures

The optimization of sandwich structures plays a crucial role in advancing engineering applications, providing a platform to fine-tune structures' configurations and materials for optimal performance. Based on the importance of optimization, we extensively reviewed previous studies that focused on optimizing sandwich structures in different terms. In this context, Dong et al. [78] studied optimizing the interface between epoxy foam core with CFRP face sheets in composite sandwich structure to enhance the final structure's compressive and impact properties. Gholami et al. [79] utilized the first-order shear deformation laminated plate theory for the optimizing composite sandwich structure as superstructure marine purposes. The study investigated the key parameters such as fiber type, matrix, core material, reinforcement and thickness. The study provided insight into crucial structural parameters for sandwich structure under out-of-plan pressure and buckling load. Lurie et al. [80] studied mass minimization for Arctic rescue vehicles to optimize sandwich structures with GFRP. Thermal protection and structural strength are optimization constraints. The study outlined potential trade-offs between mass reduction, thermal performance and structure strength. Sayed et al. [81] optimized the composite sandwich panels with honeycomb core and FRP face sheets under out-of-plane pressure. They used a Niching-Memetic Particle Swarm Optimization (NMPSO) algorithm to obtain weight minimization. The results showed that the NMPSO algorithm effectively achieved weight reduction. Weight reduction optimization for transit car bodies was introduced by Cho et al. [82]; the strategy was conducted through material selection and size optimization. The CFRP face sheet with Al honeycomb sandwich composite structures were applied under the frame and roof. The main findings are that the proposed hybrid car body provided lighter weight compared with the original ones.

Farzad et al. [83] investigated the optimization of dynamic and load-carrying performances for laminated sandwich structures. The optimization scenario utilized lamination parameters and first-order shear deformation theory, while a genetic algorithm was performed as a multi-objective optimization algorithm. The objectives involved fundamental frequency, buckling load and cost metrics. The Pareto-optimal solutions revealed an excellent trade-off between different performance metrics. In another study, the optimization of composite sandwich panels for heavy duty truck bottom panels was conducted by Sahib et al. [84]. For this purpose, combining an aluminum honeycomb core with FRP composite face sheets was considered in the investigated sandwich structure. A Classical Lamination Theory (CLT) and failure equations organized by a Multi-Island Genetic Algorithm (MIGA) reached substantial weight reduction potential, which provided insights for optimal design strategies to improve fuel efficiency. Sciuva et al. [85] investigated the optimization of mass, buckling load and maximum deflection, with fundamental frequencies serving as optimization constraints. A comparative analysis was conducted using two optimization algorithms: Genetic Algorithm (GA) and Simulated Annealing (SA). The study indicated comparable performance between the two algorithms. However, SA demonstrated a higher speed of convergence. The study by Icardi and Ferrero [86] specified minimizing the inter-laminar stress of sandwich structure laminated face sheets as the optimization objective. A blast pulse was considered to be a load on the structure. The reinforcement orientation angles were adopted as the design variable.

Pavlov et al. [87] studied optimization for minimizing the mass of the lattice structure. The considered geometry was cylindrical and helical angles, hoop ribs and helical ribs were taken as design variables. The optimization demonstrated a significant reduction in the total mass of the cylindrical body for satellite application by using a lattice structure. In another study by Yao et al. [88], a MIGA performed the lighter weight railway floating floor panel. The influence of optimization on acoustic insulation was also studied. The study found significant weight saving for the considered structure by optimizing the cross-section. Gaydachuk et al. [89] focused on optimizing shell-type composite structures with a honeycomb filler. The utilized technique provided an integrating design for weight minimizing via multi-parameter optimization. The study established a concrete basis for the rational design of such systems, which can apply to aviation, space and other load-bearing shell-type units. Alaa et al. [90] introduced a weight optimization method by replacing aluminum with FRP composite materials in aircraft pallet base plates. Different layer combinations of FRP face sheet materials and fiber orientations are investigated numerically and experimentally. A case study for an aircraft pallet base plate demonstrates a significant weight reduction compared to the standard aluminum pallet, indicating the optimization method's effectiveness. In another study achieved by Kovacs [91], designing multicellular plate structures was explored using advanced FRP laminated composites for weight reduction, corrosion resistance, stiffness and vibration damping in industrial applications. Two structures were developed: CFRP face sheets, GFRP stiffeners and CFRP face sheets and aluminum stiffeners for transport vehicles. Seven design constraints have been adopted in optimizing the structures' weight. The study's significance lies in achieving substantial weight savings compared to an all-steel structure.

2.3 Applications of ANN in the analysis of sandwich structures

Modeling by machine learning is extensively used in many engineering problems due to the spreading of digital data, improving computing power and establishing effective algorithms [92-93]. Artificial Neural Network is categorized as a popular modeling approach in the machine learning sector. Using this technique in the composite structure research field has been discussed from different perspectives.

Lefik et al. [94-95] introduced an ANN model to predict the homogenized behavior of composite material consisting of two phases of basic materials. The training data was generated from a series of analyses for an elastic-plastic model. The study conducted by Rique et al. [96] utilized Artificial Neural Network to predict the plasticity limits for foam material. The data was generated using a representative volume element under a monotonic load. The model showed good prediction ability. In another study by Laban et al. [97], developed a machine learning model to predict the load-carrying capacity range for composite structures. Two layers of ANN models showed optimal prediction performance. Khan et al. [98] developed an intelligent model for predicting transverse rupture strength, flexural modulus, impact and hardness associated with four kinds of carbon and glass fiber-reinforced composite materials. The study concluded that although problem complexity the ANN can have good stability in predicting studied properties. Fan et al. [99] combined finite elements with a Convolution Neural Network (CNN) to predict the induced deformation contours for composites. The study involved 12 kinds of stacking sequences. The study reported that the proposed model could make fast and accurate assessments in this aspect.

Jagesh et al. [100] used an Artificial Neural Network to predict sandwich structure behavior regarding vibration and damping with a central rectangular gap. The experimental and numerical approaches were used to generate the required data. The study concluded that the developed model offers an efficient tool for assessing dynamic behavior and structural health monitoring in engineering applications. Lan et al. [101] introduced the ANN model to identify the delamination in a sandwich structure. The training data was derived from finite element simulations for damage classification and regression modeling. The developed model demonstrated significant success in identifying skin damage. Yang et al. [102] used Artificial Neural Network to predict the T-joint strength of the sandwich structures for marine applications. The failure modes were generated numerically and the derived data was used to develop the model. The approach demonstrated good agreement with simulation results. Yong et al. [103] compared three machine-learning approaches for predicting the sandwich structure behavior under axial compression. The experimental data were employed to train three data-driven models: Simple Linear Regression (SLR), Artificial Neural Network and Adaptive Neuro-Fuzzy inference system (ANFIS). Comparative analysis revealed that ANFIS exhibited superior performance, followed by ANN and SLR. Sahib and Kovacs [104] used ANN to investigate a honeycomb sandwich structure's reverse design. The Monte Carlo method was performed with governing equations to generate the training data. The reverse model offered an efficient and time-saving design method compared to traditional methods. Fadlallah et al. [105] used a weight optimization technique to obtain lighter composite heliostats. The proposed structure was a honeycomb sandwich and a ANN model was used to model the structure. Then, the structure was integrated with the Particle Swarm Optimization (PSO) algorithm to predict sandwich behavior and weight optimization. The integration of ANN-PSO provided an efficient method for conducting structural optimization. Akbari et al. [106] utilized a genetic algorithm with Artificial Neural Network to increase the ultimate tensile strength and hardness of aluminum composite plates. Xiaoyang et al. [107] introduced an efficient approach for combining the ANN model with an optimization algorithm to minimize the weight of composite laminates. A finite element model with the Latin hypercube sampling technique generated the required data. The study signified that the proposed method eliminated the need for time-consuming in optimizing the studied structures. Ning et al. [108] produced an integration model for ANN with PSO to address the lightweight design for a head pressure shell in an Autonomous Underwater Vehicle (AUV). A grid sandwich structure was considered to conduct the required optimization with weight. The study emphasized that a significant weight reduction could be obtained compared to a solid pressure shell, ensuring its feasibility for AUV application. Xu-ke et al. [109] investigated using the Latin hypercube sampling method with ANN metamodel and the Nondominated Sorting Genetic Algorithm (NSGA-II) to optimize sandwich structures with double arrow auxetic core optimization. Their results showed superior blast resistance and energy absorption designs.

The review of literature studies points out gaps in the knowledge body of the optimization weight and cost for the sandwich structures, particularly in the areas of modeling techniques, optimization methodologies and materials investigations. The existing current research gaps can be summarized in the following:

1. **Materials**: Limited research has been conducted on using different kinds of sandwich structure components (i.e. cores and face sheets) for optimizing weight and cost. Investigations involving optimization weight and cost using different material types still need to be explored.
2. **Modeling techniques**: There is a shortage of studies that effectively utilize advanced modeling techniques, such as Artificial Neural Networks to design sandwich structures which will be used for structural optimization purposes.
3. **Integration of ANN with optimization**: Combining ANN with optimization algorithms in the context of cost and weight of the sandwich structures is a relatively new area, with minimal prior research.

In response to these gaps, this research focuses on optimizing sandwich structures with honeycomb core and laminated face sheets, aiming to reduce weight and cost from different perspectives. We used related sandwich structure theories, such as CLT and Beam Theory to analyze the structure. Then, it is followed by both single-objective and multi-objective optimization processes. The innovative integration of ANN with optimization methodologies is also explored to identify optimal solutions based on application requirements.

3. Elaboration of the optimization procedure of the investigated sandwich structure

This chapter outlines the elaborated methodology for sandwich structure optimization in different scenarios. The investigations involved the sandwich structures with the aluminum and Nomex honeycomb cores in various densities. The face sheets consist of an aluminum alloy or composite laminates of unidirectional Glass Fiber Reinforced Plastic (GFRP), unidirectional Carbon Fiber Reinforced Plastic (CFRP), Woven Glass Fiber Reinforced Plastic (WGFRP), Woven Carbon Fiber Reinforced Plastic (WCFRP) and Fiber Metal Laminates (FML), which combined of alter layers of composite and aluminum in different sequences. The mechanical properties of utilized materials in the face sheet and honeycomb core are illustrated in Tables 3.1 and 3.2. The manufacturers of the utilized FRP composite layers in the investigations of this dissertation were Toray composite materials, Hexcel composite materials and SGL Carbon SE.

Table 3.1. Engineering properties of facing materials for sandwich structure [110-112]

Material properties	**CFRP Toray ply**	**CFRP Hexcel ply**	**GFRP Hexcel ply**	**Al**	**WGFRP Hexcel ply**	**WCFRP SGL ply**
Longitudinal modulus: E_x [MPa]	181000	130000	43000	70000	20000	70000
Transverse modulus: E_y [MPa]	10300	10000	8000	70000	17000	60000
In-plane shear modulus: G_{xy} [MPa]	7170	5000	4300	26000	3500	4500
Poisson's ratio: v_{xy} [-]	0.28	0.28	0.25	0.33	0.13	0.05
Density: ρ_f [kg/m^3]	1600	1600	1800	2780	1.88	1.5
Lamina thickness: t_l [mm]	0.127	0.125	0.125	0.2	0.25	0.23
Longitudinal tensile strength: σ_{xt} [MPa]	1500	2000	1140	186	600	800
Longitudinal compressive strength: σ_{xc} [MPa]	1500	1300	620	186	600	800
Transverse tensile strength: σ_{yt} [MPa]	40	78	39	186	550	700

Transverse compressive strength: σ_{yc} [MPa]	246	246	128	186	550	700
In-plane shear strength: σ_{xy} [MPa]	68	68	60	110	55	60

Table 3.2. Mechanical properties for utilizing honeycomb cores [111]

Density	**Properties in *x* direction**		**Properties in *y* direction**		**Properties in *z* direction**	
ρ_c [kg/m^3]	Strength: σ_{xz} [MPa]	Modulus: G_{xz} [MPa]	Strength: σ_{yz} [MPa]	Modulus: G_{yz} [MPa]	Strength: σ_{zz} [MPa]	Modulus: E_{zz} [MPa]
Al-Honeycomb						
29	0.4	55	0.65	110	0.9	165
37	0.45	90	0.8	190	1.4	240
42	0.5	100	0.9	220	1.5	275
54	0.85	130	1.4	260	2.5	540
59	0.9	140	1.45	280	2.6	630
83	1.5	220	2.4	440	4.6	1000
Nomex-Honeycomb						
29	0.28	12	0.52	22	0.54	17
48	0.62	24	1.16	38	1.9	25
64	0.82	30	1.48	50	3.7	35
80	1.05	38	1.95	68	4.7	40
96	1.42	56	2.45	86	6.6	50
123	1.76	71	2.9	98	10	60
144	1.9	80	3.05	110	13.2	69

In this research, the design variables to be optimized are honeycomb core thickness (t_c), density (ρ_c) and face sheet configurations such as face sheet thickness (t_f) or the number of layers (N_l) and materials to minimize the weight and/or the cost of the sandwich structures.

During the optimization process, five general design constraints are considered. The constraints of the optimization problems are the core shear, face sheet stress due to bending load, face sheet wrinkling (critical stresses and load), intra-cell buckling and finally, the maximum structure deflection (bending deflection and shear deflection). These constraints are calculated to compare with the associated ultimate limits of face sheets and honeycomb core.

The optimization procedures are started by formulating the objective functions for the weight and/or the cost of the honeycomb sandwich structure. Consequently, the constraints and boundaries for the design variables are formulated. In this research, all the CLT and Beam Theory equations are formulated in Excel software. While the optimization process is conducted by integrating the optimization tool under isight software with Excel software. The Neighborhood Cultivation Genetic Algorithm (NCGA), the Multi-Island Genetic Algorithm (MIGA) and the standard Genetic Algorithm (GA) are the optimization algorithms used to solve the problems considered in this research. The main optimization steps are illustrated in the flowchart in Figure 3.1.

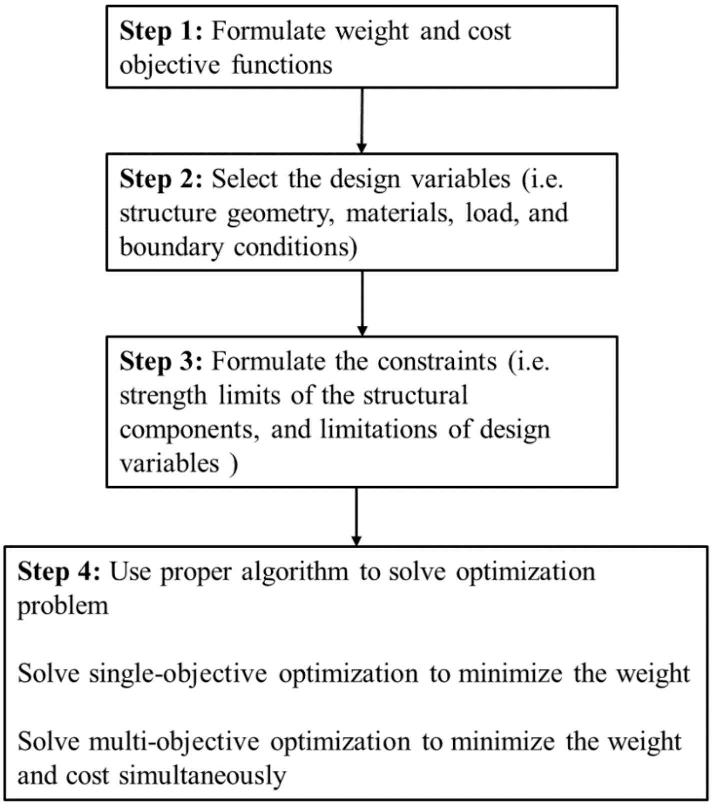


Figure 3.1. The flowchart of sandwich structure optimization procedure

In this research, the optimization process started with solving the weight minimization problem, as structure weight is a key design parameter for industrial applications. Accordingly, a single objective optimization of the sandwich structure was performed to attain a lighter weight while satisfying the material strength constraints of the sandwich structure's materials.

Then, more complex scenarios were conducted to solve the multi-objective optimization problem for the sandwich structure. The optimization method was performed to simultaneously reduce the weight and cost of the designed sandwich structure.

3.1 Objective functions

3.1.1 Weight objective function

The total weight of the investigated sandwich structure, which consists of a honeycomb core with a laminated face sheet (as detailed in Section 1.3), is formulated below as an objective function that should be minimized:

$$W_t = W_f + W_c = 2l\,b \sum_{l=1}^{n} \rho_l\, N_l t_l + l\, b\, \rho_c\, t_c \tag{3.1}$$

where: W_t is the total weight of the sandwich structure, W_f is the weight of the upper and lower face sheets and W_c is the weight of the core; furthermore, ρ_l, N_l and t_l are the density, number of layers and thickness, respectively, for each constituent layer in the face sheets, *l* is the length of the sandwich structure, *b* is the width of the sandwich structure, t_f is the thickness of the face sheet, *n* is the total number of constituent layers in the face sheets and t_c is the thickness of the core.

The total thickness of the face sheet (t_f), which is composed of *n* layers of individual constituent lamina and can be calculated by:

$$t_f = \sum_{l=1}^{n} N_l t_l \tag{3.2}$$

3.1.2 Cost objective function

Cost is another important criterion in the design of composite sandwich structures and is known to be influenced by the sum of material and manufacturing costs of the structure components. Since these materials are relatively expensive, minimizing costs can be a primary design goal. In sandwich structures, the cost function includes material and manufacturing costs. The total cost is illustrated in the below equation which should be minimized:

$$C_t = C_{mat} + C_{man} \tag{3.3}$$

where: C_t is the total cost of the structure, C_{mat} is the materials cost and C_{man} is the manufacturing cost.

The key cost drivers for the materials are the cost summation of the face sheets' and core materials, whereas the manufacturing costs include cutting, assembly and heat treatment (autoclave). The cost function can then be described as the sum of the costs for the laminated face sheets and honeycomb core materials, as well as the manufacturing costs, which can be explained below:

$$C_t = C_{face} + C_{core} + C_{cutting} + C_{assembly} + C_{autoclave} \tag{3.4}$$

where: C_{face} and C_{core} are materials costs related to the face sheets and core respectively, while $C_{cutting}$, $C_{assembly}$ and $C_{autoclave}$ are manufacturing costs associated with cutting, assembly and heat treatment of the final sandwich structure

Generally, the manufacturing cost parameters are not under the designer's control and are assumed to be fixed costs. Therefore, the material costs (i.e. laminated face sheets and core) can be considered as the principal factor for the cost index. In this research, the cost of materials is adopted in the optimization methodology. A deep survey was conducted as part of this study to estimate the costs of the constituent materials in a sandwich structure. In the interest of generalization, the unit price of each material was normalized to the price of GFRP. The cost of CFRP, the core and aluminum sheets were estimated by 1.5, 0.5 and 0.31 times of the GFRP cost, respectively.

3.1.3 Identify the best solution by Improved Minimum Distance Selection Method

Single-objective optimization is a streamlined procedure focusing on a specific goal, such as minimizing weight or cost. This approach simplifies decision-making, allowing for a clear path to achieve the desired outcome without the complexities of trade-offs.

In contrast, multi-objective optimization focuses simultaneously on multiple goals. Therefore, providing a broader perspective on trade-offs between competing objectives like cost and weight is crucial. For the multi-objective optimization, the obtained Pareto curve between cost and weight objectives represents the optimal designs of the optimization process. Therefore, additional selection procedures are needed to determine the optimal solution from the Pareto curve. In this research, the Improved Minimum Distance Selection Method (IMDSM) is used to determine the **knee point** that represents the most balancing point between weight and cost. The knee point can be obtained for the weight and cost objectives as follows [113]:

$$D_{min} = \sqrt{\left(\frac{f_{W_t}(x)}{min\ (f_{W_t}(x))} - 1\right)^2 + \left(\frac{f_{C_t}(x)}{min\ (f_{C_t}(x))} - 1\right)^2} \tag{3.5}$$

where: D_{min} identifies the minimum possible distance between the ideal point (min. weight, min. cost) and any on Pareto curve; furthermore, $f_{Wt}(x)$ refers to the weight objective function on the Pareto line while $f_{Ct}(x)$ is the cost objective function on the same line.

3.2 Design variables

Design variables are a set of independent parameters that can be changed to improve structural performance and achieve the specified objectives. In this research, the design variables include laminated FRP face sheets and aluminum layers. The totally FRP laminated face sheets are organized as one of the optimization alters to maximize structural performance while minimizing weight. These layers provide excellent mechanical properties and can be tailored to various practical applications.

The combination of FRP composite layers with aluminum layers provides FLM face sheets. The properties of final laminated face sheets are determined by the orientation of the fibers associated with FRP composite laminates, the number of layers and the final face sheet thickness. Furthermore, the design variables related to the selection of the honeycomb core varied within a wide range of densities. The design variables are summarized in Table 3.3.

Table 3.3. Design variables for investigated sandwich structures in this research

Description	Design variable	Remark
Number of face sheet layers	N_l [pieces]	discrete variable, integer values, depend on design configuration
Face sheet materials	CFRP, GFRP WGFRP, WCFRP Aluminum	as specified in Table 3.1
Orientation angle of the fibers in the composite laminate	θ_{FRP}	multidirectional
Core density	ρ_c [kg/m^3]	as specified in the Table 3.2
Core thickness	t_c [mm]	continuous value depends on the practical application

3.3 Design constraints

To define the feasible design during optimization procedures, it is necessary to distinguish between sandwich constructions that are met with a specific purpose and those that are not. In other words, design constraints are the limitations that any proposed design must be satisfied.

This research used design constraints such as maximal deflection of the structure, strength limitations and failure criteria for the sandwich structure to establish the limits that any proposed design must satisfy. The structural responses and their constraints are detailed in the next sub-sections.

3.3.1 Shear stress in the honeycomb core

Shear stress in the core of a sandwich structure is a critical factor influencing its overall performance and stability. Therefore, a proper material selection and core design are essential to optimize shear stress distribution and enhance the sandwich structure's durability. Shear stress in the honeycomb core (τ_c) can be calculated by the following equation [111], [114-115]:

$$S_{xz} \geq \tau_c = \frac{F}{db} \tag{3.6}$$

where: S_{xz} the ultimate shear strength of the honeycomb core, *F* is the maximum shear force, *b* is the sandwich structure width and *d* is the distance between the center lines of upper and lower face sheets and it can be calculated as below:

$$d = t_f + t_c \tag{3.7}$$

wehere: t_f is the thickness of the face sheet, *n* is the total number of constituent layers in the face sheets and t_c is the thickness of the core.

3.3.2 Face sheet stress

Proper face sheets design enhances sandwich structure ability in organizing applied loads while maintaining the weight at the lowest possible value, making them essential for high-performance applications. The stress in the face sheet (σ_f) and the maximum bending moment can be calculated using:

$$\sigma_{fx} \geq \sigma_f = \frac{M_{max}}{dt_f} \tag{3.8}$$

where: σ_{fx} is the yield strength of the laminated face sheet, M_{max} is the maximum moment and it can be calculated as below:

$$M_{max} = p \cdot \frac{bl^2}{8} \tag{3.9}$$

where: *p* is the distribution load in the out of plane direction, *l* is the length of the sandwich structure.

The Tsai-Wu failure criterion and the CLT were used to calculate the yield strength (σ_{fx})of the laminated face sheet.

3.3.3 Intra-cell buckling of face sheets

This phenomenon is a local buckling in some regions of the face sheet that are not supported by the honeycomb walls. The following expressions can describe the critical stress ($\sigma_{in\ cr}$) associated with this phenomenon:

$$\sigma_{in\ cr} = \frac{2E_{fx}}{1 - \upsilon_{xy}^2}\left(\frac{2t_f}{c}\right)^2 \geq \sigma_{fx} \tag{3.10}$$

where: E_{fx} is effective modulus of elasticity for the face sheet, v_{xy} is Poisson's ratio of the face sheet and c is the cell size of the honeycomb core respectively.

3.3.4 Face sheet wrinkling

Face sheet wrinkling is a structural phenomenon observed in sandwich panels, manifesting as the development of waves of local buckling or wrinkles on the face sheets. This phenomenon typically arises under in-plane shear or compression loads. The criterion for predicting wrinkling can be expressed as follows:

$$\sigma_{wr\ x} = 0{,}5\sqrt[3]{E_{fx}E_{zz}G_{\mathrm{xz}}} \geq \sigma_{fx} \tag{3.11}$$

where: $\sigma_{wr,x}$ is the face sheets' wrinkling stresses, E_{zz} is the core's modulus of elasticity in the z-direction and G_{xz} is the shear modulus in the x-z plane.

3.3.5 Maximum deflection of the sandwich structure

The maximum middle deflection is one of the critical constraints in the design of sandwich structures. The deflection of a sandwich structure consists of bending and shear components. Flexural deflection depends on the face sheet materials' relative tensile and compressive moduli. The shear deflection depends on the shear modulus of the core. It can be formulated as follows:

$$\delta = \frac{k_b P l^3}{D} + \frac{k_s P l}{S} \leq \delta_{max} \tag{3.12}$$

where: k_b = 5/384 and k_s = 1/8 [111] are the bending deflection coefficient and shear deflection coefficient for simply supported sandwich structure with distribution load, δ_{max} is the specified deflection limit according to the practical application.

The bending stiffness (D) and shear stiffness (S) of the sandwich structure can be calculated as below:

$$D = \frac{E_f t_f d^2 b}{2} \tag{3.13}$$

$$S = \frac{b d^2 G_{xz}}{t_c} \tag{3.14}$$

where: E_f is the effective elasticity modulus of the laminated face sheet calculated by the CLT and G_{xz} is the core shear modulus in the x-z plane.

4. APPLICATION OF THE ELABORATED OPTIMIZATION METHOD FOR SINGLE OBJECTIVE OPTIMIZATION OF A BOTTOM PANEL IN HEAVY TRUCK

The automotive industry continually seeks innovative designs to fulfill the demands of sustainable engineering. This trend includes the development of advanced structural designs for heavy trucks aimed at enhancing fuel efficiency. Given the inherent relationship between vehicle weight and fuel consumption, weight reduction is one of the most logical ways to meet these demands [116-117].

Improving the fuel efficiency of heavy trucks is essential for sustainable energy supply and future economic development. Consequently, new technologies are needed to enhance energy security in the transportation sector. In this context, this case study investigates the optimal design of a composite sandwich panel as a lightweight structure to replace the conventional sandwich structure in the bottom panel of a heavy truck. The investigated lightweight composite sandwich structure comprises of an aluminum honeycomb core with two FRP laminated face sheets.

This case study aims to develop a new optimum design method for composite sandwich structure to reduce heavy trucks' body mass. The design variables related to the structure's face sheets include the type of FRP layers, the number of layers and the orientation of the FRP layers. Furthermore, the thickness of the core is also considered as a design variable. The objective of the optimization process is to obtain a lighter possible weight of the structure. Moreover, the constraints of the optimization problem are set to be related to the strength limits of the face sheets and the core. The CLT and the failure equations of composite plates are formulated using Excel software. To solve the optimization problem, a Multi-Island Genetic Algorithm (MIGA) optimization algorithm is applied under the isight software environment interacting with Excel [118]. The numerical model uses Abaqus FEM software [119] to validate the optimization results.

4.1 Structure of the investigated bottom panel in a heavy truck

The primary aim of this case study is to reduce weight by utilizing a composite sandwich structure with an optimal combination of the face sheets and honeycomb core in order to reduce fuel consumption of the vehicle.

In this case study, the optimization process is to achieve the lowest weight for the bottom plate of a heavy truck while simultaneously achieving the required structural strength. To achieve this goal, the design variables include the number of composite layers of the face sheets, the orientation of the composite layers and the core thickness. The design is subject to various constraints, including face sheet failure, core failure in out-of-plane shear, face sheet wrinkling, face sheet intra-cell and the maximum deflection. The isight software, combining with the Excel software, is used to solve the optimization problem within the limits of the given design variables and constraints using the MIGA algorithm.

The sandwich structure of the bottom panel, with dimensions (as illustrated in Figure 4.1), is supported by two beams to prevent failure due to concentrated loads. The truck carries up to 20000 kg (W_{max}), described as a uniformly distributed load. The original design consists of an aluminum honeycomb core with a density of 80 kg/m^3 and an aluminum face sheets [115]. The geometrical parameters and applied loads are presented in Table 4.1.

The proposed structure consists of a hexagonal aluminum core with two composite face sheets. The face sheets are made of Woven Glass Fiber Reinforced Plastic (WGFRP) and Woven Carbon Fiber Reinforced Plastic (WCFRP). The mechanical properties of the laminae used in the face sheets were detailed in Table 3.2. The mechanical properties of the utilized core density (83 kg/m^3) were listed in Table 3.1.

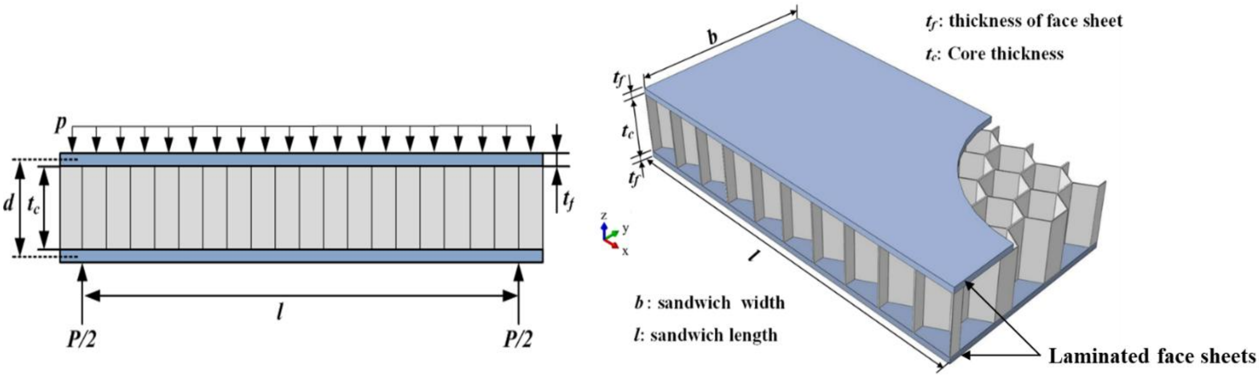


Figure 4.1. Dimensions and boundary conditions of the bottom panel for a heavy duty truck

Table 4.1. Technical data for the investigated bottom panel of a heavy truck [115]

Length l	**Width** b	**Maximal deflection** δ_{max}	**Load** W_{max}	**Equivalent distribution load** p
[mm]	[mm]	[mm]	[kg]	[Mpa]
2500	8000	10	20000	0.01

During the design of a heavy truck bottom panel, the ultimate constraint margins for the face sheets and core are set to be equal or greater than 5 times the stresses resulting in these components due to the applied load [115]. Since the intra-cell and wrinkling constraints for the face sheets were not selected in [115], the associated minimum values of the constraint margins were set to be equal to or greater than 2 times of the fracture strength of the face sheets. While the maximum allowable deflection constraint for the designed structure does not exceed 10 mm.

4.2 Application of the elaborated optimization method for the sandwich bottom panel structure

4.2.1 Weight objective function

The total weight of the investigated sandwich structure, which consists of a honeycomb core with a laminated face sheet (as detailed in Section 1.3), is formulated below as an objective function that should be minimized:

$$W_t = W_f + W_c = 2l\,b\sum_{l=1}^{n}\rho_l\,N_l t_l + l\,b\,\rho_c\,t_c \tag{4.1}$$

where: W_t is the total weight of the sandwich structure, W_f is the weight of the upper and lower face sheets and W_c is the weight of the core; furthermore, ρ_l, N_l and t_l are the density, number of layers and thickness, respectively, for each constituent layer in the face sheets, l is the length of the sandwich structure, b is the widh of the sandwich structure, t_f is the thickness of the face sheet, n is the total number of constituent layers in the face sheets and t_c is the thickness of the core.

4.2.2 Design variables to be optimized

Generally, the optimization algorithm defines the best feasible solution from the pool of alternatives. Therefore, the optimum weight for the sandwich structure is crucially related to the specified design variables. Three design variables are considered in this study, which are listed with the associated ranges in the Table 4.2.

Table 4.2. Design variable for the bottom panel of a heavy-duty truck

Design variables	Value	Remark
Number of face sheet layers	$1 \leq N_l \leq 8$ [pieces]	discrete variable, integer values
Possible WFRP laminae orientation	$-90° \leq \theta_{FRP} \leq 90°$	continuous variable, integer values
Thickness of the honeycomb core	$1 \leq t_c \leq 100$ [mm]	continuous variable

4.2.3 Design constraints used during the optimization

To precisely define the optimization procedures, it should be recognized between those sandwich structures that are fit for the considered purpose and those that are not. This fitness for purpose is identified by a number of design constraints or requirements that any designed sandwich must satisfy. The constraint values, calculated using equations (3.6-3.12) are listed below:

1. Core shear strength: the core shear strength must have a constraint margin equal to or greater than 5 times the resulting shear stress [115];
2. Face sheet strength: the ultimate strength of the face sheets must have a constraint margin equal to or greater than 5 times the resulting face sheets stress [115];
3. Face sheet intra-cell: the intra-cell stress must have a constraint margin equal to or greater than 2 with respect to the ultimate strength of the face sheets;
4. Face sheet wrinkling: the wrinkling stress must have a constraint margin equal to or greater than 2 with respect to the ultimate strength of the face sheets;
5. Maximum deflection: the structural deflection must be below 10 mm [115].

4.3 Single-objective optimization results for sandwich structure of a bottom panel in a heavy truck

The aim of the optimization in this case study is to identify the optimum sandwich assembly that provides the lowest weight. The optimization procedure was performed by setting objectives, design variables and constraints as detailed in Section 4.2.

Figure 4.2 depicted the relationship between the sandwich structure's weight (kg), core thickness (mm) and the number of face sheet layers (pcs) for a sandwich structure with glass WGFRP face sheets. For instance, the structure showed the lowest weight of about 140 kg obtained with a maximum core thickness of about 60 mm while reducing the core thickness associated with more added layers in the face sheets, which reflected in the heavier structure.

Figure 4.3 depicted the effect of core thickness and face sheet layers on the total weight of the sandwich structure in the case of carbon WCFRP layers. In general, adding more layers in the face sheets provides lower core thickness but results in an increase in the structure weight. However, a lighter structure of approximately 92 kg can be achieved by carefully balancing core thickness and the number of face sheet layers.

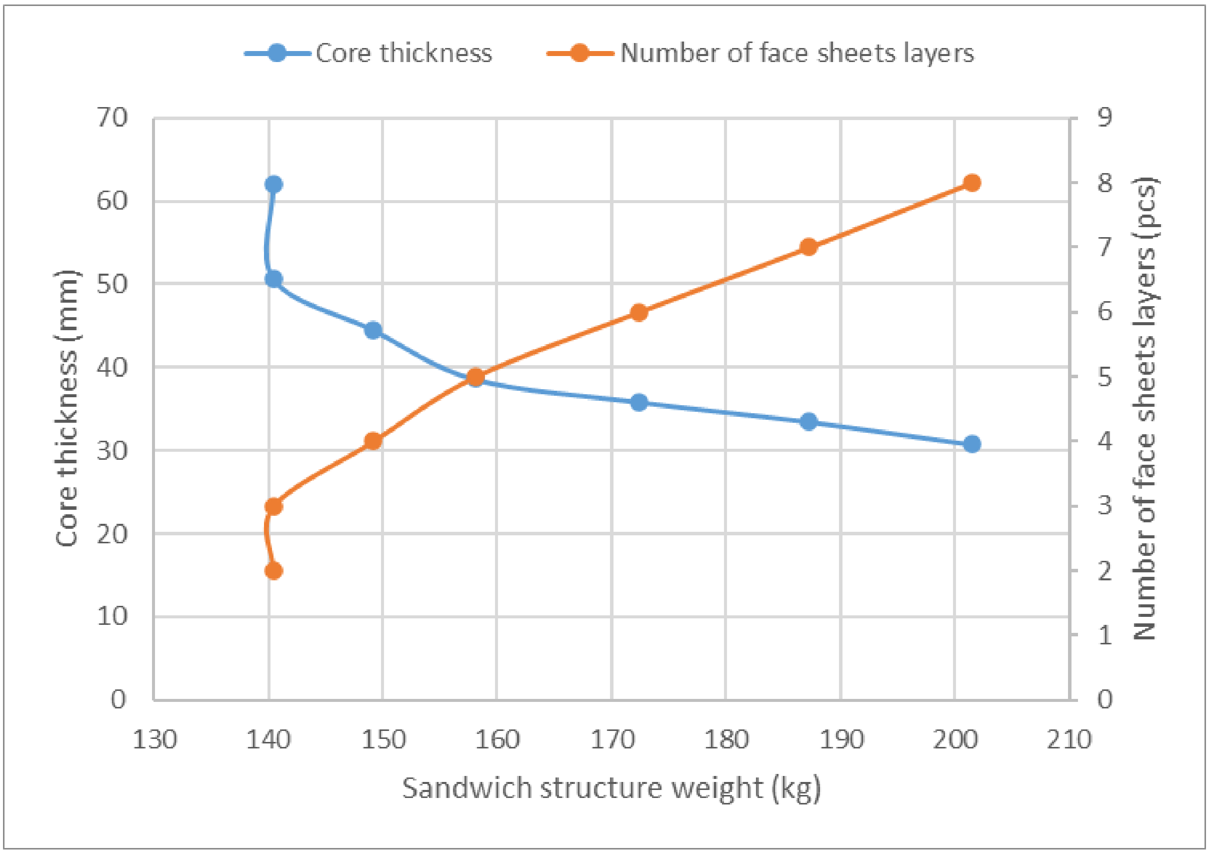


Figure 4.2. Weight of the sandwich structure versus core thickness and face sheets' layer number in case of WGFRP face sheets and Al honeycomb core

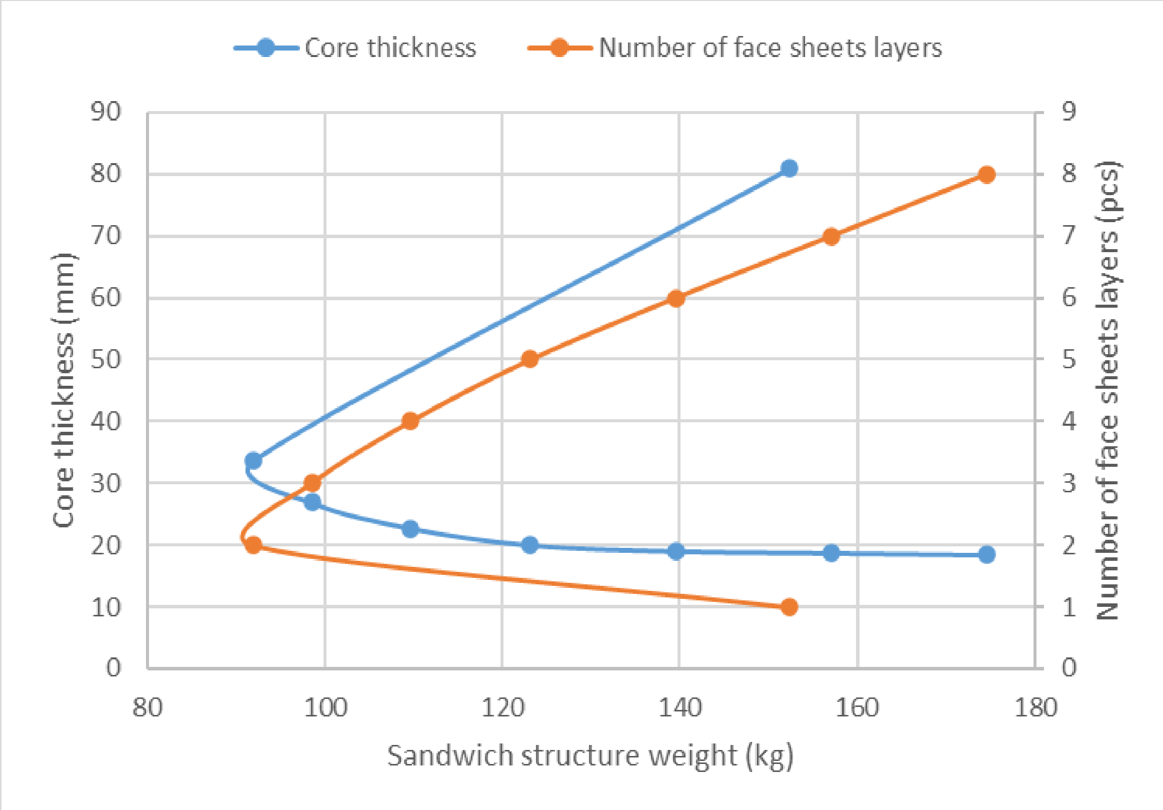


Figure 4.3. Weight of the sandwich structure versus core thickness and face sheets' layer number in case of WCFRP face sheets and Al honeycomb core

Based on Figures 4.2 and 4.3, it can be noticed that the weight of the investigated sandwich structure depends mainly on the number of composite layers in the face sheets and the thickness of the core. A lower number of face sheet layers required a higher core thickness to increase the flexural modulus of the sandwich structure against out-of-plane loads. However, increasing core thickness led to greater overall weight of the structure. On the other hand, increasing the number of composite layers in the face sheets and reducing the core thickness should be done in a controlled manner. As can be seen in Figures 4.2 and 4.3, the optimal values for the number of face sheet layers for both glass WGFRP and carbon WCFRP were two layers.

Tables 4.3 and 4.4 show the details of the feasible and optimal designs for the glass WGFRP and carbon WCFRP sandwich structures, respectively.

Table 4.3. Optimization results for using WGFRP material in the face sheets

Face sheet layers [pcs] and **orientation of the composite layers** [°]	t_c [mm]	δ [mm]	W_t [kg]
(2 layers) 5° ; -5°	61.98	9.99	**140.48**
(3 layers) -85°; 5°; 0°	50.66	9.985	140.5
(4 layers) -10°; 0°; -15°; -90°	44.55	9.897	149.16
(5 layers) 0°; 10°; 5°; 0°; 5°	38.62	9.982	158.11
(6 layers) 0°; 10°; -80°; 65°; -5°; -5°	35.88	9.98	172.36
(7 layers) -85°; 80°; -60°; 85°; -85°; 0°; 75°	33.51	9.925	187.22
(8 layers) 0°; 85°; 5°; 65°; -35°; 10°; -80°; -5°	30.78	9.999	201.5

Table 4.4. Optimization results for using WCFRP material in the face sheets

Face sheet layers [pcs] and **orientation of the composite layers** [°]	t_c [mm]	δ [mm]	W_t [kg]
(1layer) -80°	80.89	4.387	152.29
(2 layers) -80°; -5°	**33.73**	**9.995**	**92**
(3 layers) 85°; 90°; -10°	26.86	9.958	98.58
(4 layers) 10°; 0°; -5°; 80°	22.7	9.873	109.69
(5 layers) 15; 5°; -20; 15; -80°	19.99	9.957	123.19
(6 layers) 10°; 0°; 0°; -70°; 55°	19.03	9.808	139.6
(7 layers) 30°; -85°; -30°; -25°; -80°; -20°; -5°	18.73	9.325	157.1
(8 layers) -75°;-35°;-75°; -80°; -50°; 80°; 90°; -15°	18.43	8.112	174.6

For WGFRP face sheets alternatives, the analysis showed that as the number of layers increased from 2 to 8, the core thickness decreased significantly, from 61.98 mm to 30.78 mm, while the total weight increased from 140.48 kg to 201.5 kg. The maximum deflection of the sandwich structure remained close to the maximum allowable limit of 10 mm across all alternatives. This highlighted the optimization algorithm's ability to maintain the specified constraints.

For WCFRP face sheets alternatives, the structure showed a similar trend with core thickness decreasing from 80.89 mm for a single layer to 18.43 mm for 8 layers, while the weight begins at 152.29 kg and reached 174.6 kg for the 8 layer design. As noticed previously the maximum deflection was kept at allowable limits.

It can be concluded that the sandwich structure with WGFRP's face sheets produced various alternatives with an optimum weight of 140 kg. In comparison with WGFRP face sheet structures, the sandwich structure with WCFRP face sheets maintained a lower overall weight across its alternatives, with an optimum weight of 92 kg. This highlighted the advantage of using WCFRP to achieve the necessary structural weight reductions in the investigated structure, where minimizing weight is essential for improving fuel efficiency.

Figures 4.4 and 4.5 offered a comparative analysis of WCFRP and WGFRP layers used in the face sheets of the investigated sandwich structure. Figure 4.4 illustrated the weights for the sandwich structure designs using eight different configurations, each representing a different number of face sheet layers. Figure 4.5 presented the corresponding thickness for the same configurations.

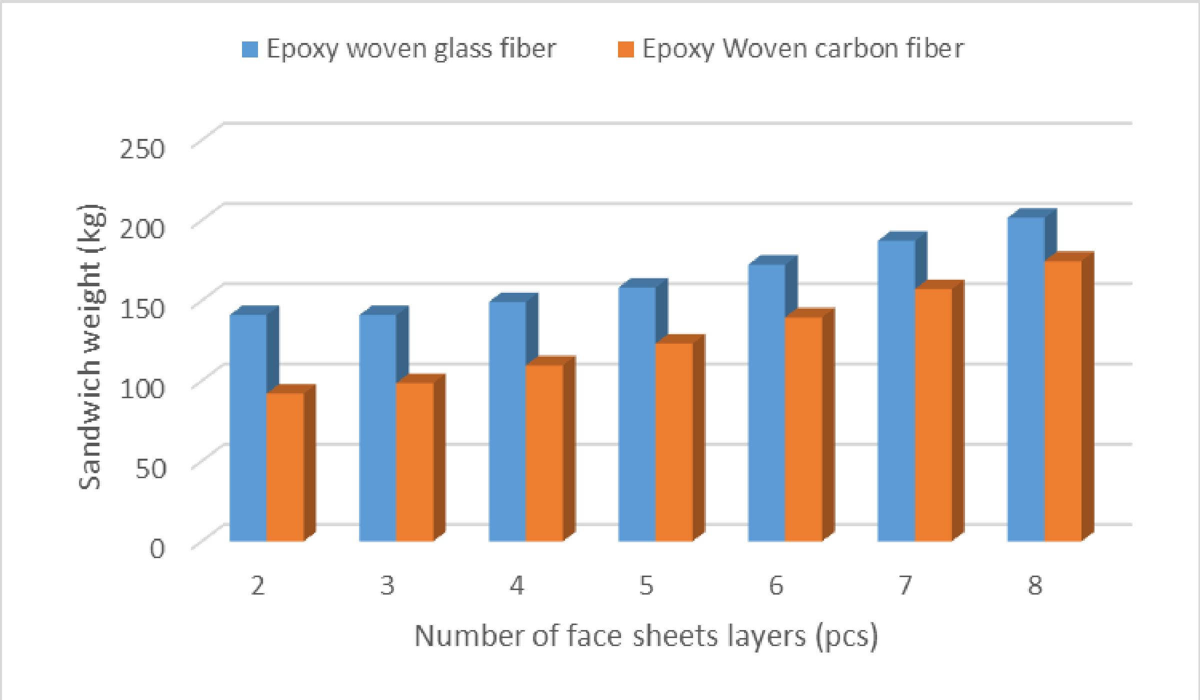


Figure 4.4. Compassion of weight for the structures with WCFRP and WGFRP face sheets and Al honeycomb core

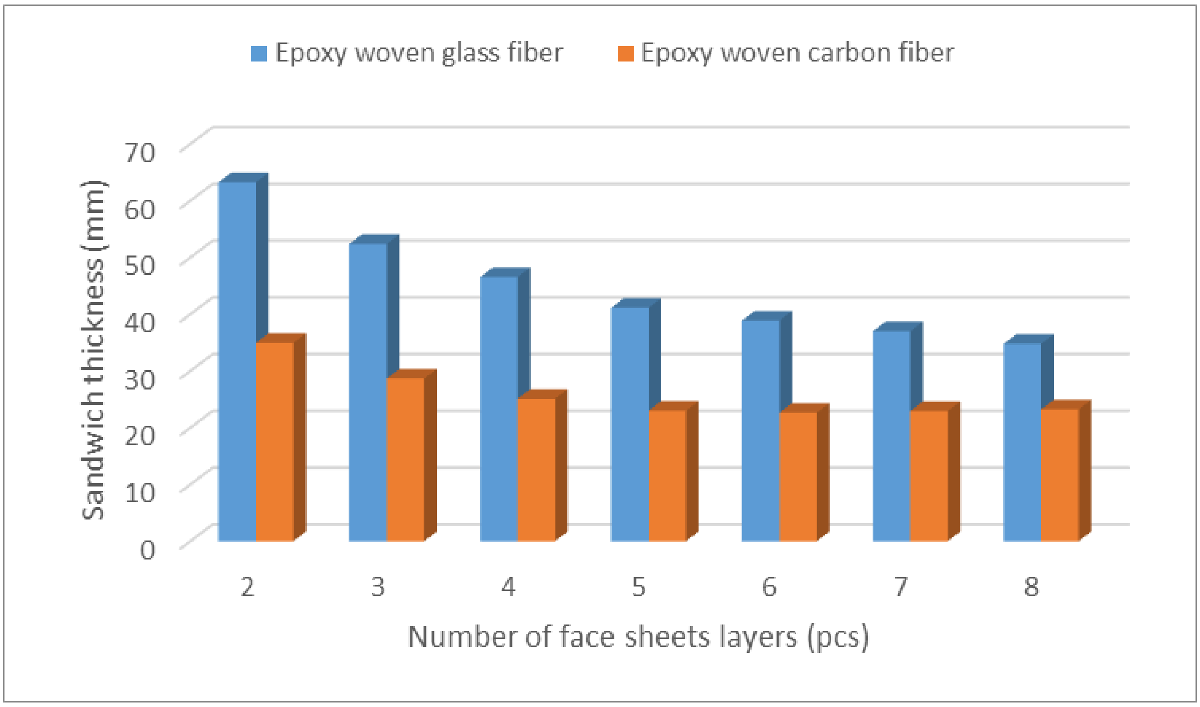


Figure 4.5. Compassion of the total thickness for the structures with WCFRP and WGFRP face sheets and Al honeycomb core

In Figure 4.4, the face sheets made of WCFRP layers offer a lighter weight compared to WGFRP face sheets for the investigated structure. Furthermore, the thickness of the sandwich structure can be significantly reduced when using WCFRP as face sheets compared to WGFRP layers, as shown in Figure 4.5.

A comparison between the original design of the bottom panel in a heavy truck, which included an aluminum honeycomb core with aluminum face sheets [115] and the optimum designs was performed in Table 4.5.

Table 4.5. Comparison between original and optimum designs for the bottom panel of a heavy duty truck

Design	**Weight** [kg]	**Weight saving** [%]
Original design consists of Al face sheets with Al honeycomb core [115]	183	-
Optimum sandwich structure consists of WCFRP with Al honeycomb core	92	- 49
Optimum sandwich structure consists of WGFRP with Al honeycomb core	140.48	- 23

A significant weight reduction of 49% was achieved when using the WCFRP layers as face sheets in the investigated structure, while the WGFRP face sheets achieved a 23% weight reduction.

The above mentioned analysis highlighted that replacing aluminum face sheets with composite layers significantly reduced the overall weight of the sandwich structure. Among the optimized designs, the structure with WCFRP face sheets provided the greatest weight savings. However, the WGFRP face sheets are still considered an option for structure weight saving compared to the original one.

4.4 Validation of optimization results by using Finite Element Method

A numerical model for the optimum design of a heavy truck bottom panel was created to validate the optimization results using Abaqus Cae software. The modeled structure consisted of a honeycomb core with a thickness of 33.73 mm and two WCFRP layers with orientation angles -80^o; -5^o, which provided the minimal weight (see Table 4.4). The laminated face sheets were modeled as composite shell elements and the homogenized mechanical properties of the core were used with a solid layer to reduce computation time [120-121]. The optimal design parameters, load and boundary conditions were set in the numerical model to obtain the maximum deflection at the mid-span of the investigated sandwich panel. Figure 4.6 shows the deflection contour that resulted from the numerical modeling.

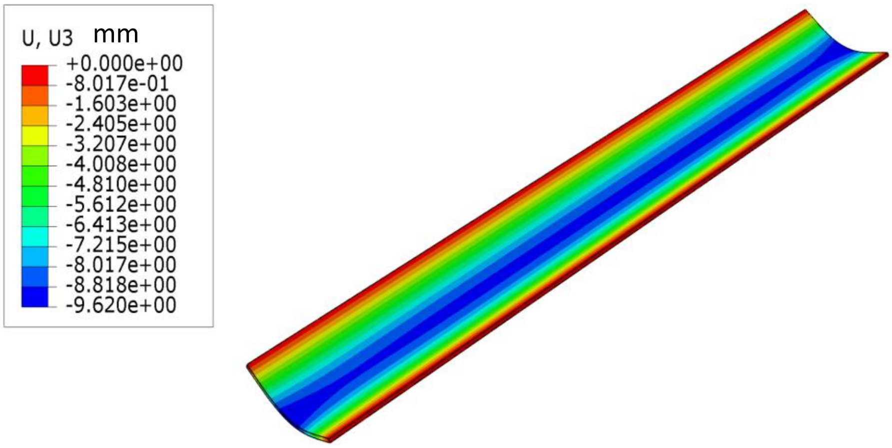


Figure 4.6. The numerical results of the structure consist of laminated WCFRP face sheet with honeycomb core for the bottom panel

The obtained deflection from the numerical solution was compared with the optimization results. In this context, the numerical results of the maximum sandwich deformation showed good agreement with the optimization results. The deflection value of the numerical model was 9.62 mm, as shown in Figure 4.6. The value obtained from the optimization process was 9.99 mm, as shown in Table 4.4. Concluding that the difference between FEM and optimization results was only 3.7%, which confirms that the results provided by the elaborated method were confident.

4.4 Conclusions and new added value of the case study carried out for the single-objective optimization

In this case study, the weight objective optimization of an investigated bottom panel of a heavy truck was carried out. The weight reduction can be achieved by using a lightweight composite sandwich structure. Therefore, the optimization problem was solved by formulating the corresponding mathematical expressions in Excel and linked to isight software. The Multi-Island Genetic Algorithm (MIGA) optimization algorithm plays a vital role in finding a compromise between the strength and weight of the designed sandwich structures. For this purpose, the design variables [number of layers (N_l) in the face sheets, the orientation of the layers (θ_{FRP}) in the face sheets and thickness of the core (t_c)] were changed in a continuous loop between Excel and the isight software until the optimal variables were reached. The main conclusions from this case study can be summarized as below:

- The weight of a sandwich structure is mainly dependent on the thickness of the core and laminated face sheets. Therefore, weight reduction can be achieved using different layups of composite face sheet layers with the core thickness.
- Two composite materials (WGFRP and WCFRP) were used as face sheet materials with an aluminum honeycomb core. It can be concluded that using WCFRP as face sheets resulted in lighter sandwich structures compared to WGFRP face sheets.

The main added values of this case study can be summarized as below:

- The optimization method for the bottom panel of heavy trucks was elaborated to define the optimal combination of the materials alternatives and geometrical parameters of the honeycomb core and the laminated face sheets.
- The achieved weight reductions comparing to the original design were about 50% in the case of the application of the WCFRP layers in the face sheet; furthermore, 23% in the case of the application of WGPRF layers for the same core density.
- Various analytical and numerical methodologies and software were integrated, to solve the optimization problem, starting with Excel to obtain the sandwich structure behavior, moving to isight for conducting optimization and concluding with FEM for the required validation.

5. APPLICATION OF THE ELABORATED OPTIMIZATION METHOD FOR MULTI-OBJECTIVE OPTIMIZATION OF A HIGH-SPEED TRAIN FLOOR

Weight and cost optimization are critical aspects in the design of high-speed train structures. Advanced composite sandwich structures have been used as a promising solution to achieve lighter train floors, thereby reducing consumption energy. Significant efforts have been made in the railcar industry to utilize composite materials for weight reduction. However, optimizing weight and cost for high-speed train floors remains limited.

This chapter focuses on the elaboration of the multi-objective optimization of high-speed train floor sandwich panels by using the Neighborhood Cultivation Genetic Algorithm (NCGA). The NCGA algorithm was used to search a design space that was defined by Sandwich Theory and the considered material data provided in Tables 3.1 and 3.2.

In this case study, the main aim of the structural optimization of a composite sandwich structure is to minimize the structural weight and cost while achieving the structural integrity of the final design. The optimization takes into consideration the weight and the cost objective functions to optimize a high-speed train's floor using a lightweight composite sandwich structure. It is worth mentioning that the investigated objective functions conflict with each other. It is essential to ensure that the components of the sandwich structure have the required strength to withstand the applied loads. To achieve structural durability, the strengths of the structural components have been defined as design constraints. The investigated sandwich structure consists of Fiber Metal Laminate (FML) face sheets (see in Section 1.1) and an aluminum honeycomb core with various densities (see in Section 1.2). The structure was subjected to distributed load on the upper face sheet and simply supported fixation on the lower face sheets. The design details will be thoroughly explained in the following sub-sections.

5.1 Structure of the investigated high-speed train floor

Figure 5.1 illustrates the floor structure of a high-speed train, which consists of an exterior supporting element as part of the main vehicle structure and a series of sub-panels supported by seats with hard rubber to reduce vibrations on the interior. The sub-panel model can be considered as a unit of the train's floor.

This case study focuses on the optimal design of the investigated sub-panel, which is considered a sandwich structure (inner floor) with a lightweight honeycomb core and two face sheets, as shown in Figure 5.2.

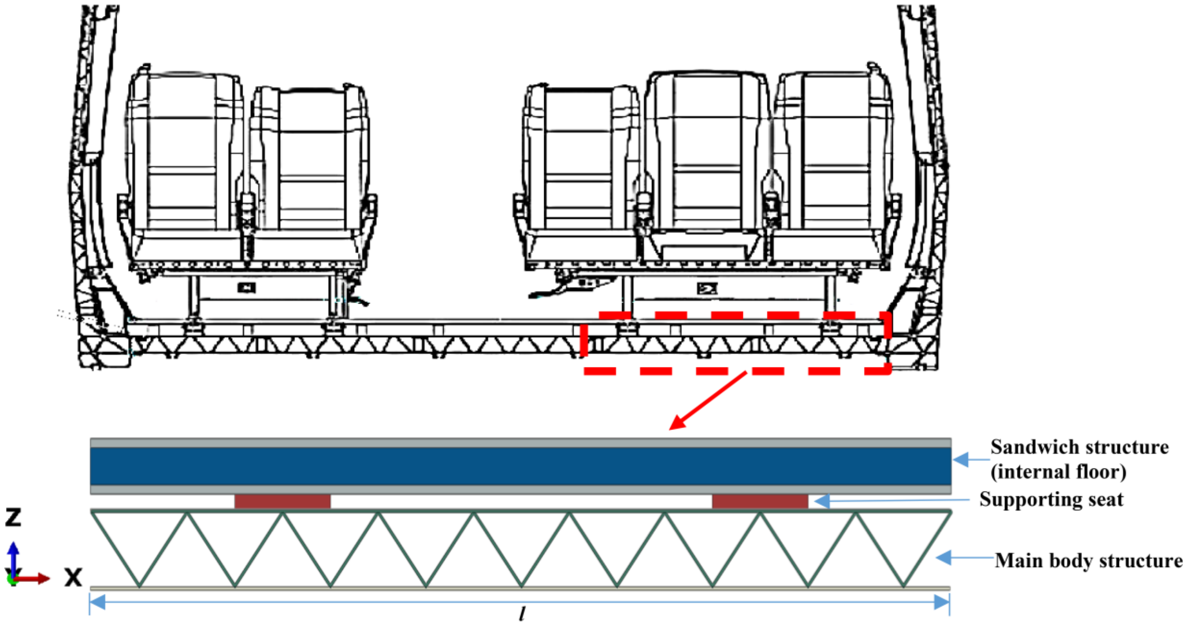


Figure 5.1. Structure of sub-panel of the high-speed train floor

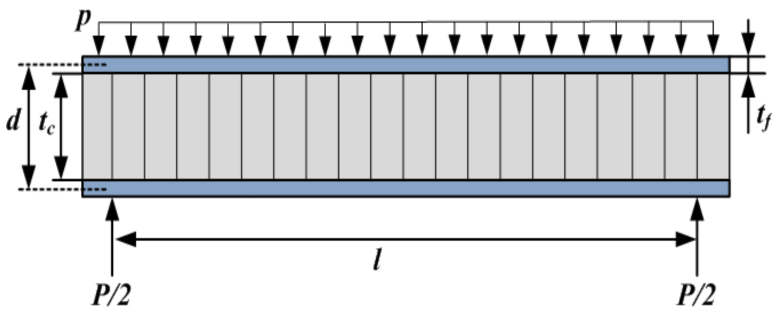


Figure 5.2. Loading and boundary conditions of the investigated sandwich structure

In this study, the investigated sandwich structure of the internal floor sub-panel has a longitude length (l) of 960 mm and a transverse length (b) of 582 mm. Each sub-panel is installed on four supporting seats. Without considering the effects of floor fatigue, it can be assumed that the loads are uniformly distributed. The value of the load (p) acting on the floor is estimated to be 4.142 kPa [122]. The sub-panel was selected as a representative structure to study the loading conditions of the sandwich structure. The loading condition of the floor sub-panel implies that the sandwich structure is simply supported by support seats and subjected to a distribution load in the out-of-plane direction, as shown in Figure 5.2.

5.2 Materials of the investigated sandwich structure

In this study, the sub-panel of the train floor is analyzed as a sandwich structure consisting of hybrid composite face sheets made of FML and an Aluminum honeycomb core. In recent years, FMLs have gained considerable attention due to their superior strength-to-weight ratio, which making them particularly suitable for applications in weight-sensitive industries. Figure 5.3 shows the alternating structure of an FML. The Classical Lamination Theory has been proposed as a method to calculate the final mechanical properties of the investigated FMLs [123]. CLT offers the possibility of adjusting the properties of the laminated face sheets by changing the number of face sheet layers and the orientation of the unidirectational FRP layers, as explained in the following section.

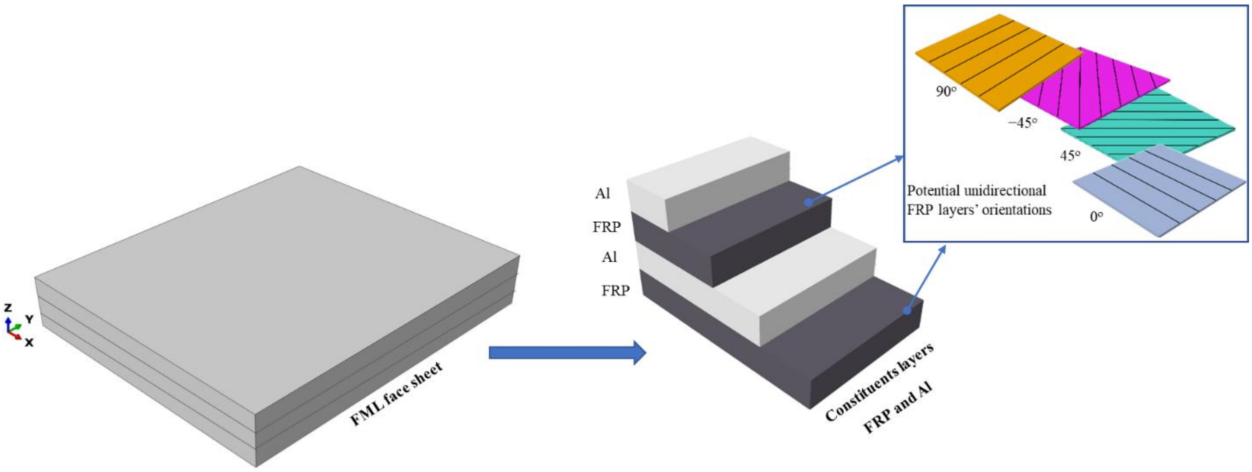


Figure 5.3. Face sheet layup with FML material

FML face sheets result from the combination of 1.) CFRP, 2.) GFRP and 3.) Aluminum layers. As depicted on the right side of Figure 5.3, the possible orientations of the FRP layers in the laminated face sheet are 0°, ± 45° and 90°. The FRP layers utilized are listed in Table 3.1. The honeycomb core is also a critical component in the design of the sandwich structure, as its mechanical properties depend on the core's base material and relative density. Therefore, the Al honeycomb core, which is commercially available (as listed in Table 3.2), is utilized in the analysis.

5.3 Application of the elaborated optimization method for a high-speed train floor with an own developed integrated software

I developed a technique to integrate Excel and isight software in this case study. The Classical Lamination Theory and Beam Theory were formulated in Excel, along with the materials data. The optimization tool under the isight environment was linked with Excel, which in turn fed Excel with design variables and received the objective and constraint values. This loop continued until the optimum solution was obtained in term of the Pareto curve.

The optimization procedures are used the NCGA optimization algorithm, which is implemented through the isight software environment integrated with Excel software as explained previously. The optimization results are validated with the FEM method for the obtained key designs. The main steps of the optimization and FEM validation processes are illustrated in the flowchart shown in Figure 5.4.

The applied objective functions involved minimizing both the weight and cost of the investigated composite sandwich structure. The weight and cost objective functions are adopted as detailed in equations 3.1 and 3.4. In the context of the floor structure under consideration, the aim is to identify the Pareto solution of sandwich constructions that is optimal for achieving the lowest weight and lowest cost simultaneously.

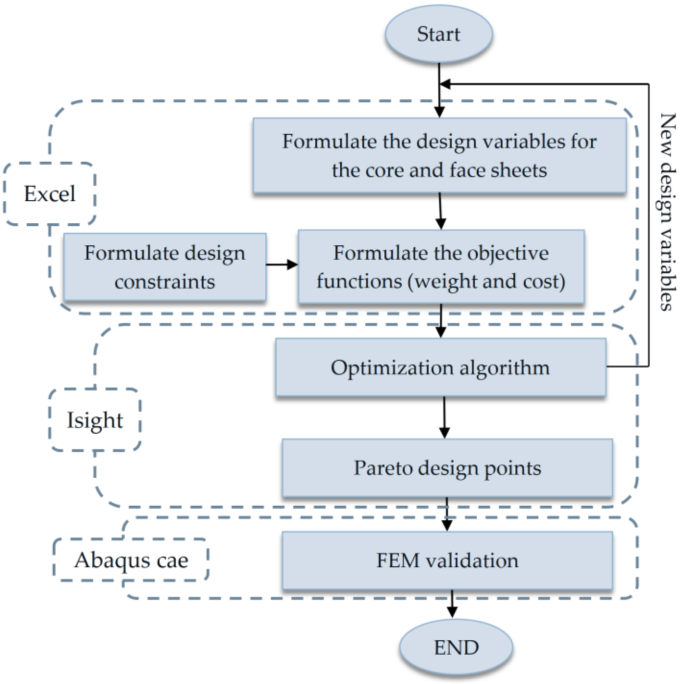


Figure 5.4. Flowchart of the elaborated multi-objective optimization method for the investigated composite sandwich structure

It is common in multi-objective optimizations to find a Pareto curve that includes optimal solution points. In this study, the Pareto curve is generated by non-dominated solution sets associated with optimal weight and cost objectives. From the Pareto curve, the optimal solution can be selected by the Improved Minimum Distance Selection Method (IMDSM), which is formulated in equation 3.5 at Section 3.1.3.

5.3.1 Design variables to be optimized

In this case study, the design variables include face sheets of different FRP composite materials, such as CFRP and GFRP and aluminum layers. The FML face sheet properties are determined by the orientation of the fibers associated with FRP composite laminates, the number of layers and the final face sheet thickness. Furthermore, the selection of the core density varied within a range of Al honeycomb cores. In this context, the design variables are summarized in Table 5.1.

Table 5.1. Design variables of the train floor

Design Variables	Value	Remark
Number of face sheet layers	$1\leq N_l \leq 15$ [pieces]	discrete variable, Integer values
Face sheet materials	CFRP layer: identified by **No. 1** GFRP layer: identified by **No. 2** Aluminum layer: identified by **No. 3**	discrete variable, Integer values
Possible FRP composite layup orientation	θ_{FRP} = 0°,90°,+45°,-45°	discrete variable
Core density	ρ_c [kg/m^3]	discrete, as specified in the Table 3.2
Core thickness	$5 \leq t_c \leq 20$ [mm]	continuous value

5.3.2 Design constraints used during the optimization

Design constraints, such as maximal deflection of the structure, strength limitations and failure criteria for the sandwich structure, were used to establish the limits that any proposed design must satisfy. The main structural constraints, as formulated in Section 3.3, are listed below:

1. Core shear strength: the core shear strength must have a constraint margin equal to or greater than 1 with respect to the resulting shear stress;
2. Face sheet strength: the ultimate strength of the face sheets must have a constraint margin equal to or greater than 1 with respect to the resulting face sheets stress;
3. The face sheet intra-cell: the intra-cell stress must have a constraint margin equal to or greater than 1 with respect to the ultimate strength of the face sheets;
4. Face sheet wrinkling: the wrinkling stress must have a constraint margin equal to or greater than 1 with respect to the ultimate strength of the face sheets;
5. Maximum deflection and overall sandwich structure thickness: the structural deflection and the total thickness of the structure must remain within the specified limit [122].

5.4 Numerical modeling of the investigated structure

The numerical modeling aims to prove the accuracy of the developed optimization method. A commercial finite element package, Abaqus Cae is used to numerically model the examined sandwich structure. The common shell element S4R simulates the laminated composite face sheets. A general contact with a tangential friction property and a normal "hard" contact are specified. The honeycomb core meshed with 2925 solid elements, while 4557 shell elements were created to mesh the face sheets. The distribution load defined in Section 5.2 was applied to the upper face. The geometric model of the support seats is also modeled and described as a rigid body. A coupling constraint is used between the support seats and the Reference Points (RP) and then a fully fixed constraint is applied to RP, which follows the fixation nature of the sub-panel. The main design parameters for optimal structural design were used in FEM modeling. The general FEM model of the composite sandwich structure is shown in Figure 5.5.

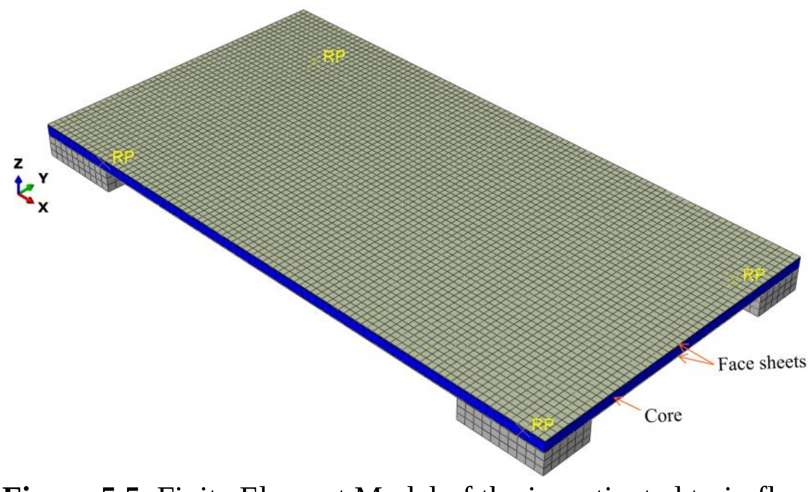


Figure 5.5. Finite Element Model of the investigated train floor

5.5 Multi-objective optimization results for sandwich structure of a high-speed train floor

According to the formulation of the multi-objective optimization functions defined in equations 3.1 and 3.4. The optimization aims to reduce the overall weight (W_t) and total cost (C_t) while fulfilling the design constraints. In this case study, different densities of honeycomb cores and hybridized face sheets (FML) with their associated parameters were used as design variables to achieve the final objectives. The optimization results provided about 16600 feasible alternatives for this study. The changes in weight and cost for the optimized alternatives are shown in Figure 5.6.

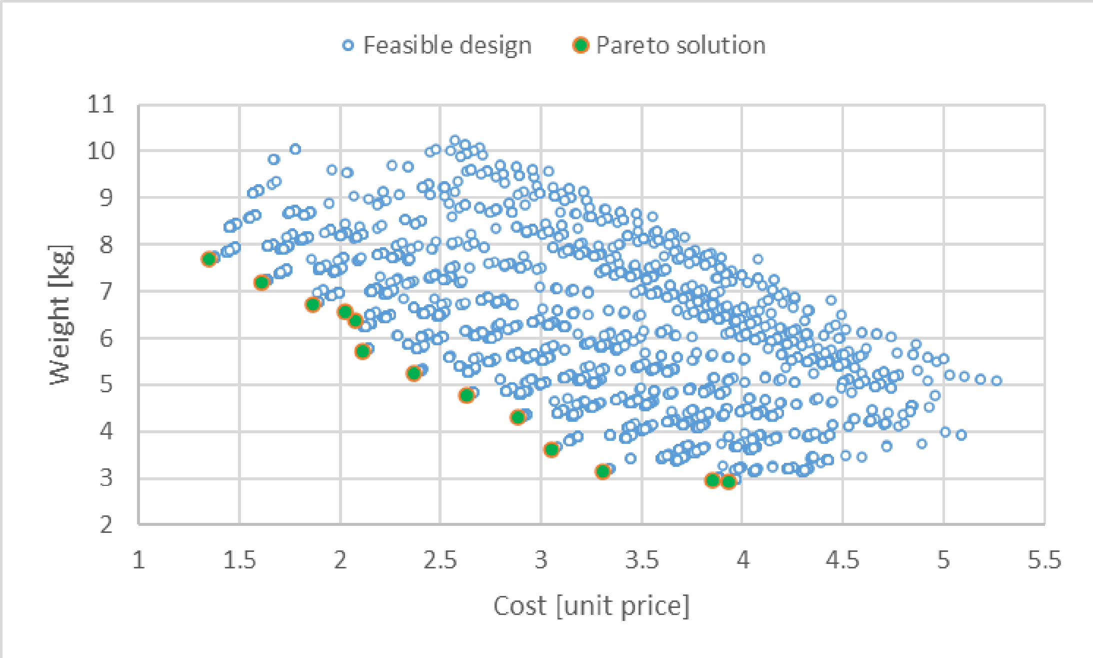


Figure 5.6. Feasible design points for the investigated sandwich structure

The blue hollow circles represent the feasible solutions for the optimization problem, which satisfy all the design constraints. The green solid circles represent the set of non-dominated solutions, which achieve the best trade-off between multiple competing objectives, also known as the Pareto set and represent the optimal solution for the investigated structure.

The NCGA algorithm acquired 13 data points, which are highlighted in Figure 5.7, representing the Pareto points. The Pareto curve of the optimized sandwich structures plotts the relationship between cost (unit price) and weight (kg). This type of graph is commonly used in multi-objective optimization problems where there are trade-offs between two or more objectives, in this case study, minimizing both cost and weight simultaneously

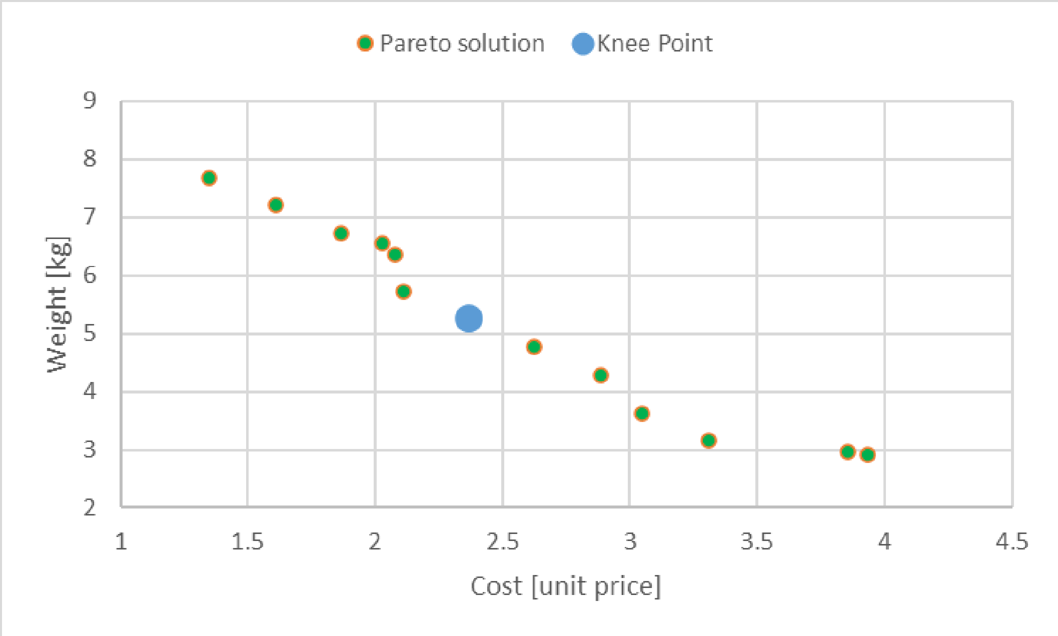


Figure 5.7. Pareto optimal points and the knee point of the investigated sandwich structure

Pareto points distribution tend to be convexly due to the behavior of the conflicting objectives. Whenever the weight decreases, the cost of the sandwich structure increases and vice versa. Therefore, the knee point represents the point on the Pareto curve where the trade-off between objectives is balanced. This point was considered as the optimum design from the perspective of balancing reduction for the cost and weight objectives.

Table 5.3 presents the Pareto curve data points that resulted from the multi-objective optimization for investigated sandwich structures in terms of minimizing weight and cost. The results explored various alternatives for the investigated sandwich structure. The considered design variables were the number of layers, material of the face sheet layers, core density and thickness. In the aspect of the face sheet, the results covered the structural alternatives from totally FRP to totally Aluminum, with several hybrids (FML) in between. The various core densities and thickness effects were also explored. The main key designs were totally FRP face sheets, totally Al face sheets and FML face sheets, which are represented the lowest weight, lowest cost and knee point designs respectively.

Table 5.3. Results of the Pareto optimal design

Face sheet materials and fiber orientations	**Number of layers in the laminate**	**Core thickness** t_c	**Face sheet thickness** t_f	**Core density** ρ_c	**Cost** C_t	**Weight** W_t
CFRP layer: identified by **No. 1** **GFRP** layer: identified by **No. 2** **Aluminum** layer: identified by **No. 3**	[pieces]	[mm]	[mm]	[kg/m^3]	[unit price]	[kg]
<u>1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°)</u>	**10**	**18.2**	**1.25**	**37**	**3.93**	**<u>2.92</u>**
1(0°), 2(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°)	10	18.02	1.25	37	3.85	2.96
1(0°), 3, 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°)	9	18.47	1.2	37	3.31	3.15

1(0°), 3, 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 3, 1(0°)	9	18.47	1.275	37	3.05	3.63
1(0°), 3, 1(0°), 1(0°), 1(0°), 3, 3, 1(0°), 1(0°)	9	17.88	1.35	54	2.88	4.29
3, 3, 1(0°), 1(0°), 1(0°), 1(0°), 3, 1(0°), 3	9	17.97	1.425	54	2.63	4.77
<u>3, 3, 1(0°), 1(0°), 1(0°), 3, 3, 1(0°), 3</u>	**9**	**18.04**	**1.5**	**54**	**<u>2.37</u>**	**<u>5.25</u>**
3, 3, 1(0°), 3, 1(0°), 3, 3, 1(0°), 3	9	18.13	1.575	54	2.11	5.73
3, 3, 3, 1(0°), 3, 3, 3, 1(0°), 3, 2(0°)	10	18.2	1.775	42	2.08	6.36
3, 3, 3, 3, 1(0°), 3, 3, 1(0°), 3	9	18.13	1.65	83	2.03	6.55
3, 3, 3, 1(0°), 3, 3, 3, 1(0°), 3, 3	10	17.8	1.85	37	1.86	6.72
3, 3, 3, 3, 3, 3, 3, 3, 3, 1(0°)	10	17.93	1.925	37	1.61	7.2
<u>3, 3, 3, 3, 3, 3, 3, 3, 3, 3</u>	**10**	**17.94**	**2**	**37**	**<u>1.35</u>**	**7.68**

For the totally FRP face sheet sandwich structure, the 10 FRP layers were used in the face sheets and all layers were oriented in 0°. The core thickness of the structure was 18.2 mm, while the total face sheet thickness was 1.25 mm and the core density of 37 kg/m³. The structure with totally FRP face sheets design achieved the lowest weight among the highlighted alternatives at 2.92 kg, but it came at the highest cost with 3.93 unit price. This design prioritizes weight savings, which is crucial for high-speed train applications, but at a premium in terms of material costs.

The all Al face sheet structure consisted of 10 aluminum layers. Compared to the all-FRP face sheet structure, all-Al performed with a slightly thinner core of 17.94 mm but a thicker face sheet with a thickness of 2 mm. It maintains the same low core density of 37 kg/m³. This structure achieved the lowest cost with a 1.35 unit price, making it the most economical option. However, it resulted in the highest weight at 7.68 kg.

The multi-objective optimized sandwich structure (knee point), which resulted from FML face sheets, represented a compromise between the all FRP and all Al options. The face sheets consisted of 9 layers with a mix of aluminum and 0° oriented FRP layers. The core was 18.04 mm thick, with a face sheet thickness of 1.5 mm and a core density of 54 kg/m³. This structure achieved a balance in both cost (2.37 unit price) and weight (5.25 kg). The knee point design offered a balanced solution, providing moderate weight savings compared to the all-aluminum design while keeping costs lower than the all-FRP option. This makes it an attractive choice to achieve a good balance between weight and cost.

To summarize the obtained results, a comparison was conducted between a train floor made of an all-Al structure, which is considered as a base design with the totally-FRP face sheet structure and a FML face sheet structure in terms of weight and cost. The optimal material selection (Table 5.3) showed that the maximum weight reduction among the considered alternatives was about 62% for the all-FRP face sheet structure, while the associated cost increased by about 190%. The knee point was reached at a weight reduction of 32% and a cost increase of 75% compared to an all-Al structure.

It is important to note that although the weight reduction was achieved and made the structure at a higher cost, the benefits of reduced weight include lower energy consumption and lower maintenance costs of the high-speed train in long transport way, resulting in significant cost savings over time.

This case study considered the percentage of the FRP materials in terms of weight and cost, as depicted in Figure 5.8.

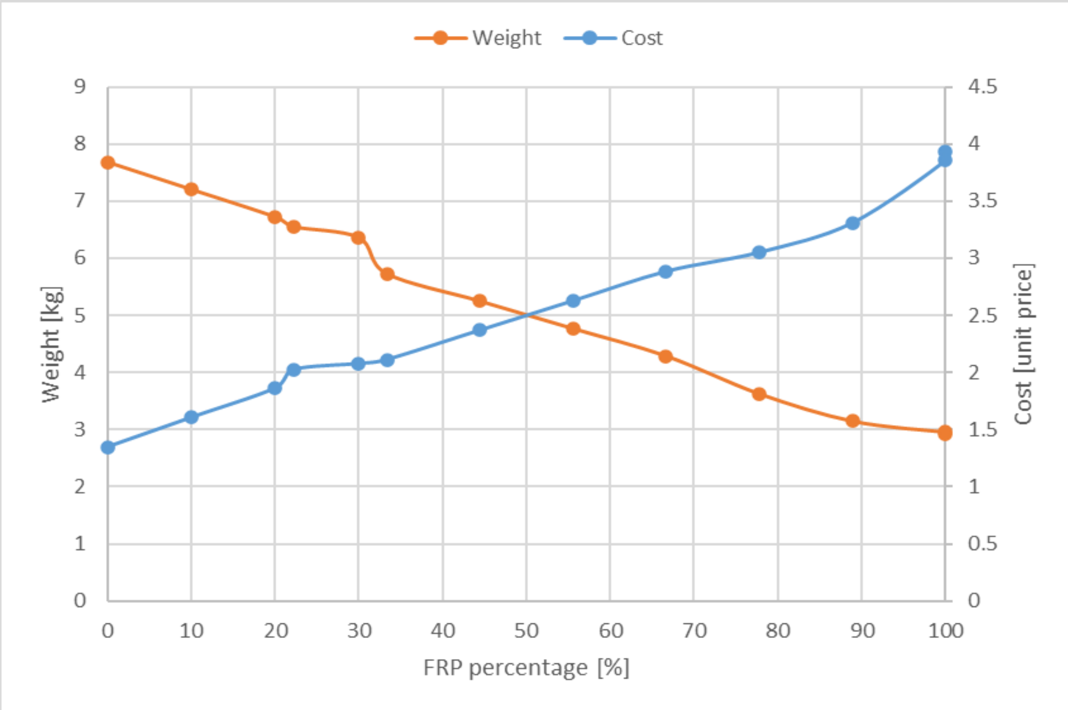


Figure 5.8. Effect of FRP percentage on weight and cost of the sandwich structure

The figure indicated that a higher percentage of FRP results in a lighter and more expensive sandwich structure, whereas reducing the FRP materials tends to result in a heavier and cheaper structure.

5.6 Finite Element Method results and optimization validation for the investigated sandwich structure

Three points on the Pareto front were selected as input parameters for finite element simulations to validate the results of the elaborated optimization method. These 3 points were chosen to represent 1.) the structure which provides minimal weight (result of single weight optimization), 2.) the structure which provides minimal cost (result of single cost optimization) and 3.) the knee point (result of multi-objective cost and weight optimization) that provides a compromise between cost and weight minimization. The related data have been listed in the Table 5.4 for FEM modeling.

Table 5.4. The design parameters for FEM simulation

Face sheet layup	**Face sheet materials and fiber orientations** **CFRP** layer: **No. 1** **GFRP** layer: **No. 2** **Aluminum** layer: **No. 3**	**Number of layers in the laminate** [pieces]	**Core thickness** t_c [mm]	**Face sheet thickness** t_f [mm]	**Core density** ρ_c [kg/m^3]	**Remarks**
Totally FRP	1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°), 1(0°)	10	18.2	1.25	37	minimal weight
Totally Al	3, 3, 3, 3, 3, 3, 3, 3, 3, 3	10	17.94	2	37	minimal cost
FML	3, 3, 1(0°), 1(0°), 1(0°), 3, 3, 1(0°), 3	9	18.04	1.5	54	knee point

Figures 5.9-5.14 illustrated the sandwich structure deflection patterns and the stress distribution in the face sheets for the structures which provided minimal weight, minimal cost and knee point designs respectively.

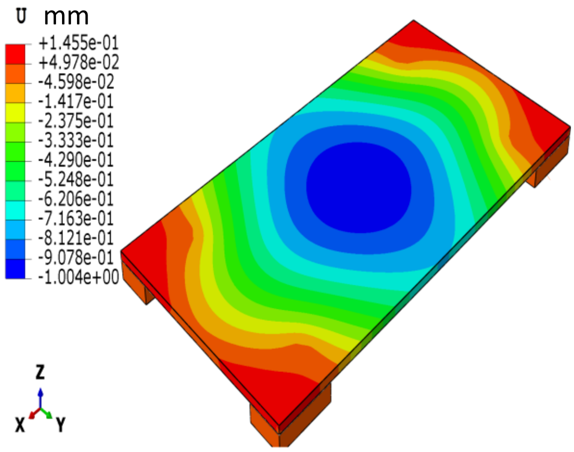


Figure 5.9. Deflection of the structure which provides minimal weight

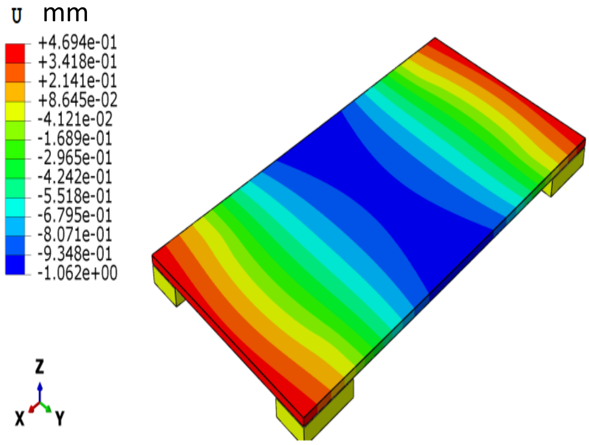


Figure 5.10. Deflection of the structure which provides minimal cost

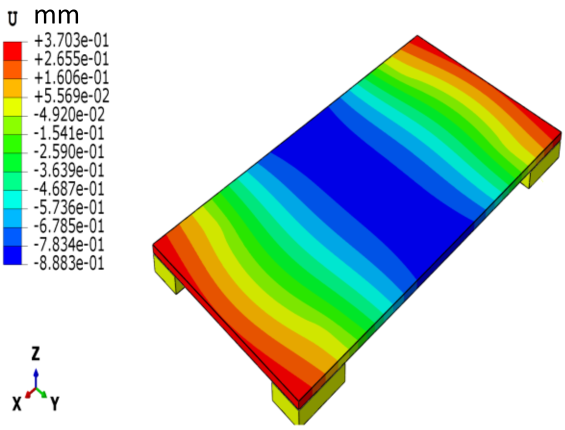


Figure 5.11. Deflection of the structure which provides knee point design

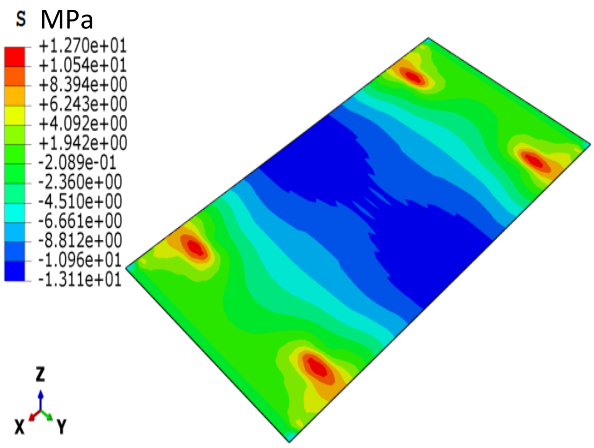


Figure 5.12. Stress in the structure's upper face sheet which provides minimal weight

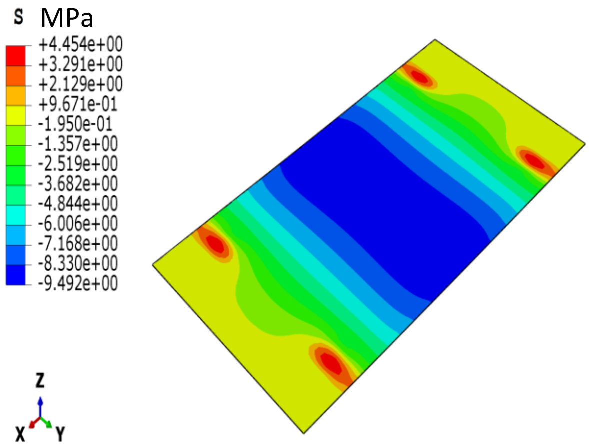


Figure 5.13. Stress in the structure's upper face sheet which provides minimal cost

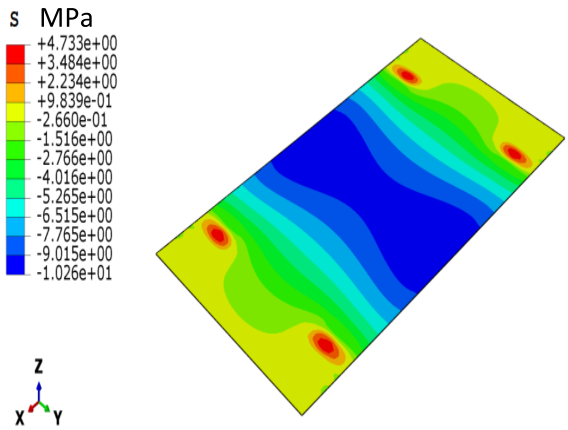


Figure 5.14. Stress in the structure's upper face sheet which provides knee point design

From Figures 5.9, 5.10 and 5.11, it can be observed that the deflection values for the three designs were close and they fulfilled the constraint margin which assigned previously (see Section 5.3.2).

The stress distributions in the upper face sheets were depicted in Figures 5.12 (minimal weight), 5.13 (minimal cost) and 5.14 (knee point design). The stress values in the upper face sheets were at close values across the three designs; however, in general, the face sheet with a lower thickness exhibited a higher value of the face sheets' maximum stress.

These FEM results provide a crucial visual insights into how different optimization priorities affect the structural behavior of the sandwich panels, enabling engineers to make decisions based on specific application requirements, balancing factors such as weight, cost, deflection tolerance and stress management in the face sheets.

To evaluate the optimization procedures accuracy, a comparison of the optimization results and the FEM simulation outcomes was conducted and presented in Table 5.5.

Table 5.5. Comparisons of optimization and FE solutions.

Design points	**Maximal deflection** [mm]			**Maximal stress in the face sheet** [MPa]			**Remarks**
	Optimization result	**FEM result**	**Difference** [%]	**Optimization result**	**FEM result**	**Difference** [%]	
Minimal weight	0.9957	1.004	0.83	13.655	13.11	3.99	single weight optimization
Minimal cost	1	1.062	6.20	8.695	9.49	9.14	single cost optimization
Knee point	0.9999	0.883	11.69	11.3333	10.26	9.47	multi-objective weight and cost optimization

The FEM outcomes revealed a good agreement between the FEM and optimazation results. This agreement indicates that the results provided by the elaborated optimization method were reliable and accurate with only minor discrepancies.

5.7 Conclusions and new added value of the case study carried out for the multi-objective optimization

This study aimed to develop a multi-objective optimization method for high-speed train floors, focusing on weight and cost. The sandwich floor structure under consideration consisted of laminated face sheets and a hexagonal honeycomb core, with various FMLs configurations used as face sheets alongside aluminum honeycomb cores. The structural optimization sought to identify the optimal sandwich structure to minimize weight and cost. The NCGA was employed to solve this optimization problem, considering weight and cost objective functions alongside five design constraints.

The NCGA optimization yielded approximately 16600 feasible designs that met the design constraints, of which 13 were identified as Pareto optimal solutions. A detailed analysis of these solutions was conducted to explore the relationship between weight and cost objectives. The findings of this study can be summarized as follows:

- The analysis showed that, at the expense of cost, using CFRP as a face sheet provided a maximum weight reduction of about 62% in this study, compared to the aluminum face sheet as a basic structure,
- A knee point was identified that strikes a balance between weight and cost, resulting in a weight reduction of approximately 32% using FML materials. This provides valuable insights for designers who must consider both weight savings and cost-effectiveness,

The added value of this case study can be summarized as below:

- A new optimization method was elaborated, the proposed multi-objective optimization method utilizing the NCGA algorithm with diverse constituent materials and structural components presents a novel contribution to weight reduction and cost-effectiveness that has not been previously explored.
- A balance between minimal weight and minimal cost was achieved, the results of this case study suggested that sandwich configurations using composite materials are a promising approach to realizing lightweight and cost-effective train floors. Low-density core materials and stiff outer skins can achieve an optimal balance between weight reduction, structural performance and cost efficiency.
- The optimization method and results were validated, the present study conducted an optimization process and subsequently validated its outcomes through FEM simulations.

6. USING ARTIFICIAL NEURAL NETWORK FOR MODELING OF SANDWICH STRUCTURES

In the field of artificial intelligence, the most popular modeling methodology is the Artificial Neural Network technique. It includes a sequence of computational steps that learn and develop the input parameters to create the model prediction. This technique is widely used in various sectors, including but not limited to chemical technology, economics, environmental science and engineering [124]. At their core concept, the created network learns relationships between input and output data through a training process.

Artificial Neural Networks were invented to mimic the human brain in solving complex problems. ANNs consist of computational elements (neurons) arranged in interconnected layers, namely input, hidden and output layers. Each neuron receives inputs that are weighted according to their importance [125].

The data features are fed as input to the first layer of the network. Each input node corresponds to a design variable. No calculations are performed in the input layer and it simply transfers the input values to the next layer. In the input layer, the dimensions of the input data are determined, which affects the number of parameters and the network's complexity. After leaving the input layer, the data forwards to the hidden layers. The hidden layers perform the learning patterns and establish complex nonlinear features from the provided data. These layers can be represented as a set of transformations that map the input and output domains. Moreover, by applying a nonlinear activation function, intermediate computations and transformations are performed on the data. As illustrated in Figure 6.1, each neuron contains weights, activation functions and a bias [126-127].

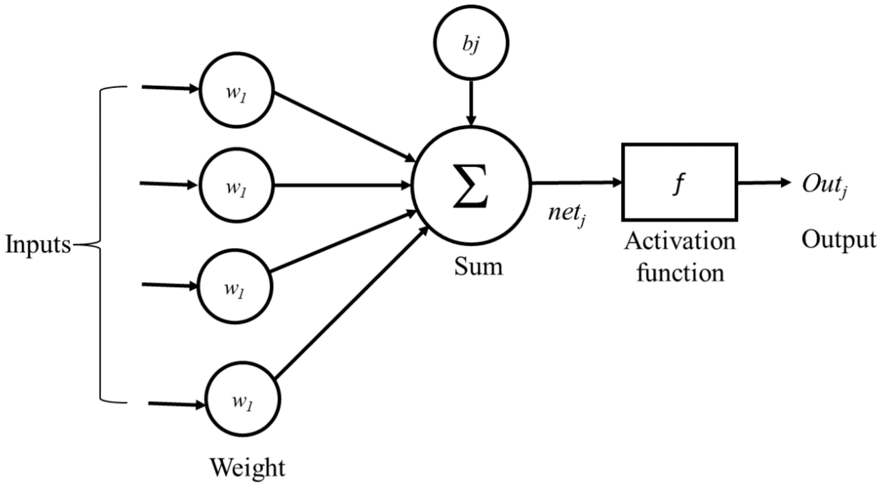


Figure 6.1. Schematic structure of artificial neuron

The mathematical representation of the neuron can be expressed as in the following equations:

$$net_j = \sum_{i=1}^{n} w_{ij}x_i + b_j \tag{6.1}$$

$$Out_j = f(net_j) = f\left(\sum_{i=1}^{n} w_{ij}x_i + b_j\right) \tag{6.2}$$

where:

net_j is the sum weights vector (j) neuron for the input data with n neurons,

w_{ij} is the weight vector from neuron (i) in the previous layer to (j) neuron in current layer,

x_i is the output of (i) neuron in the previous layer,

b_j is the bias value of (j) neuron in the hidden layer,

Out_j is the output of the (j) neuron.

During the training process, the network adjusts the weights to improve the mapping between inputs and outputs. Specifying inputs and outputs is crucial to create an accurate and reliable Artificial Neural Network model. Also, access to more sampling data allows the network to learn more precise relationships between input and corresponding output. The number of hidden layers and neurons within each hidden layer depends on the complexity of what the network is trying to model. More complicated problems might require deeper networks with additional computational elements.

A new methodology and an integrated software tools (as illustrated in Figure 6.3) were developed for modeling sandwich structures. A detailed explanation of this approach will be presented in Chapter 9. During the sandwich structure modeling, nonlinear processing at hidden layers must be applied to represent the relationship between inputs and outputs data associated with the sandwich structure, this can be accomplished by using nonlinear activation functions at respective neurons. The activation function is a crucial network component that introduces nonlinearity to the model and enables it to learn complex mappings between inputs and outputs. Each neuron in the hidden and output layers of the ANN uses an activation function to apply nonlinear mappings to the network.

A Multi-Layer Perceptron (MLP) framework is used to model the sandwich structure with different configurations. The fed data is divided into three main groups: training, testing and validation sets. The MATLAB Artificial Neural Network toolbox and related programming scripts are used to establish the ANN model for the sandwich structure design problem. In our investigations, the Backpropagation Feedforward Network (BFFN) training method was utilized for modeling the sandwich structure due to its exceptional ability to solve complex problems [126].

MATLAB software has been characterized as an effective tool for modeling the design parameters and responses of the sandwich structure by using ANN toolbox. Figure 6.2 illustrates the block diagram of the network system [128]. This simple topology demonstrates the fundamental building blocks of an Artificial Neural Network. The steps of creating an ANN model are discussed in the following subsections.

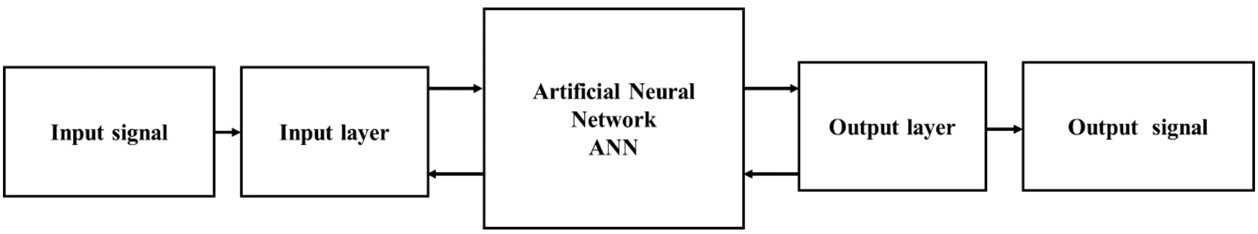


Figure 6.2. Block diagram of the ANN system [127]

Classical Lamination Theory and Beam Theory are used along with Monte Carlo simulation to generate the design data for the investigated composite sandwich structures. Multi-layer feedforward neural networks are used to predict the components' strength limits, cost and weight of the designed structures based on the following inputs: core density, core thickness, combinations of face sheet materials and applied load. Figure 6.3 illustrates main steps and software of the newly developed inegrated methodology and software conception that utilized for modeling the investigated sandwich structures by ANN.

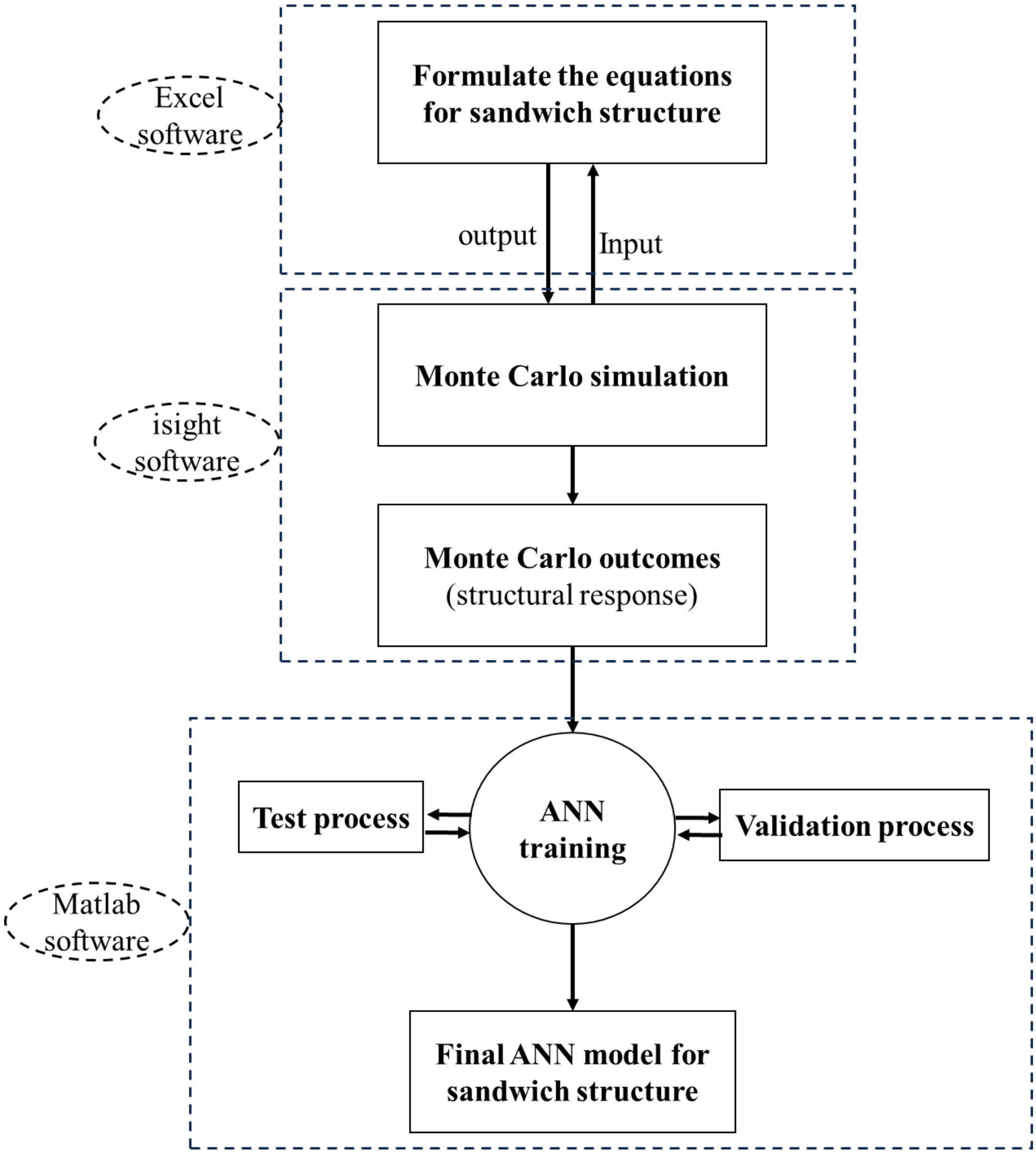


Figure 6.3. Flowchart schematic for creating ANN model of the sandwich structures [Own compilation]

6.1 Data set sampling technique

The performance of machine learning models is closely tied to the availability of large data sets for training, validation and testing. In this research, the isight software is integrated into an Excel spreadsheet in order to formulate the governing equations. These equations related the key design variables, which included the face sheets' materials properties, the honeycomb core density and the geometrical parameters. Additionally, the equations performed for the relevant structural constraints, which include the strength and stiffness limits of the structural components. Finally, the objectives, namely the weight and cost considerations. As detailed previously, isight software uses sophsticated techniques that can effectively capture the inherent variability in product designs and their operating conditions.

To organize the input data for determining the required responses of the investigated sandwich structures, the Monte Carlo method [129] is used within the isight software environment. Monte Carlo simulation provides a reliable tool for incorporating randomness into the design process and allows to explore the design space and evaluating the effects of the design parameters variations on the sandwich structure responses.

The general steps for performing a Monte Carlo simulation using simple random sampling are as follows:

Step 1: Identify the key design parameters for the sandwich structure, such as material properties, dimensions and boundary conditions.

Step 2: Determine the simulation iterations to be executed (depending on the required data quantity for the investigated structure).

Step 3: Allocate the range of design parameters (components, materials, applied load and dimensions).

Step 4: Generate uniformly distributed random values for each input parameter.

Step 5: Simulate the process using the specified values of the random design variables within the linked component (an Excel spreadsheet in this research).

Step 6: Repeat steps 4 to 5 for the simulation iterations specified in step 2.

Step 7: Perform post-processing by extracting the response data from the output platform.

6.2 Data acquisition for the Artificial Neural Network model

To develop a generalized model, core densities (as shown in Table 3.2), along with design parameter variations, including load, core thickness and facing materials, are considered design variables. Monte Carlo simulation in isight software was used to organize and generate the required data set. Following the steps described in Section 6.1, a big data sets of structural responses within selected ranges can be obtained, each representing a unique design configuration for the examined composite sandwich structure. The dataset is then divided into a training set, a validation set and a test set.

6.3 Normalization of acquired data

Data normalization is a crucial preprocessing step in ANN applications to ensure fair representation of the generated data and to improve the convergence during network training. In this process, the input data is transformed into a standardized range to prevent certain features from dominating the learning process. Properly normalized data contributes to the effective use of ANN models and improves their overall performance. For the sandwich structure, the normalization step was conducted for key design variables and corresponding structural responses. In this research, the generated data are normalized to the range [0.1, 0.9] using the following equation [130]:

$$x_i = \lambda_1 + (\lambda_2 - \lambda_1)\left(\frac{z_i - z_i^{min}}{z_i^{max} - z_i^{min}}\right) \tag{6.3}$$

where: λ_1 and λ_2 are upper and lower limits of normalized parameters, x_i denotes the normalized value of certain parameter, z_i is the original data of certain parameters, z_i^{min} and z_i^{min} are minimum and maximum values of z_i respectively.

6.4 Creating an Artificial Neural Network model for sandwich structure

In this research, the BFFN technique was chosen as the modeling approach for the sandwich structure design due to its effectiveness in addressing complex problems. As illustrated in Figure 6.4, the architecture of the ANN includes input, hidden and output layers, where each layer contains a number of neurons. In the case of BFFN, the network learns the relationship between the input and output layers through a multi-step training process that depends on the selected training algorithm.

In our study, the Levenberg-Marquardt (LM) and Bayesian Regularization (BR) training algorithms are used to train the network model. The LM algorithm involves three different processes, namely training, validation and testing. Accordingly, the data are randomly divided into three subsets: training, testing and validation. When utilizing the BR training algorithm, the data will be divided into a training set and a test set, as this algorithm has built-in validation function. The number of hidden layers is selected depending on the problem complexity, while the activation functions in this research are "*tansig*" and "*logsig*". The output layer, on the other hand, used the linear transfer function "*purelin*".

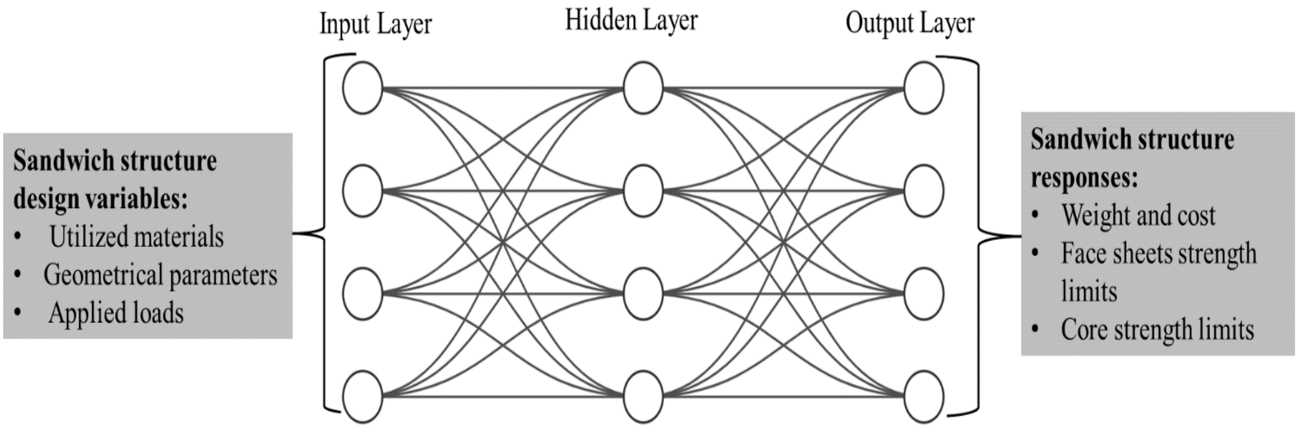


Figure 6.4. Artificial Neural Network structure for modeling sandwich structure

The aim of using ANN techinque is to model the invesitgated sandwich structures and obtain the associated structural outputs. Given this, constraints parameters such as face sheet strength, face sheet wrinkling stress, face sheet intra-cell, structural deflection, weight and cost are performed as the ANN outputs. The face sheet material, face sheet thicknesses, applied load and core densities are considered as an inputs. Figure 6.5 illustrates a detailed flowchart of the ANN training process.

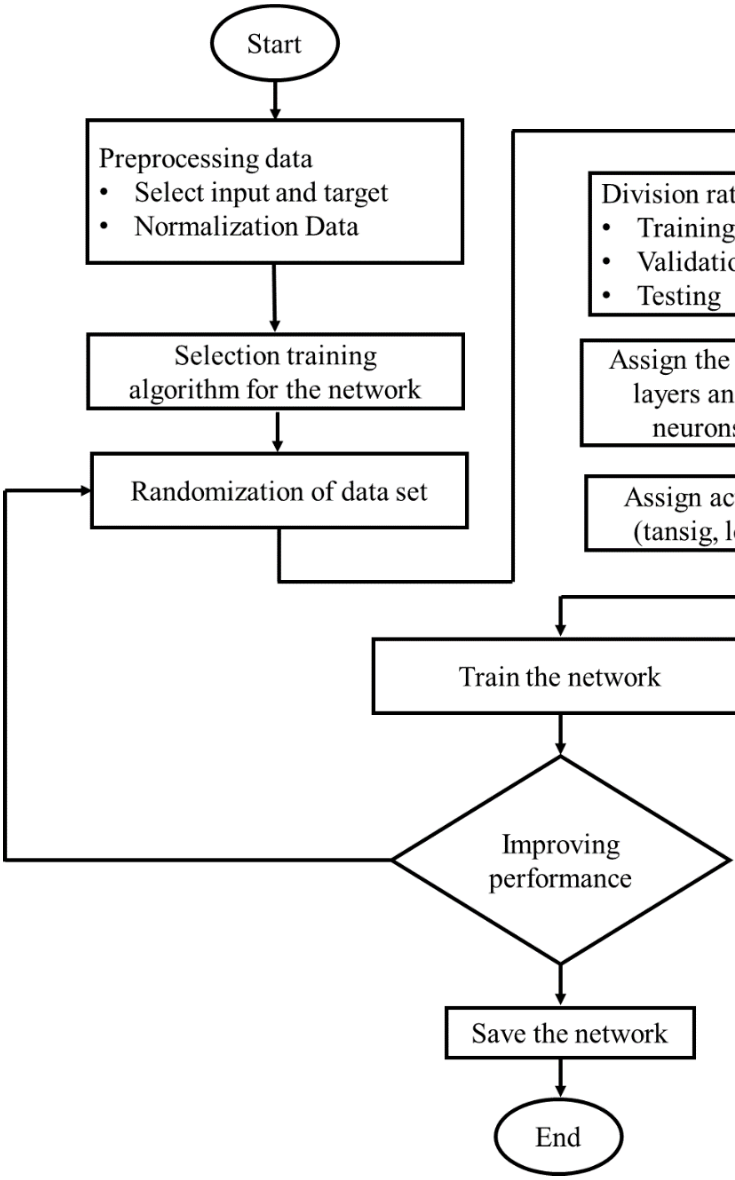


Figure 6.5. Flow chart for training ANN model of sandwich structures

6.5 ANN performance in the modeling sandwich structures

The difference between the predicted output by the ANN and the actual target data is referred to as the prediction error. The objective of the training process is to minimize this error as much as possible. This process provides generalization to the neural network model, enabling accurate predictions for new unseen data.

The assessment of the ANN accuracy in this research utilized the Mean Square Error (*MSE*), which reflects the prediction accuracy. The other performance metric is the coefficient of determination (R^2), which is specified to evaluate the correlation strength between the predicted values and the actual data. As higher R^2 (typically $R^2 > 0.98 \sim 0.99$), a strong predictivity of the ANN is expected, while a low *MSE* is signed for better accuracy. The coefficient of determination (R^2) and Mean Square Error (*MSE*) can be computed using the following equations [131].

$$MSE = \frac{1}{n}\sum_{i=1}^{m}\left(x_{act\,i} - x_{pred\,i}\right)^2 \tag{6.4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}\left(x_{act\,i} - x_{pred\,i}\right)^2}{\sum_{i=1}^{n}\left(x_{act\,i} - x_{avg}\right)^2} \tag{6.5}$$

where: m denotes the number of data points, $x_{act\,i}$ represents the actual data points obtained from the Monte Carlo simulation, $x_{pred\,i}$ represents the predicted value obtained from the established network and x_{avg} denotes the mean of the $x_{act\,i}$ values.

7. ELABORATION OF A REVERSE DESIGN METHODOLOGY FOR THE SANDWICH STRUCTURES BY USING ANN

Sandwich structures are widely utilized in practice; however, most research efforts have focused on conventional design approaches for sandwich structures (i.e. analytical and numerical methodologies). Although significant advancements have been achieved in theoretical methods and modeling tools, the design space for specific structural configurations remains wide. Consequently, it is challenging for designers to determine the structural configuration that meets the requirements for industrial sandwich structure applications. A time-consuming and tedious trial-and-error process is the only conventional design method available to obtain the desired designs. Therefore, the need has arisen to develop unconventional design approaches that are time-effective and computationally efficient by using ANN.

The term "reverse design" in this study refers to one of the structural responses, maximum deflection, which would be one of the inputs to ANN. In addition, the core and face sheet thicknesses, which are considered inputs in conventional designs, become outputs in the ANN reverse model.

Until now, no studies have investigated the "reverse design" technique for sandwich structures, which includes the selection of requested structural deflection as an input design parameter. As a result, the newly elaborated method provides a novel and practical tool for designing sandwich structures with sufficient accuracy while avoiding the trial-and-error repetition required by traditional design methods. This study links artificial intelligence-based design and traditional design by addressing a problem that is important from a practical point of view.

In the newly elaborated reverse design approach, it can be specified the dimensional parameters, the characteristics of the core material and the applied load. In other words, the structure width (b), the length/width ratio (l/b), the core density (ρ_c), the distribution load (p), the maximum requested deflection (δ_{Req}) and the distance between the centers of the face sheets (d). The core thickness of the sandwich structure (t_c) and the face sheet thickness (t_f), as well as the core safety factor (SF_C) and the face sheet safety factor (SF_F), are the results on the output side of ANN. Thus, the required thicknesses for the core and face sheets (i.e. t_c and t_f) can be determined for the structure to meet design constraints at the preliminary design stage. The safety factors are crucial design parameters that can defined as:

- The core safety factor (SF_C) is the ratio of the resulting core shear stress, which can be calculated using equation (3.6), to the ultimate core shear strength. The value is equal to or greater than 1 means the core can withstand the applied loads.
- The face sheet safety factor (SF_F) is the ratio of the resulting face sheet stress, which can be calculated using equation (3.8), to the ultimate face sheet strength. The value is equal to or greater than 1 means the face sheets can withstand the applied loads.

These safety factors help engineers to ensure the structure's reliability under various circumstances.

This study represents a new sophisticated approach that provides the designers of sandwich structures with a useful, flexible and time-saving tool to optimize and adapt the structural performance of honeycomb sandwich structures for different types of applications. The main steps of ANN-based reverse design is illustrated in Figure 7.1.

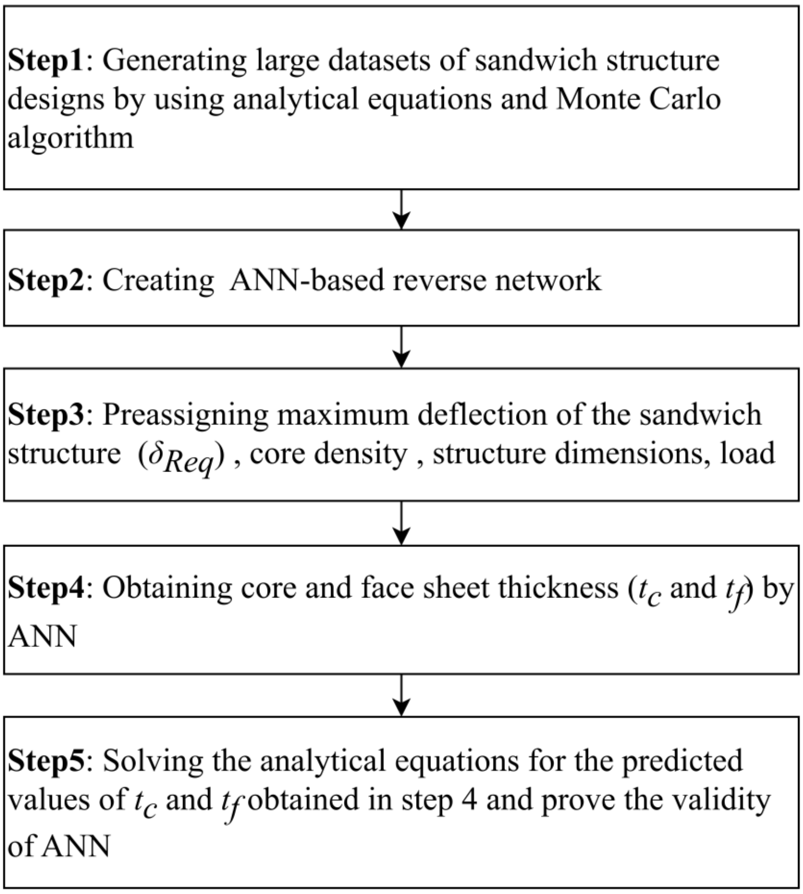


Figure 7.1. Main steps of the newly developed reverse design procedure

7.1. Elaboration Artificial Neural Network model for reverse design of a sandwich structure

The face sheets of the sandwich structure in this study are considered CFRP composite laminate. The constituent unit of the laminated face sheet is a thin composite layer (lamina). The laminate is characterized by the number of laminae and their orientation. A commercial 3003 aluminum (Al) honeycomb core manufactured by Hexcel in various densities is used as the core of the sandwich panel.

The Toray ply (Table 3.1) is considered the base material for the face sheets, as illustrated in Figure 7.2. The final face sheets consist of successive laminae stacked in a cross-ply (0/90^o) sequences. The structure is considered under a distributed load (p) with simply supported edges, as depicted in the figure below.

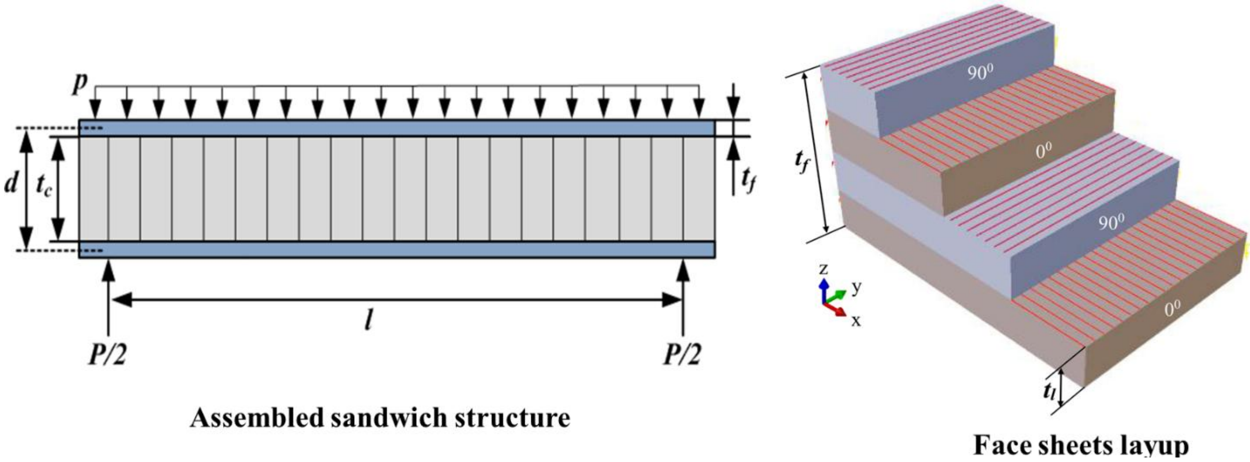


Figure 7.2. Sandwich structure and face sheet configurations

– *Data generation of the investigated sandwich structure*

To create a generalized model for the sandwich structure, the design variables in this study, including core density, width of the sandwich structure, length/width ratio of the sandwich structure distributed load, core thickness and face sheet thickness, are taken across a wide range of values, as listed in Table 7.1

Table 7.1. Design variables used for generating ANN training data

Core density ρ_c	**Width** b	**Length/width ratio** l/b	**Distribution load** p	**Core thickness** t_c	**Face sheet thickness** t_f
[kg/m^3]	[mm]	-	[MPa]	[mm]	[mm]
29, 37, 42, 54, 59, 83	750-1000	1.25-2	0.005-0.027	20-100	0.254-3.81

The study considered the core failure, face sheet failure and maximum deflection of the sandwich structure. Therefore, equations 3.6-3.9 and 3.12-3.14 are formulated in an Excel spreadsheet and linked to isight software. Consequently, the structure's design variables are configured using the Monte Carlo simulation in the isight software. About five thousand sample points were obtained, each representing a single design for the sandwich structure to be designed.

– *Normalization of training data for ANN modeling*

As described previously, normalizing the obtained data is a crucial step to prevent data with larger values from dominating data with smaller values. Given this, the obtained data are normalized to the range [0.1, 0.9] by using the related equation in Section 6.3.

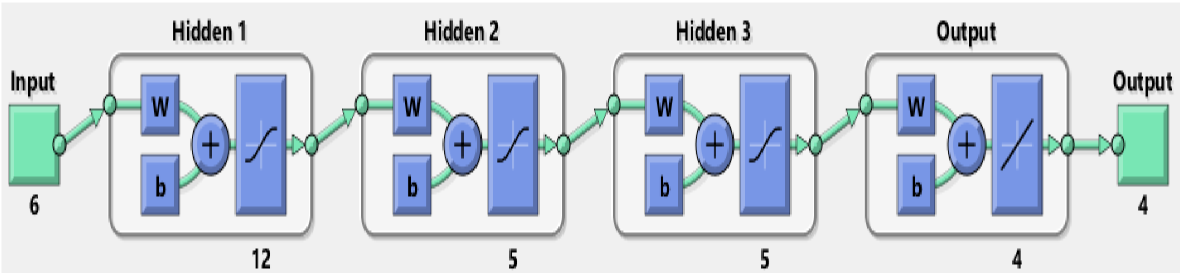
– *Creating an Artificial Neural Network model for the investigated sandwich structure*

The Back-propagation Feedforward Network (BFFN) was chosen to design the investigated sandwich structure. The data is divided into three phases during the training process: 1) Training, 2) Validation and 3) Testing. Accordingly, the input data were randomly divided into 70% for training, 15% for testing and 15% for validation.

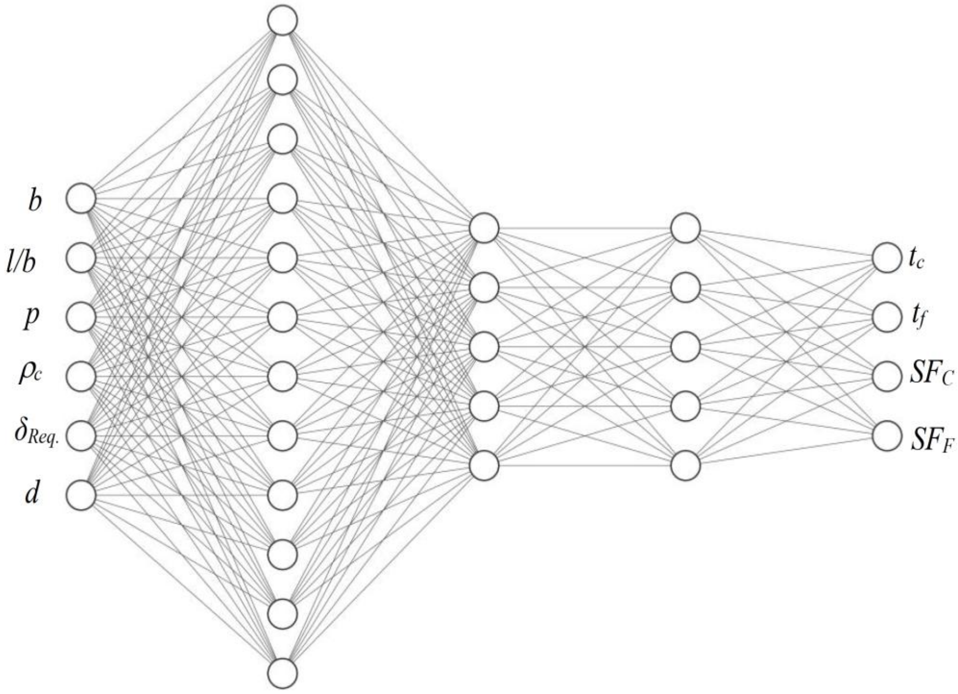
The number of hidden layers was set to 3 layers with 12, 5 and 5 neurons in the respective layers. However, the activation functions for the neurons are (*tansig*) transfer functions. The linear transfer function (purelin) is used in the output layer.

A reverse design scenario is conducted to design the sandwich structure, where the maximum structure deflection is set as the requested deflection (δ_{Req}), along with the other input parameters (b, l/b, p, ρ_c, d). Meanwhile, four parameters (SF_F, SF_C, t_f, t_c) are considered as output parameters.

Given this, Figure 7.3(a) illustrates a schematic representation of the proposed network. While Figure 7.3(b) defines the input and output data used in the creation of the ANN.



(a) Schematic of the neural network layers



(b) Input and output parameters of the neural network

Figure 7.3. Neural network structure for reverse design model

7.2. Results of the elaborated reverse ANN model

The ANN with three hidden layers was configured to predict the structural design of the investigated sandwich structure. Its performance was assessed using *MSE* and R^2 values. Figure 7.4 showed the *MSE* curves for the ANN, where minimizing *MSE* contributes in creating an accurate model. In the graph, the *MSE* curves for the training, validation and test datasets were plotted against the number of iterations (epochs).

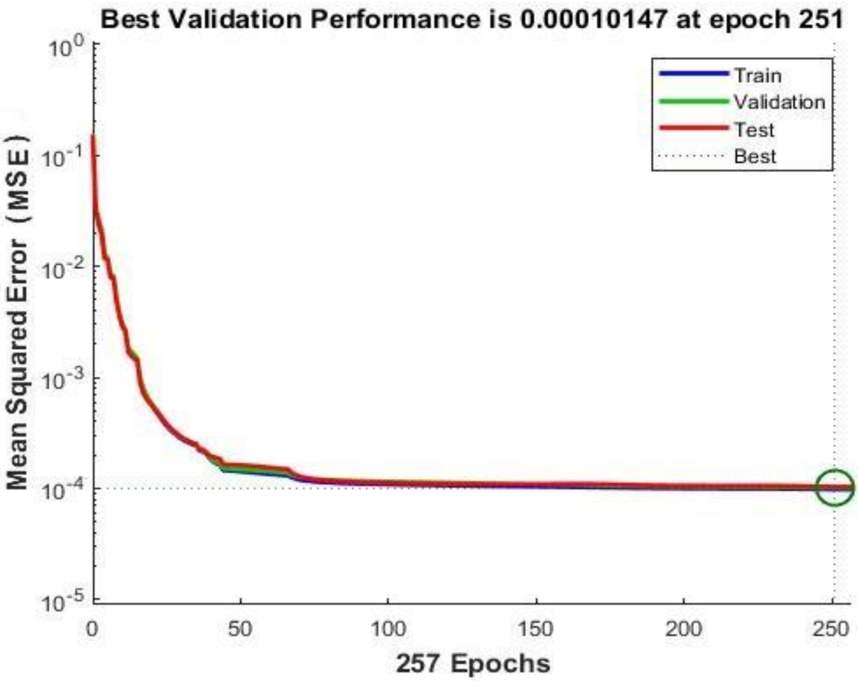


Figure 7.4. Neural network performance (*MSE*)

All three curves showed a rapid decrease in *MSE* during the initial epochs, this indicating that the ANN model quickly learned the relationship to minimize errors. The best ANN performance occurred at epoch 251, with a *MSE* of 10^{-4}, marked by the green circle. This signified that the model achieved the best performance in predicting the parameters for the reverse design of the sandwich structure.

The other performance factor of the ANN was the coefficient of determination (R^2). Figures 7.5-7.7 showed the regression relationship between the analytical data and the prediction of ANN for the training, validation and test data sets.

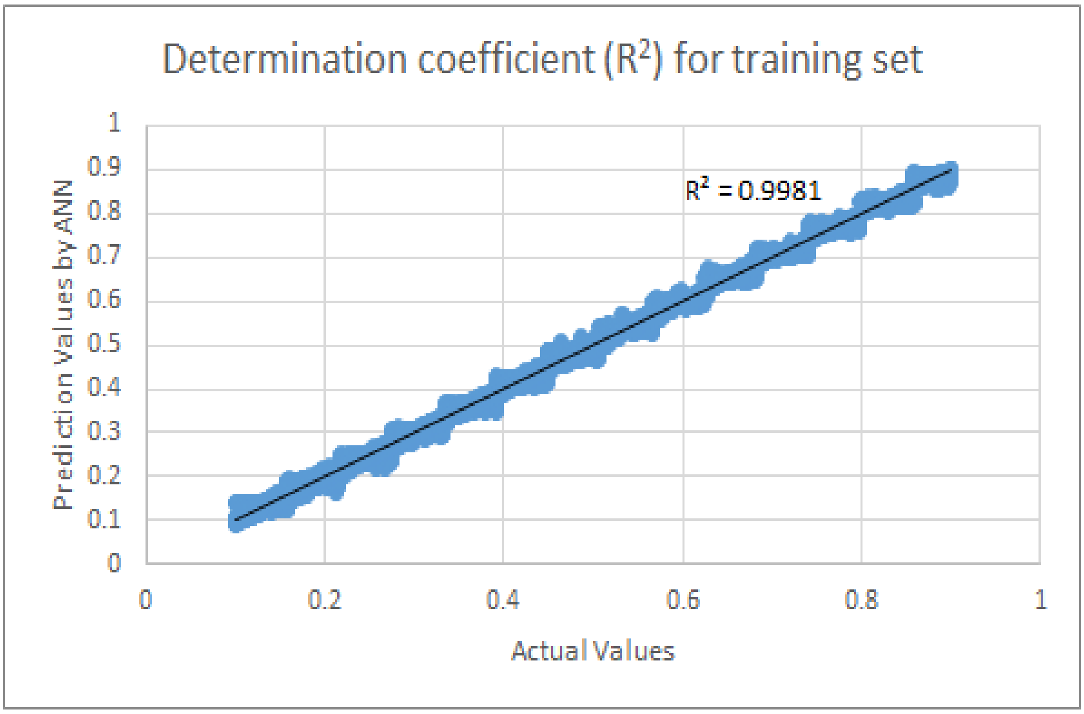


Figure 7.5. Neural network performance determination coefficient – training set

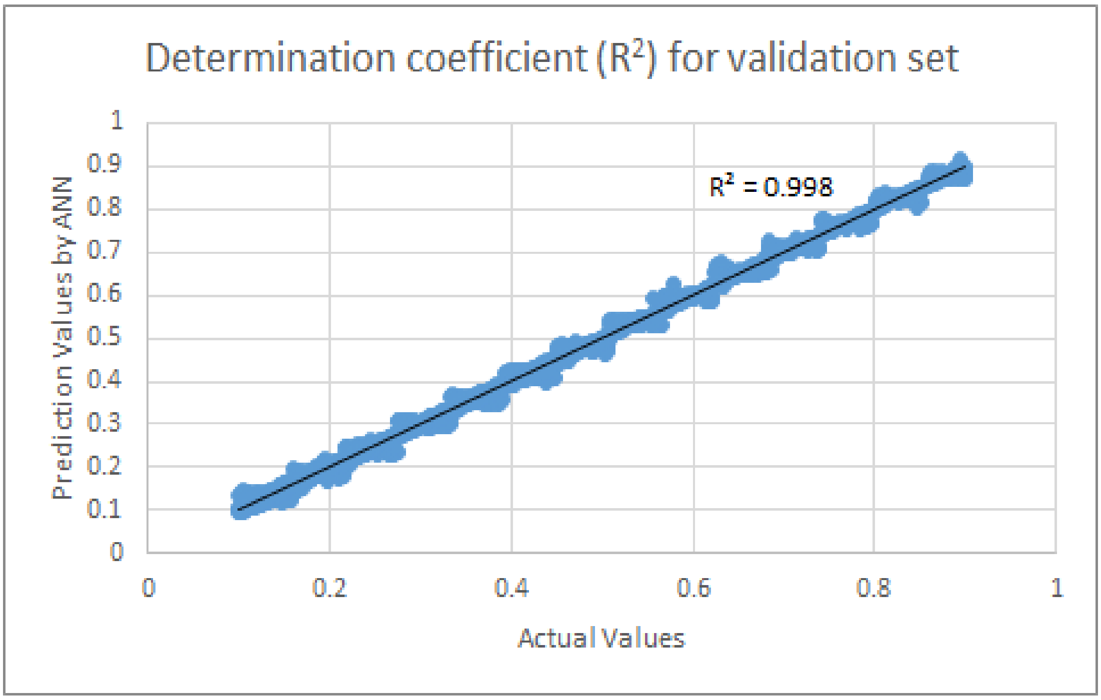


Figure 7.6. Neural network performance determination coefficient – validation set

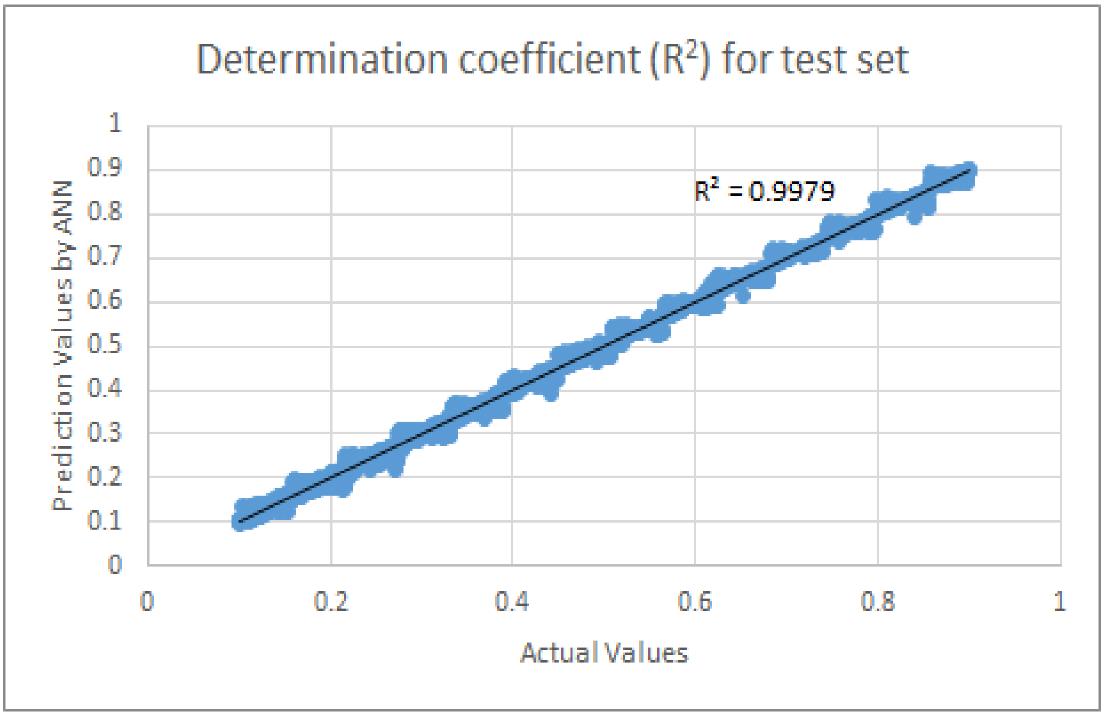


Figure 7.7. Neural network performance determination coefficient – test set

In the results, it can be seen that the (R^2) values were close to one for all three phases. The minimum *MSE* and maximum (R^2) reflected the excellent performance of the reverse neural network model for predicting the output parameters (i.e. t_c, t_f, SF_C and SF_F) corresponding to the input parameters, which were dimensional parameters, core density, requested deflection and distributed load.

Figures 7.8 to 7.11 compared the values of t_c, t_f, SF_C and SF_F obtained from the analytical model with those predicted by the ANN model. For clarity, only the results of 20 data points (each representing a particular sandwich design) are shown.

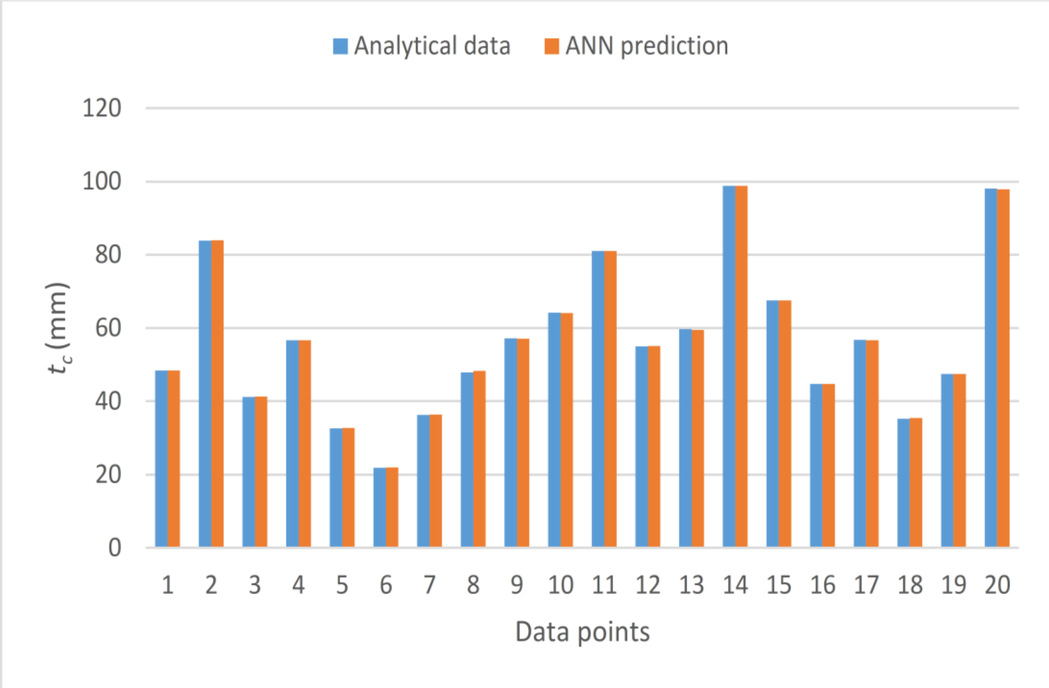


Figure 7.8. ANN prediction for the core thickness (t_c)

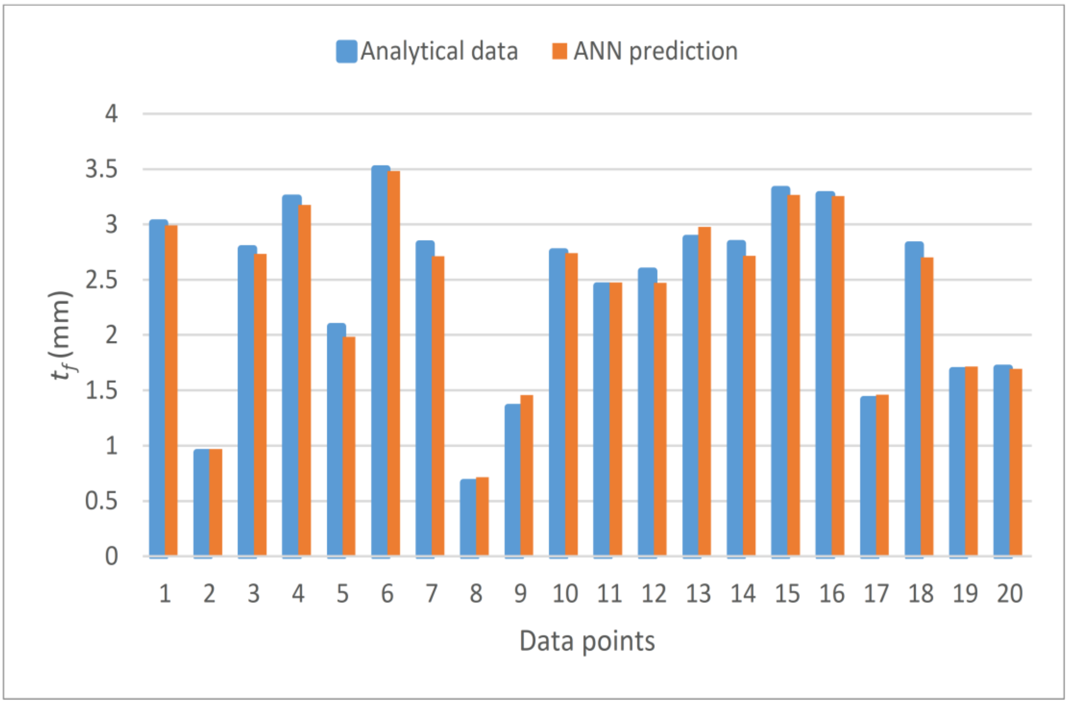


Figure 7.9. ANN prediction for the face sheets thickness (t_f)

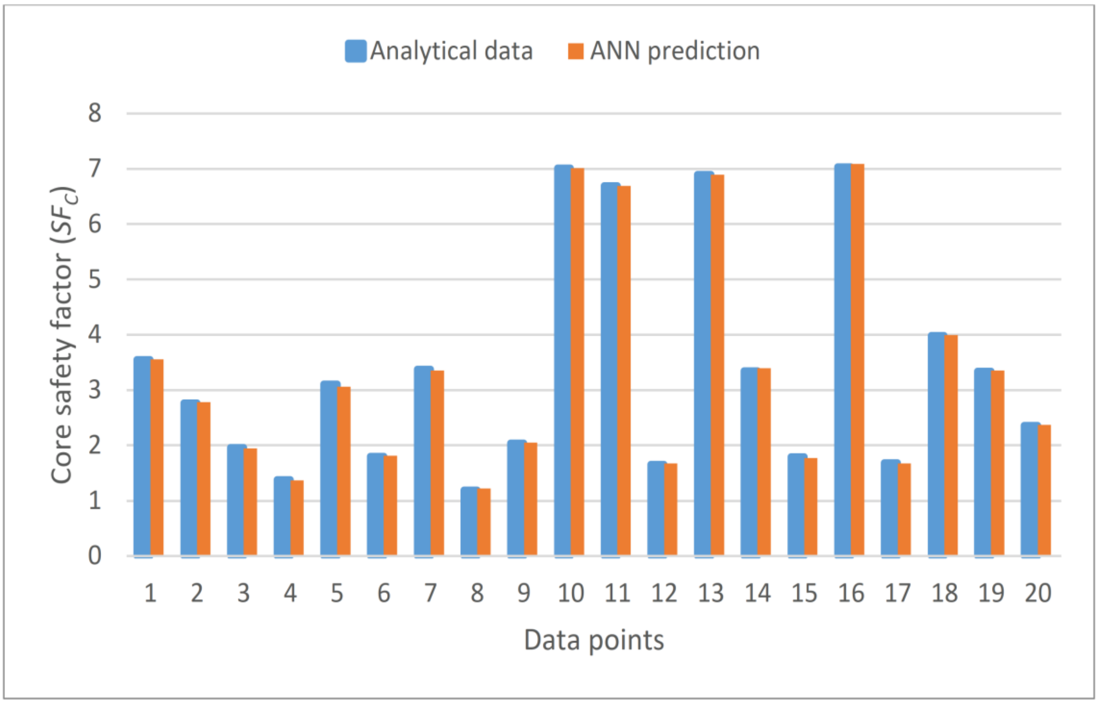


Figure 7.10. ANN prediction for the core safety factor (SF_C)

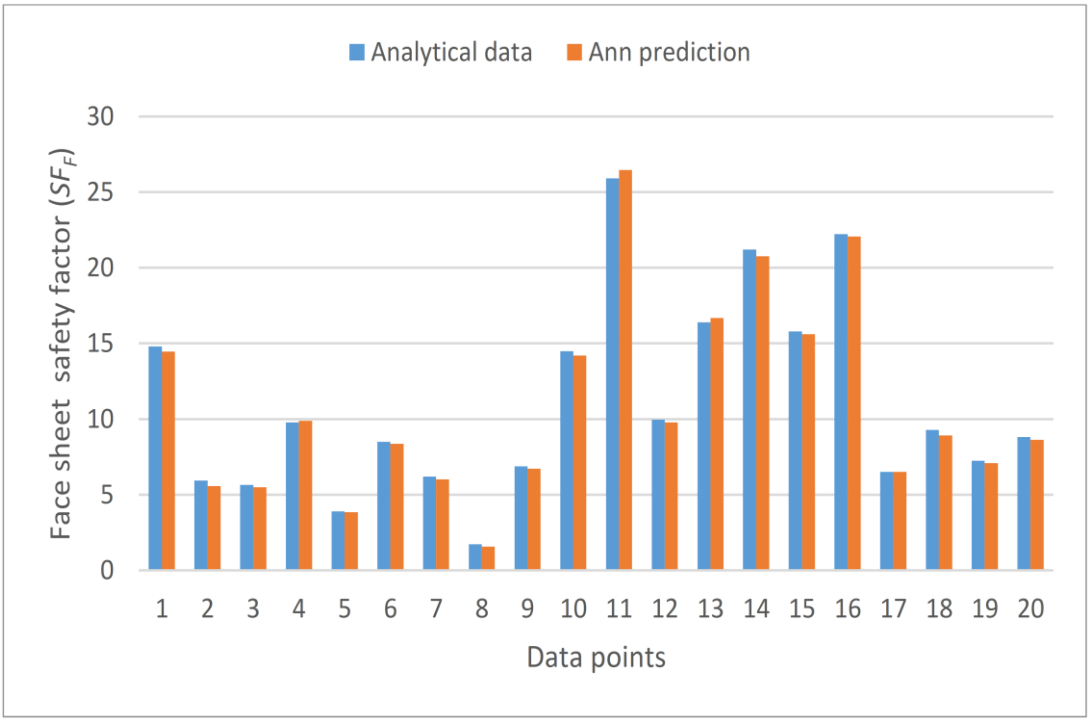


Figure 7.11. ANN prediction for face sheet safety factor (SF_F)

Figures 7.8-7.11 illustrated that the results of the ANN model agreed very well with the analytical values. Therefore, the new reverse neural network model exhibited good predictive ability and high accuracy, which increases our confid ence in its use in further analysis, especially when using neural networks in sandwich structure optimization problems.

To determine the ability of the newly developed reverse design neural network model to predict core thickness (t_c), face sheet thickness (t_f) and safety factors (SF_C, SF_F), the neural network model was tested with specific sample points as it listed in Table 7.2. The reserved output (t_c and t_f), which are predicted by ANN, are used to calculate the sandwich structure's middle deflection and safety factors analytically using the equations 3.6-3.9 and 3.12-3.14. The results were presented in Tables 7.2 and 7.3, which included 10 data points, each representing a distinct design for the sandwich structure.

Table 7.2. Design prediction results by the new reverse Artificial Neural Network model

No.	ANN input						ANN prediction			
	b	l/b	ρ_c	P	δ_{Req}	d	t_c	t_f	SF_C	SF_F
	[mm]	[-]	[kg/m^3]	[Mpa]	[mm]	[mm]	[mm]	[mm]	[-]	[-]
1	773	1.6	59	0.02	2.4	52	48.7	2.7	3.59	13.45
2	910	1.9	54	0.02	12.1	44	41.5	2.6	1.96	5.287
3	958	1.8	29	0.02	6.6	60	56.8	3.1	1.4	9.81
4	873	1.9	83	0.02	16.8	35	32.6	2.2	3	4.155
5	922	1.4	59	0.02	8	25	22.1	3.3	1.86	8.051
6	788	2	83	0.02	9.4	39	36.4	2.8	3.38	6.119
7	828	1.8	37	0.02	5.4	59	57.1	1.4	2.08	6.904
8	935	1.5	83	0.02	2	67	63.9	3	6.8	14.96
9	1000	1.4	37	0.02	4.2	58	55.3	2.2	1.68	8.89
10	760	1.8	59	0.0200	4.8	49.10	47.19	1.88	3.250	7.536

Table 7.3. Analytical solution depending on ANN prediction

No.	δ_{Anal}	SF_C	SF_F	δ_{diff}	$SF_{C.diff}$	$SF_{F.diff}$
	[mm]	[-]	[-]	[%]	[%]	[%]
1	2.403	3.562	13.291	0.14	0.72	1.19
2	12.421	1.968	5.225	2.59	0.30	1.19
3	6.445	1.390	9.899	2.41	0.48	0.89
4	16.647	3.002	4.194	0.92	0.18	0.94
5	8.045	1.861	8.233	0.56	0.15	2.21
6	9.493	3.388	6.191	0.98	0.10	1.17
7	5.328	2.077	6.987	1.36	0.02	1.19
8	1.994	6.807	14.666	0.31	0.18	2.01
9	4.138	1.679	9.048	1.50	0.10	1.75
10	4.615	3.230	7.910	4.02	0.63	4.72

The reverse input deflection (δ_{Req}) set by the designer, considered as one of the ANN inputs, was compared with the analytical output parameter (δ_{Anal}), which calculated by the analytical equations. Notably, both values were in good agreement, with a maximum difference of about 4.0% for the considered data points. On the other hand, the safety factors predicted by the reverse ANN model and those calculated by the analytical model were very close to each other. The maximum difference in this context was about 4.7%. Based on these results, it can be concluded that ANN is able to predict the reverse design parameters (i.e. t_c and t_f) for the sandwich structure based on the reverse input (δ_{Req}). The advantage of this model is that it provides the designer with a robust tool to control the maximum deflection of the structure to meet the application requirement.

7.3 Conclusions and new added value of the case study

The present study investigated the application of the ANN technique to build a novel model for predicting the structural design parameters of honeycomb sandwich composite structures based on requested deflection limits.

We began by solving analytical equations organized by the Monte Carlo method to obtain the required data set for building a reverse ANN model. The data included different configurations of sandwich structures considering different geometric and loading conditions. An ANN was trained, tested and validated using the data from the previous step. A network model with three hidden layers, Levenberg-Marquardt (LM) training algorithm, transfer function (tansig) and with (12-5-5) neurons in the hidden layers showed good prediction performance.

The results showed that the created model is able to predict reverse structural design parameters (t_c, t_f) of the investigated sandwich structure. In this context, the designer has to select the dimensions of structure, the applied load, core density and maximum deflection (which is reverse input) of the sandwich structures. While the proposed intelligent model is able to predict the core thickness and the thickness of the face sheets (reverse outputs), the model is also able to predict the safety factors of the honeycomb core and face sheets.

The main added values can be summarized as below :

- A "reverse design" methodology carried out by ANN was elaborated, the study introduced a reverse design methodology using the ANN technique to predict the design parameters of the investigated sandwich structures, offering a novel approach compared to traditional FEM and analytical methods.
- The design time and computational cost for the sandwich structure were reduced, the ANN reverse design model significantly reduced the time and computational resources that needed for designing or redesigning sandwich structures compared to FEM and analytical methods.
- High accuracy prediction for the structural responses of the sandwich structure was obtained, the reverse ANN model demonstrated high accuracy with a low *MSE* and a coefficient of determination (R^2) close to unity, this indicated reliable predictions of structural parameters.
- A practical design tool for the sandwich structure was developed, the model provided a practical tool for designers, enabling the optimization of sandwich structures for various applications with sufficient accuracy and flexibility, making it highly useful for real-world engineering problems.

8. ELABORATION OF A NEW OPTIMIZATION METHOD COMBINED WITH ANN FOR SANDWICH STRUCTURES

Recent advancements in machine learning techniques, particularly Artificial Neural Networks, suggest their potential utility in designing sandwich structures. ANN modeling offers an effective methodology to replace computationally expensive traditional methods of the design, providing an opportunity to streamline the design and optimization processes for the sandwich structures.

On the other hand, the optimization of sandwich structures is crucial goal due to their increasing use in industries that demand high-performance structures with lightweight characteristics. Our investigations are associated with optimizing the sandwich structures from the weight and cost minimization perspectives. It is essential in the optimization procedure to ensure that the optimized structures fulfill design constraints while reducing overall weight and costs. In this study, the Genetic Algorithm (GA) is used because of its ability to optimize the design variables of the sandwich structures and achieve the specified objectives. Based on the literature review, no existing procedures combine ANN modeling with GA optimization in designing and optimizing sandwich structures. This integration of ANN's predictive capabilities with GA's optimization power represents a novel approach in the sandwich structure optimization field.

A novel optimization method for weight and cost minimization has been developed an Artificial Neural Network and Genetic Algorithm (ANN-GA) integration technique. The ANN model is trained to predict the structural performance of the investigated sandwich structure. ANN-GA model aims to find an optimal structural configuration that minimizes the weight and cost of the structure while satisfying stiffness and strength design constraints. Such a ANN-GA model could be benefit for the designers by facilitating optimization problems and attaining specific structural designs more efficiently. Concerning the design and optimization of sandwich structures, this integrated method represents a promising technique for tailoring composite sandwich structures for various practical applications.

The ANN-GA model procedure utilized three software: Excel, isight and Matlab. Excel was used to formulate the sandwich structure equations and store materials data. While, isight processed data generation required for training the ANN. Finally, two Matlab tools (ANN and optimization toolboxes) were combined by developing scripts in Matlab to obtain the optimum Pareto front.

The case study for applying ANN and GA integration methodology will be elaborated to optimize the footbridge deck in terms of weight and cost minimization. The main design parameters of the sandwich structure to be optimized are the face sheet materials, honeycomb core types and distributed load. Meanwhile, the constraints (i.e. face sheet strength, core strength and total deflection of the structure) and optimization objectives (i.e. total weight and total cost of the structure) are considered as the structural responses of the investigated sandwich structures. In the following subsections, the developed methodology is introduced in detail.

8.1. Creating ANN model for the investigated footbridge deck

The structure under consideration is a footbridge deck. The geometry of the unit panel on the bridge consists of a composite sandwich structure supported by two beams. The practical and equivalent analytical models of the investigated structure are illustrated in Figure 8.1 [132].

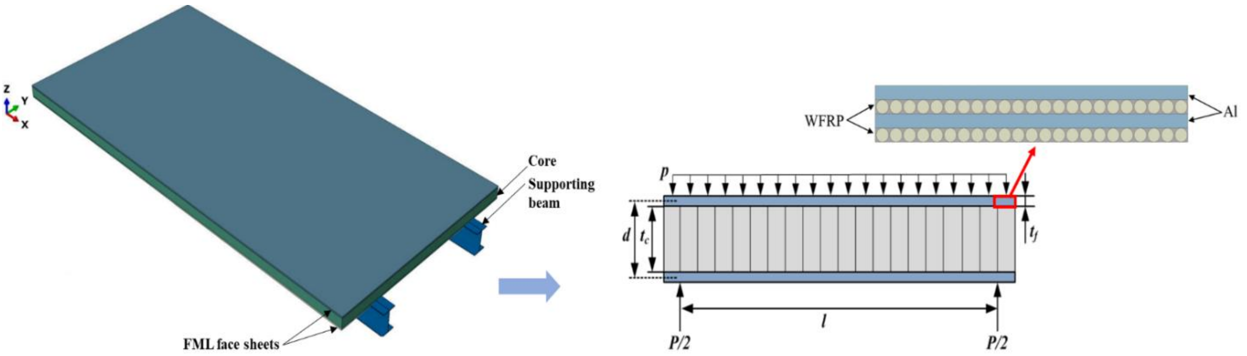


Figure 8.1. Footbridge deck geometry and configuration

The analytical model is considered as a simply supported beam subjected to a distribution load. The dimensions and operating load that are considered in this study are listed in Table 8.1 [132].

Table 8.1. Geometry and loading parameters.

Length of the sandwich structure *l*	**Width of the sandwich structure** *b*	**Distributed load** *p*
[mm]	[mm]	[MPa]
1800	5000	0.006

To generate the necessary data for the ANN, the equations outlined in Chapter 3 are formulated and solved for the investigated sandwich structures. The performance of the training model depends crucially on a wide range of data coverage; therefore, variations in design parameters are performed to involve a broad spectrum of structural designs. Table 8.2 illustrates the main design parameters used for generating the required data with the ranges for the core density, distributed load, core thickness and number of layers.

Table 8.2. Design parameters used for generating ANN data.

Core density ρ_c	**Distribution load** p	**Core thickness** t_c	**Number of layers** N_l	**Possible face sheet materials**
[kg/m^3]	[MPa]	[mm]	[pieces]	
Al and Nomex cores in Table 3.2	0.001-0.006	15-200	3-6	Al, WCFRP, WGFRP

The Monte Carlo simulation under the isight software framework is used to generate about 9000 design samples. By normalization process, the data is scaled at range [0.1, 0.9] and the normalized data is later used in ANN training. In this study, the Bayesian Regularization (BR) training algorithm divided the data into two subsets, with 60% used for training and 40% for testing. The number of hidden layers is set to three with 30, 29 and 28 neurons, respectively. The sequential hidden layers are activated by the transfer function "*logsig*" which is built into each neuron at the hidden layer. The output layer, on the other hand, used the linear transfer function "*purelin*" which is built into each neuron at the output layer.

The ANN model is organized to predict the constraints and objectives of the sandwich structure as an output. These parameters included the core shear constraint margin, constraint margin of face sheet fracture stress, constraint margin of intra-cell for the face sheet and constraint margin for the face sheet wrinkling. Additionally, the maximum deflection limit (C_δ) and the total thickness of the sandwich structure (t_{sw}) are also specified as design constraints. The optimization objectives are the total cost of the sandwich structure (C_t) and the total weight of the sandwich structure (W_t). While, the design parameters included core density (ρ_c), core thickness (t_c), facing material layers (WCFRP, WGFRP and Al), number of layers (N_l) and applied load (p).

Figure 8.2 depicts the architecture of the developed ANN for the investigated sandwich structure, along with the corresponding input and output data utilized in the model.

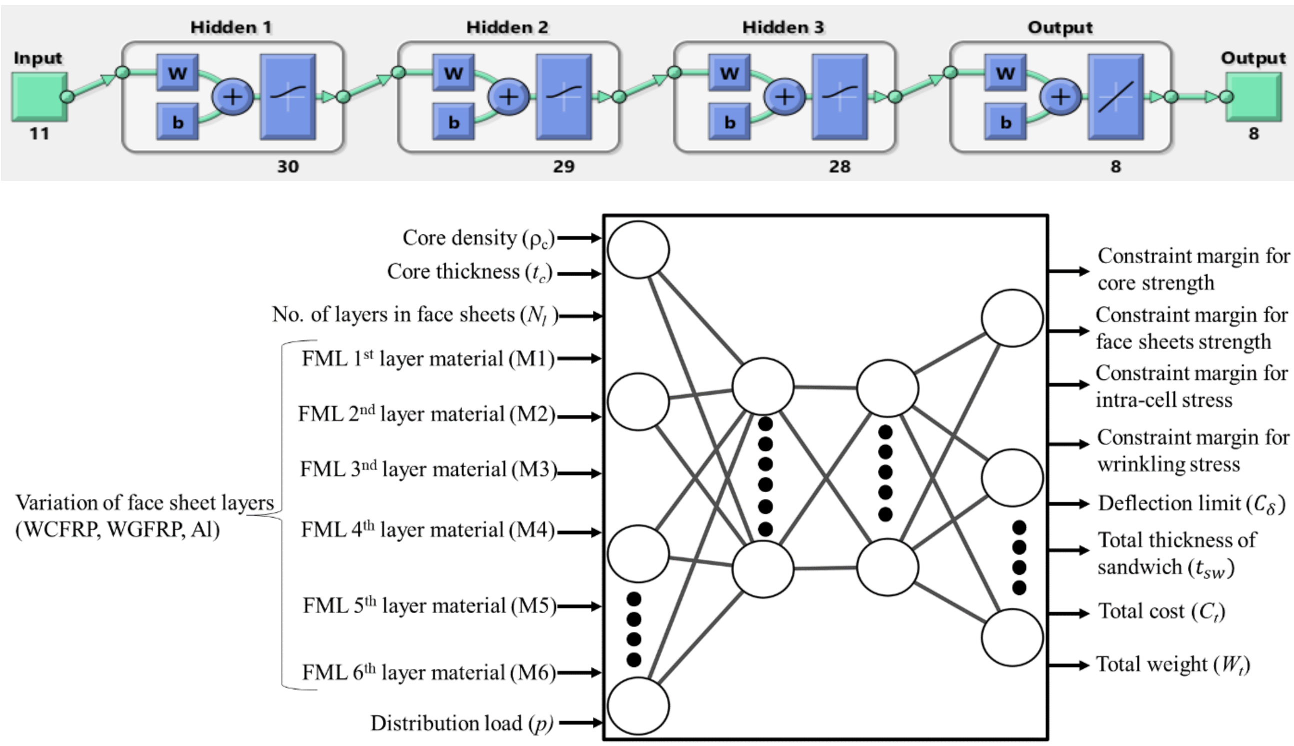


Figure 8.2. Neural network structure model for the investigated sandwich structure

8.2 Application of the elaborated optimization method for the investigated sandwich structure with an own developed integrated software

The elaboration of the optimization framework is depicted in Figure 8.3. Initially, a model of the composite sandwich structure is developed based on the governing equations of Classical Lamination Theory and Beam Theory. Subsequently, this model is employed to create a required data set using Monte Carlo simulation. The generated data is utilized to train and test an ANN network. Finally, a Multi-Objective Genetic Algorithm (MOGA) is integrated with the ANN model to identify the non-dominated solutions and determine the optimal solution. The methodology details will be explained in the following subsections.

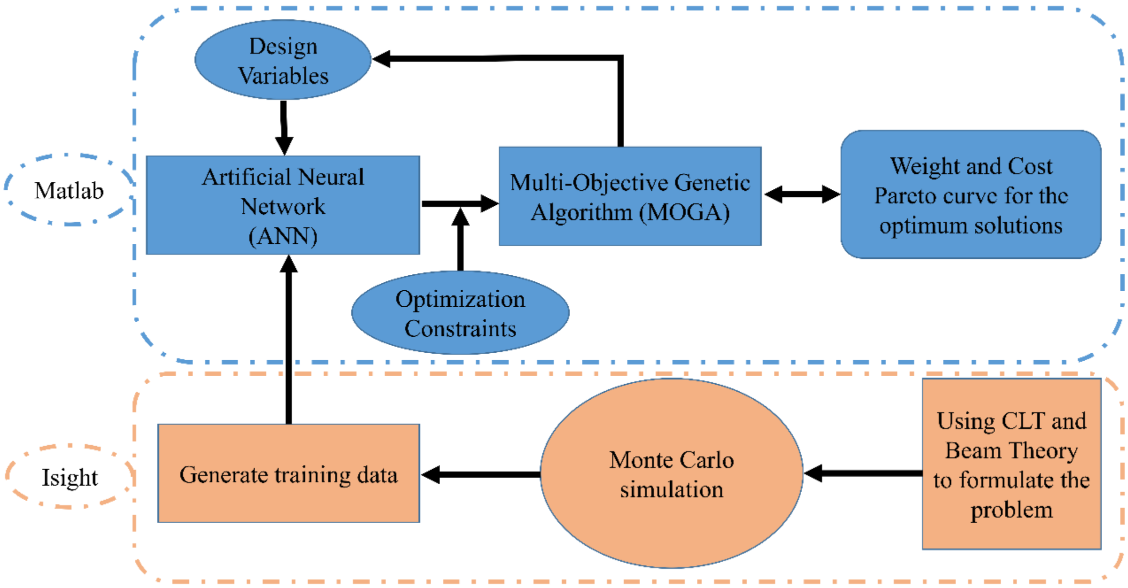


Figure 8.3. Newly developed optimization framework of the proposed structures

8.2.1 Weight and cost objective functions used during the optimization

The main aim of the optimization phase is to optimize weight and cost simultaneously for the investigated sandwich structure (Figure 8.1). To achieve this, a well-trained ANN is used as a fitness function, which is integrated with the MOGA algorithm in the optimization framework. The dependent objective functions are as indicated in equations 3.1 and 3.4.

8.2.2 Design variables to be optimized

The design variables play a critical role in determining the key properties of an optimal sandwich structure. In our case study (Figure 8.1), these variables include Nomex and Al honeycomb cores in different densities and with a wide range of thicknesses. Additionally, the face sheet structure is composed of different layers of WCFRP, WGFRP and Aluminum, with varying number of layers ranging from three as the minimum to six as the maximum number of layers. The face sheets are specifically characterized as fiber metal laminates and their final properties are influenced by the relative proportions of each constituent material. However, the load was not considered as a design variable; rather, it was treated as a flexible input parameter determined by the designer based on specific requirements for the desired maximum load. The design variables for this study are summarized in Table 8.3.

Table 8.3. Design variables of the optimization

Design Variables	Value	Remark
Number of layers in face sheets	$3 \leq N_l \leq 6$ [pieces]	discrete variables
Combination of face sheet materials	WCFRP layer: identified by **No. 1** WGFRP layer: identified by **No. 2** Aluminum layer: identified by **No. 3**	discrete variable, integer values

Core density	ρ_c [kg/m^3]	discrete variables as specified in Table 3.2
Core thickness	$30 \leq t_c \leq 200$ [mm]	continuous value

8.2.3 Design constraints used during the optimization

To ensure a successful optimization procedure, it is crucial to determine the sandwich alternatives that meet a specific purpose and those that do not. In this case study, constraint margins for the core shear, face sheet stress fracture, face sheet intra-cell and the face sheet wrinkling must be greater than 1 for any feasible design, additionally the maximum deflection limitation (C_δ) of the structure; furthermore, the total thickness of the sandwich structure is set to define the required boundaries that any proposed design must be satisfied. The constraints listed below can be acquired from the output of the ANN model.

1. Core shear strength: the core shear strength must have a constraint margin equal to or greater than 1 with respect to the resulting shear stress;
2. Face sheet strength: the ultimate strength of the face sheets must have a constraint margin equal to or greater than 1 with respect to the resulting face sheet stress;
3. The face sheet intra-cell: the intra-cell stress must have a constraint margin equal to or greater than 1 with respect to the ultimate strength of the face sheets;
4. Face sheet wrinkling: the wrinkling stress must have a constraint margin equal to or greater than 1 with respect to the ultimate strength of the face sheets;
5. Maximum deflection: the structural deflection must be below the sandwich structure length divided by 400, i.e. ($\frac{l}{400}$) [133];
6. The overall thickness of the sandwich panel: the total thickness of the sandwich structure must be below 200 mm [132].

8.3. Multi-objective optimization results of a footbridge deck applying the elaborated combined Artificial Neural Network – Multi-Objective Genetic Algorithm (ANN-MOGA) Model

8.3.1. ANN model performance for the investigated sandwich structure

In the present study, an ANN model was used to establish a correlation between input variables (i.e. design variables) and output variables (i.e. objectives and design constraints). Consequently, an evaluation for the model predictability was performed. Figure 8.4 illustrates the *MSE* throughout the model training process.

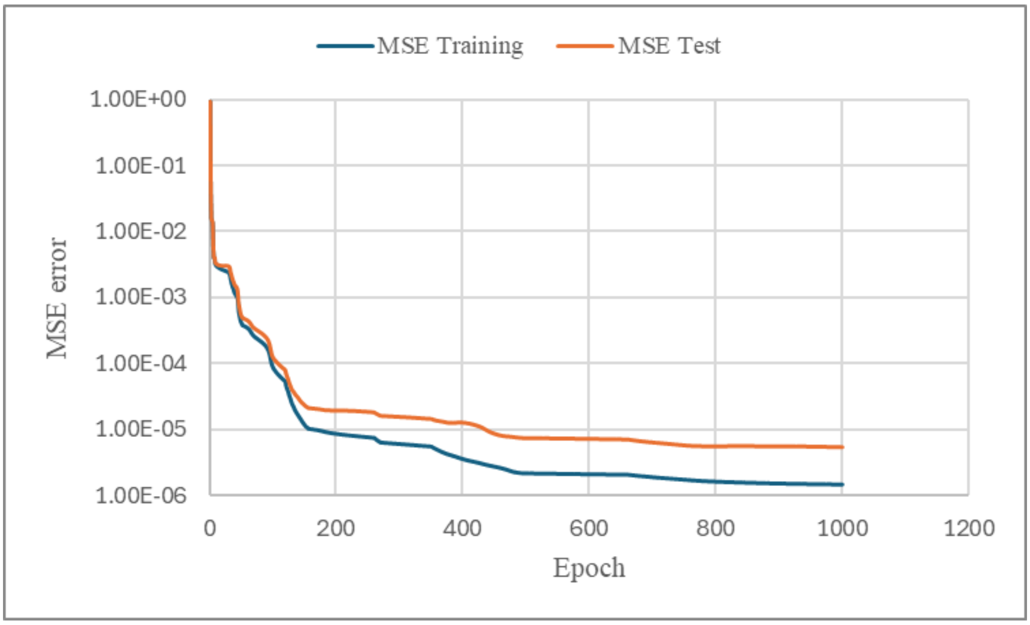


Figure 8.4. Mean Square Error (*MSE*) for the ANN model

The lower *MSE* values indicated a higher predictive ability of the ANN, highlighted its effectiveness in capturing the relationships between input variables and their corresponding outputs. Notably, the *MSE* exhibited consistent behavior across training and testing sets, further confirming the robust performance of ANN. The best *MSE* was approximately ($1.4{\cdot}10^{-6}$), which was obtained after 1000 epochs.

The coefficient of determination (R^2) was also used to evaluate the ANN performance. As depicted in Figures 8.5-8.6.

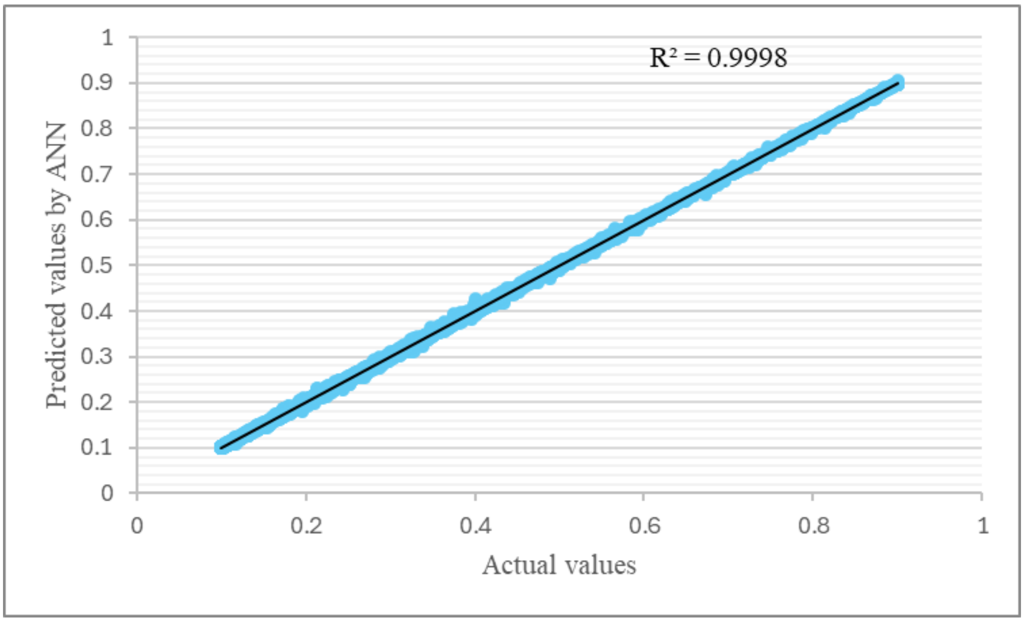


Figure 8.5. ANN prediction vs. actual values (training) for the sandwich structure

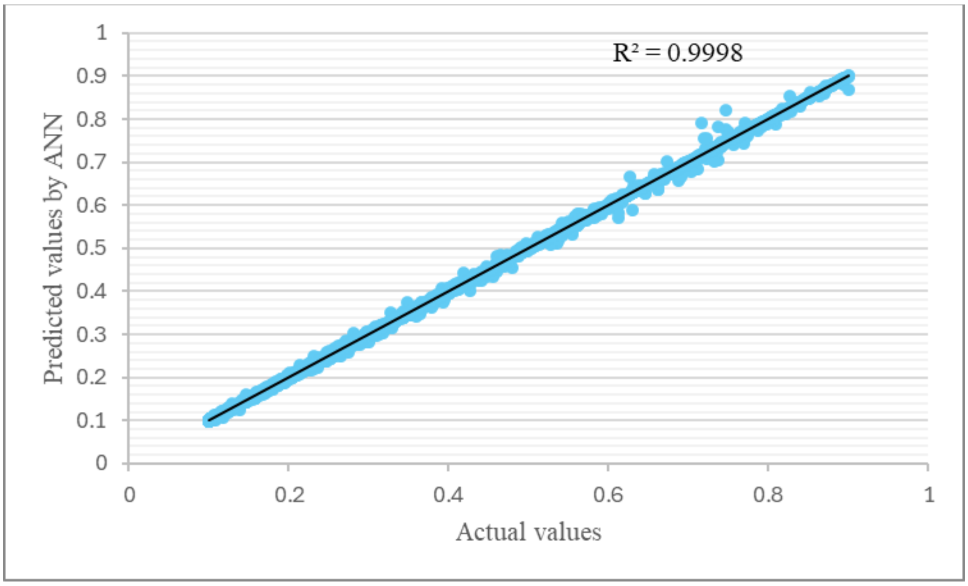


Figure 8.6. ANN prediction vs. actual values (test) for the sandwich structure

The R^2 values approach unity, indicating a close correspondence between the predicted and actual data. This observation emphasized the high predictive accuracy of the proposed ANN model.

8.3.2 Optimization results for the investigated footbridge deck

After successfully creating an accurate ANN model to predict the structural performance of the composite sandwich footbridge deck based on its configurations, the focus shifted to the optimization of the sandwich composite structure using the MOGA combined with ANN. The design variables considered to achieve the final objectives included different densities of honeycomb cores, core thickness, hybridized face sheets (FML) with their respective parameters and number of layers in the face sheets.

During multi-objective optimization, achieving the best possible values for all objectives simultaneously is challenging because these objectives often conflict with each other. Hence, the Pareto curve offers a spectrum of alternative solutions to facilitate decision-making. The solutions along the Pareto curve represent a range of compromises between the competing objectives, with each point on the curve corresponding to a unique combination of objective values. In our investigation, reducing the weight of the sandwich structure led to an increase in cost. Consequently, further improvement in one objective must necessarily sacrifice the other.

Notably, any point on the Pareto curve is an optimal solution. For instance, if weight reduction is prioritized, a combination of lighter materials should be considered. As a result, the overall cost would be increased and conversely, considering cost as the primary objective would lead to a weight increase. Figure 8.7 demonstrates that all solutions align as individual design points on the Pareto curve. In this case study, a Pareto curve consisted of 6 points as a result of the optimization process.

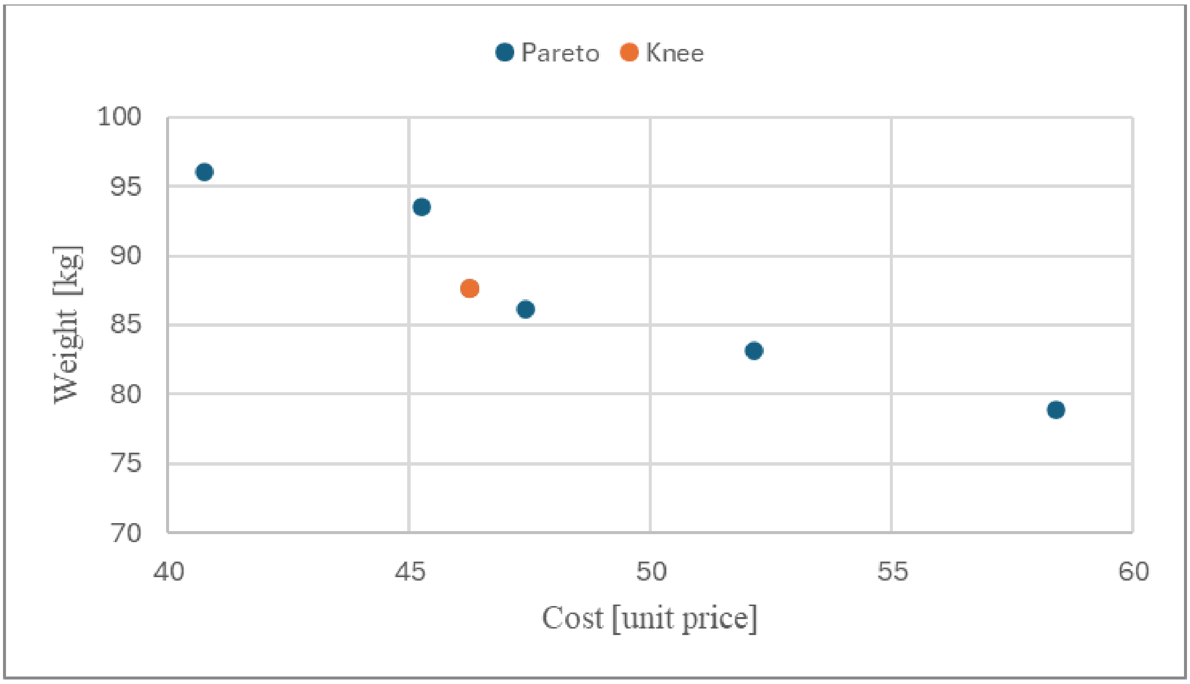


Figure 8.7. Pareto and knee points of the investigated structure optimal solutions

The selection method to determine the most satisfactory solution, commonly known as the IMDSM method, was used to determine the "knee point". Comprehensive details and relevant descriptions can be found in Section 3.1.3. In Figure 8.7, the shortest distance (D_{min}) represented the best access to the ideal point (minimum weight and minimum cost) and the knee point should be identified as the optimal solution with C_t = 46.23 unit price and W_t = 87.68 kg, which will contribute to an ideal response with balance among the conflicting objectives. The comprehensive data for the Pareto design points are presented in Table 8.5.

Table 8.5. Details of Pareto points design.

Core density ρ_c	**Core thickness t_c**	**No. of layers in the face sheet N_l**	**Face sheet materials**	**Cost C_t**	**Weight W_t**
[kg/m^3]	[mm]	[pieces]	WCFRP layer: identified by **No. 1** WGFRP layer: identified by **No. 2** Aluminum layer: identified by **No. 3**	[unit price]	[kg]
59	**105.78**	**4**	**3,3,3,3**	**40.74**	96.09
54	113.93	4	3,3,2,3	45.25	93.53
42	**109.74**	**5**	**3,3,2,2,3**	**46.23**	**87.68**
42	131.94	4	3,2,3,2	47.41	86.17
42	107.65	5	3,1,2,2,3	52.13	83.16
42	**106.01**	**5**	**3,2,2,1,1**	58.4	**78.93**

Among the design points on the Pareto line, the minimum cost (Design 1), minimum weight (Design 2) and knee point (Design 3) hold the utmost importance. These points capture critical insights into the design space. We have separated relevant data for these design points to be utilized for further analysis, as listed in Table 8.6.

Table 8.6. Parameters of single- and multi-objective optimization structures

Design No.	**Core density** ρ_c	**Core thickness** t_c	**Number of layers in the face sheet** N_l	**Face sheet materials**	**Cost** C_t	**Weight** W_t
	[kg/m^3]	[mm]	[pieces]	WCFRP layer: identified by **No. 1** WGFRP layer: identified by **No. 2** Aluminum layer: identified by **No. 3**	[unit price]	[kg]
Design 1	59	105.78	4	3,3,3,3	**<u>40.74</u>**	96.09
Design 2	42	109.74	5	3,3,2,2,3	**<u>46.23</u>**	**<u>87.68</u>**
Design 3	42	106.01	5	3,2,2,1,1	58.4	**<u>78.93</u>**

In general, the sandwich structure composed of totally aluminum face sheets exhibited a higher weight of 96.09 kg and a **minimal cost** of 40.74 units (Design 1). On the other hand, the **minimal weight** structure was 78.93 kg and 58.4 unit price (Design 2). This provided a weight reduction by 17.8 % for the FML face sheet sandwich structure compared to the all-aluminum face sheet configuration, but at the expense of increasing cost by about 30.2%.

The **knee point** was identified as the most satisfactory solution (Design 3). Within the Pareto curve, the knee point provided a weight of 87.68 kg and a unit price of 46.23, respectively, representing a weight reduction of 9.0% and a cost increase of 13.0% compared to the higher weight and minimal cost structure.

The weights of single- and multi-objective optimized structures were compared with the original structure, which included panels made of adhesively bonded pultruded structure, as detailed in the literature [132]. The weight of the original structure is 450 kg, while the estimated cost, according to the materials prices survey, is 33 unit price. Compared with the three optimal points that obtained from the optimization process, the provided weight reductions were 78.65 %, 80.52 % and 82.46 %, for Desgin 1, Desgin 2 and Desgin 3, respectively. In contrast, the costs were increased by 23.4%, 40% and 76.9% for the same alternatives.

It is obvious that solving the optimization problem in this study produced a significant reduction of the weight for all Pareto points compared with the original structure. This, in turn, provides a flexible options to consider the more convenient design in aspects of weight and/or cost that vary gradually along the Pareto optimum line. The geometrical characteristics and sandwich components configuration for these three optimal points will be used in FEM simulation, as can be seen in the next subsection.

8.4. Finite element modeling of the optimal footbridge deck structures for verification of the elaborated optimization procedure

Finite element analysis is used to investigate the sandwich structure's deformation patterns and face sheets stress distribution, thus providing valuable insights for structural design and optimization. The geometrical parameters and materials of the sandwich structure were used for the three optimal points, as illustrated in Table 8.6.

As highlighted previously, the honeycomb core was represented in the FEM model as a homogeneous solid layer with detailed mechanical properties to improve computational efficiency. The three-dimensional stress elements C3D8R were used to model the honeycomb cores, while the shell elements type S4R were used to simulate the laminated composite face sheets. A tie contact formulation was implemented to define the interaction between the face sheets and the core.

The honeycomb core was discretized with approximately 24000 elements, while approximately 11000 shell elements were used to mesh the face sheets. The prescribed distribution load, as defined in Section 8.1, was applied to the upper face sheet of the structure. Additionally, the modeled structure was fixed by applying simply supported boundary conditions in the lower face sheet edges. Figure 8.8 shows an illustrative finite element schematic for the modeled sandwich structure.

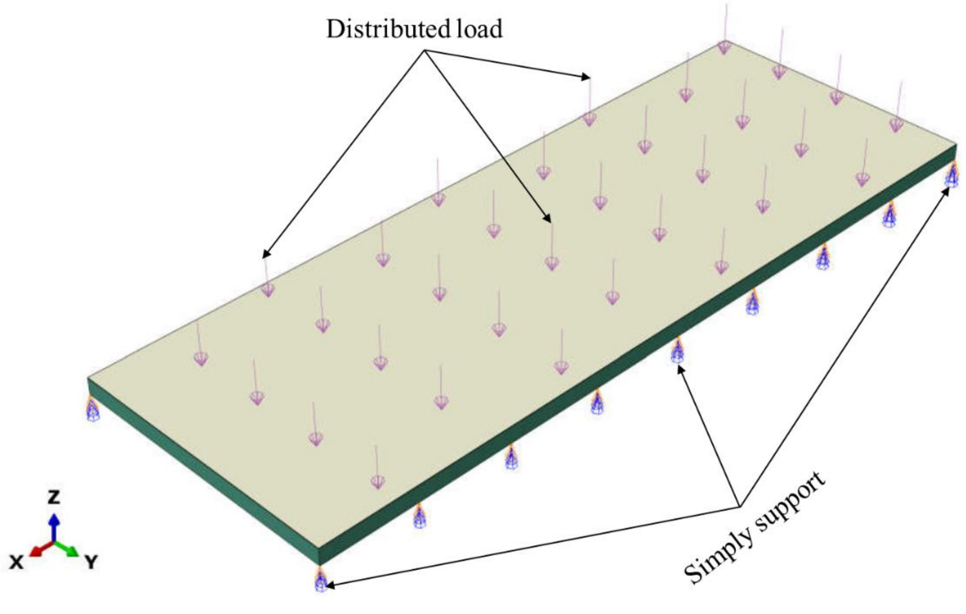


Figure 8.8. Finite Element Model of the investigated foot bridge deck

8.4.1 Finite Element simulation results of the optimal sandwich structures

The previously described FEM model was used to validate the results of the elaborated ANN-MOGA model for the investigated sandwich structure. Due to the computational challenges associated with performing FEM simulations for all points on the Pareto curve, it was decided to focus on simulating the three optimal points. These points included the minimal cost, minimal weight and knee points. The FEM modeling data included the key parameters related to the geometrical properties and configurations of the sandwich structure components for the specified designs, as listed in Table 8.6. The distributed load was set to be 6.00 KPa as it was specified in the practical for the footbridge deck.

The FEM simulations primarily focused on two critical aspects: the maximum deflection of the structure and the maximum stress experienced by the face sheets. The FEM results were illustrated in the Figures 8.9-8.14.

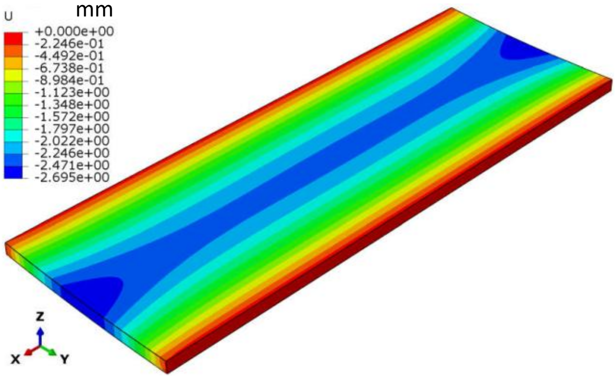


Figure 8.9. Deflection of the structure which provides the minimal weight

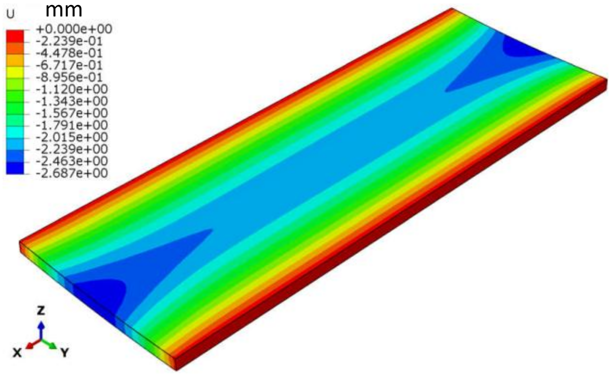


Figure 8.10. Deflection of the structure which provides the minimal cost

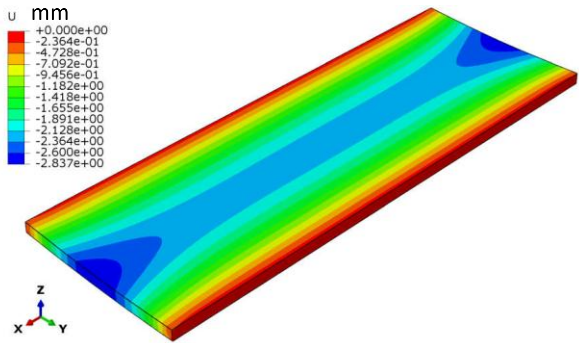


Figure 8.11. Deflection of the structure in case of the multi-objective optimization result (knee point)

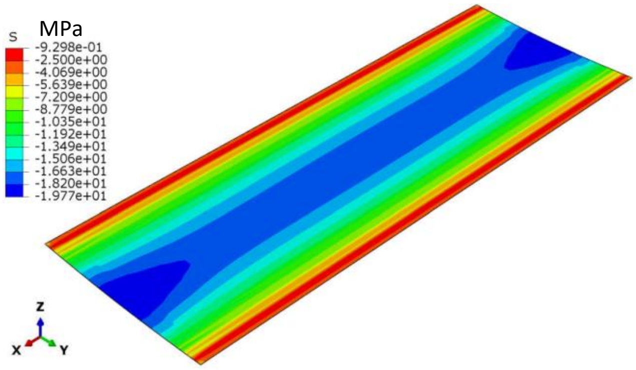


Figure. 8.12. Stress in the face sheet of the structure which provides the minimal weight

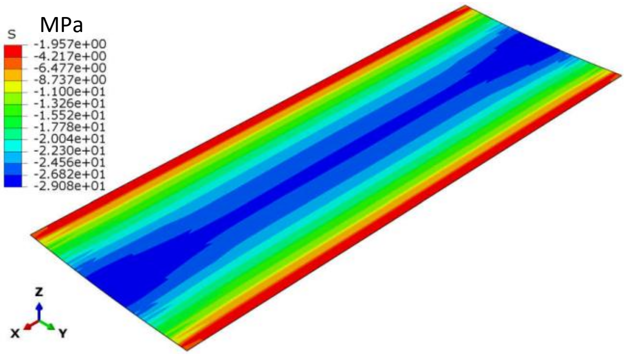


Figure 8.13. Stress in the face sheet of the structure which provides the minimal cost

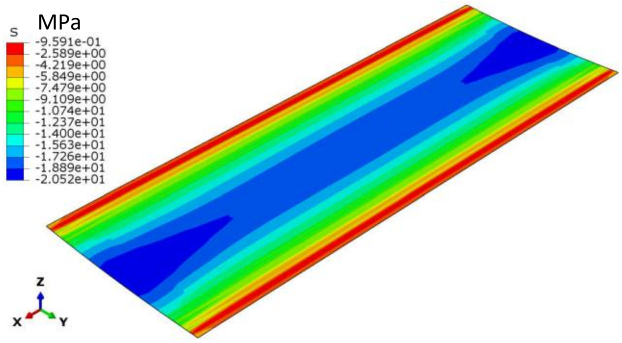


Figure 8.14. Stress in the face sheet of the structure which provides the multi-objective optimization result (knee point)

As shown in Figures 8.9-8.11, the deflection patterns indicated that the structure attained the highest deflection in the middle span of the structure. Despite variations in design, the contour profiles displayed remarkable consistency, with all alternatives maintaining deflection levels below 4.5 mm. This confirms that the structural deflection remained within the specified limits and the designs (i.e. minimum weight, minimal cost, or knee point) complied with the deflection constraint.

Figures 8.12-8.14 revealed that the maximum stress occurs in the face sheets. The all-aluminum face sheet, with four layers, recorded the highest stress at approximately 29 MPa. In contrast, the hybridized face sheet (FML), which incorporates five layers of different materials, exhibited a lower stress of around 20 MPa at the same location. This reduction in stress can be attributed to both the increased number of layers in the hybrid design (FML) and the thicker core. These factors demonstrate that adding layers to the face sheet and increasing core thickness effectively reduce the stress on the face sheets.

8.4.2 Verification of the elaborated optimization procedure by FEM

In order to confirm the reliability and accuracy of the developed optimization approach, a comparative analysis is performed between the obtained optimization results and the corresponding results obtained from the simulations using the FEM models. The summarized results, presented in Table 8.7, show good agreement between the two sets of results, indicating the reliability and accuracy of the optimization process with minor observed differences.

Table 8.7. Comparisons of FE and optimization results

Designs	**Maximal deflection** [mm]			**Maximal stress in the face sheet** [MPa]		
	Optimization result	FEM	Difference [%]	Optimization result	FEM	Difference [%]
Design 1	2.818	2.695	4.36	19.546	19.77	1.15
Design 2	2.741	2.687	1.97	28.50	29.08	2.04
Design 3	2.814	2.83	0.57	19.931	20.54	3.06

Finally, the results of the optimization process showed strong agreement with the finite element analysis, indicating the effectiveness of the proposed approach. The optimized structural design of the sandwich structure with a honeycomb core and laminated face sheets exhibited excellent performance and met the desired objectives. The close correlation between the optimization and FEM results confirms the reliability and accuracy of the optimization method in achieving the desired structural properties. This result highlights the effectiveness of combining ANN with a Genetic Algorithm for the optimal design of sandwich structures and provides a promising avenue for further progress in this research field.

8.5 Conclusions and new added value of the case study

This case study presents an efficient multi-objective optimization method for foot bridge deck structure that focuses on minimizing weight and cost by integrating Artificial Neural Network with a multi-objective optimization algorithm model. The developed model inputs include core density, core thickness, face sheets materials, number of layers at the face sheets and the applied load. To generate the necessary database, the Monte Carlo method was used to determine the combinations of inputs and the corresponding outputs, considering the weight and cost objectives along with the associated design constraints for the elaborated models.

The developed model exhibits high goodness of fit, with R^2 values of 0.99 for the training and testing phases. The corresponding mean square error values are $1.4{\cdot}10^{-5}$, indicating the ability of the elaborated models to predict the design objectives and design constraints with negligible errors.

The combination of ANN and GA generates a set of Pareto-optimal solutions that represent the optimal trade-off between weight and cost. Artificial Neural Network serves as a reliable predictor of the structural performance of the sandwich structures, while GA enables exploration of the design space and identification of non-dominant solutions. The accuracy of the optimization results is confirmed by comparison with FEM simulation results, showing good agreement between the two methods. The results of this study provide valuable insight into the design requirements for improving the stiffness of sandwich structures while minimizing weight and cost.

The added values of this study can be summarized as below:

- A new optimization approach was developed, the ANN and GA integration provided a novel methodology for optimizing the cost and weight of composite sandwich structures. This integration was characterized by reducing computational time compared with analytical and FEM modeling and exploring a wider design space to obtain cost-effective and lightweight structures.
- Various combinations of materials were utilized, the study discovered the potential use of hybrid materials (FML) (which utilize the advantageous properties of light-weight FRP and Al materials) for obtaining significant weight reduction and attaining structural integrity of the sandwich structure at the same time.
- The investigations were achieved robust validation, the strong agreement between the optimization results and FEM simulations confirmed the reliability of the newly elaborated combined ANN-GA methodology, making it a robust tool for structural optimization.
- The ANN-MOGA model can provide future research directions in the field of sandwich structures. These directions include expanding the range of materials and loading conditions. Furthermore, it involves investigating alternative optimization algorithms and utilizing various machine learning techniques.

9. EXPERIMENTAL MEASUREMENTS FOR VALIDATION OF ANN MODELING

The three-point bending test is a widely used experimental method to evaluate the flexural properties of sandwich structures. In our experimental work, the experimental tests involved four groups of sandwich structure specimens consisting of laminated Woven Carbon Fiber Reinforced Polymer (WCFRP) face sheets and a Nomex honeycomb core. The number of layers in the face sheets was 3, 4, 5 and 6. These alternatives allowed for a comprehensive analysis of how different configurations of the face sheets affect the mechanical behavior of the whole sandwich structure.

The investigations in this chapter involved modeling composite test specimens using the ANN technique to predict structural deflection and face sheet stress. Initially, the formulation of the three-point test was used for considered sandwich structures. Then, the Monte Carlo sampling tool was employed to generate the necessary data for the ANN training.

The same sandwich structures were simulated using FEM to predict the structural deflection and face sheet stresses. In the FEM simulation, the materials, dimensions, boundary conditions and loading parameters were modeled to match the experimental tests. This included defining the properties of the WCFRP face sheets and Nomex honeycomb core, as well as applying the maximum experimental load for the three-point bending test. The FEM model provided detailed insights into the stress distribution in the face sheets and deflection across the sandwich structure, offering a numerical comparison to the ANN results.

The purpose of this experimental work is to validate the ANN modeling technique by comparing its predictions with both experimental measurements and FEM simulations for the tested sandwich structures. By demonstrating that the ANN model can accurately predict the mechanical behavior observed in experiments and FEM, the reliability and applicability of the ANN for designing and optimizing sandwich structures are confirmed. Figure 9.1 provides a detailed flowchart of the methodology, illustrating the integration of experimental data, ANN predictions and FEM simulations. This comprehensive approach ensures robust validation of the computational models.

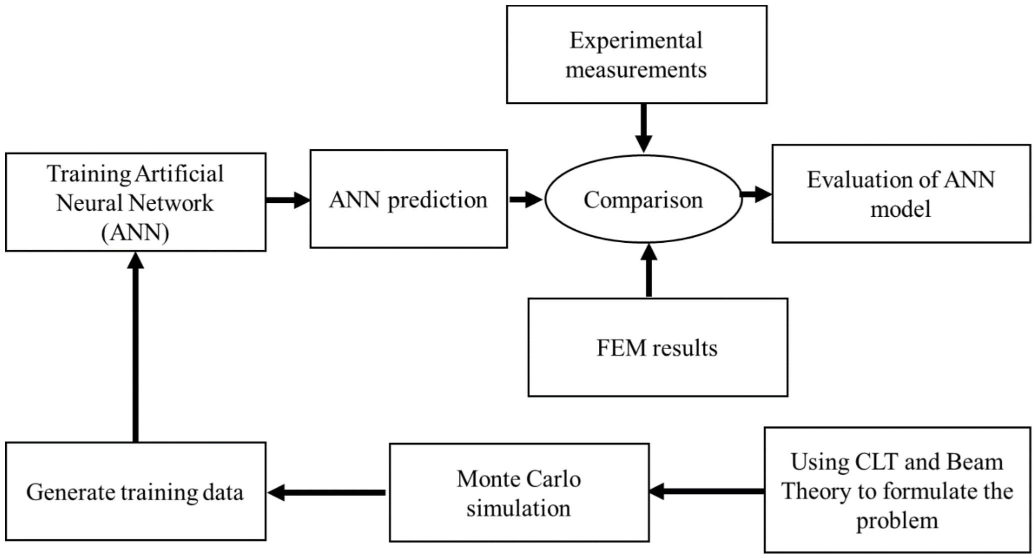


Figure 9.1. Validation methodology flowchart of ANN and FEM modeling by measurements

9.1 Three-point bending of the investigated structure

To generate the required database for training the ANN model, the related equations are formulated and solved for the investigated sandwich structures. The three-point test is commonly conducted to explore the mechanical behavior of the sandwich structure. The investigated sandwich structure is considered from Al or Nomex cores with different combinations of Al, WCFRP and WGFRP layers for the face sheets. A wide range of core and face sheet materials will provide insight to investigate the structure's behavior and offer diverse design alternatives. The loading and boundary conditions for the considered structure are illustrated in Figure 9.2, where a span length (l) between the supporting rollers is 200 mm, with a fixed width of the test specimen (b) at 50 mm.

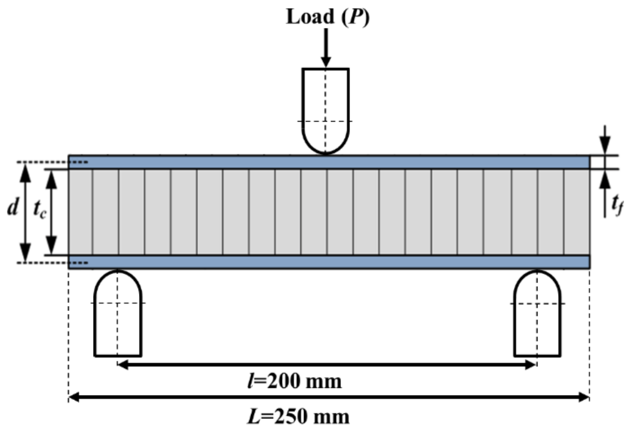


Figure 9.2. Loading configuration of the investigated sandwich structure

To explore Artificial Neural Network capability in modeling of the sandwich structure, it is necessary to generate a diverse dataset that covers various configurations of the investigated sandwich structure. The structural responses in terms of the maximum deflection of the total sandwich structure and maximum stress in the face sheets are considered. Hence, the related mathematical expressions are provided by the following equations [111], [115].

9.1.1 Total deflection of the investigated sandwich structure

One of the most critical design constraints of composite sandwich structures is the maximum deflection. Generally, the deflection in a sandwich structure is induced in two forms: bending and shear components, respectively. It is noteworthy that the flexural deflection is proportional to the tensile and compressive moduli of the face sheet materials, whereas the shear deflection is influenced by the shear modulus of the honeycomb core. Based on beam theory calculations, the mathematical expression of maximum deflection is as follows:

$$\delta = \frac{Pl^3}{48D} + \frac{Pl}{4S} \tag{9.1}$$

where: δ is the total midspan deflection, P is the applied concentrated load; furthermore, D and S are bending stiffness and shear stiffness which can be calculated by equations 3.13 and 3.14.

9.1.2 Maximum face sheets stress

Another commonly used design constraint for composite sandwich structures that needs to be validated is the face sheet stress. Based on beam theory, the following equation can be used to calculate the stress in the face sheet (σ_f):

$$\sigma_f = \frac{M_{max}}{dt_f} \tag{9.2}$$

where: the maximum moment (M_{max}) can be calculated by:

$$M_{max} = \frac{P \cdot l}{4} \tag{9.3}$$

9.2 Artificial Neural Network modeling of the investigated structure

A feedforward neural network approach is employed due to its suitability for achieving broader generalization in the considered problem.

The performance of ANN models is crucially influenced by the availability of sufficient data for training, validation and testing. In our research, Monte Carlo simulation under isight software is integrated with an Excel spreadsheet to generate the required data by solving the governing equations of the designed sandwich structure. To create a general ANN model, the design variables utilized in this study are illustrated in Table 9.1.

Table 9.1. Design variables of the investigated sandwich structure

Design Variables	**Value**	**Remark**
Number of layers in face sheets	N_l : 3, 4, 5 or 6 [layers]	discrete variable, integer values
Combination of face sheet materials	WCFRP layer: identified by **No. 1** WGFRP layer: identified by **No. 2** Aluminum layer: identified by **No. 3**	discrete variable, integer values
Core density	ρ_c [kg/m^3]	Al and Nomex cores in Table 3.2
Applied load	$100 \leq P \leq 2000$ [N]	continuous value
Core thickness	$5 \leq t_c \leq 18$ [mm]	continuous value

The obtained data relating to design parameters, constraints and objectives are normalized to the range [0.1, 0.9] to achieve fair data representation and training convergence. The properly normalized data provides effective ANN models and improves their overall performance. Equation 6.3 is utilized to obtain the normalized data.

The scope of this analysis is focused on the applied loading conditions lower than the failure limits. Therefore, the adopted analytical models are based on the sandwich structure behavior within elastic deflection limits. Consequently, only combinations of loads that introduce maximum deflection in the structure below the failure threshold are taken into account.

Given this, the extracted sampling data from the Monte Carlo simulation consisted of 6000 sandwich structure design points with associated structure responses in terms of structural deflection and maximum face sheet stress. In general, the architecture of backpropagation feedforward ANN comprises an input layer, one or more hidden layers and an output layer. Each layer is fully interconnected with the next layer. As illustrated in Figure 9.3, the input layers consisted of 10 neurons, which represent the input variable (i.e. core density, core thickness, face sheets materials and applied load), while 3 hidden layers are used with 18 neurons for each, the output layer included 2 neurons for the maximum deflection and maximum face sheets stress.

The Bayesian Regularization (BR) back-propagation algorithm is employed to train the ANN model. Generally, the BR algorithm is not included in the validation set, as it has a built-in validation function to determine optimal parameters during the training process [134]. Accordingly, the data are randomly divided into two subsets, with 60% allocated for training and 40% for testing. Figure 9.3 illustrates the ANN structure of the investigated sandwich structure.

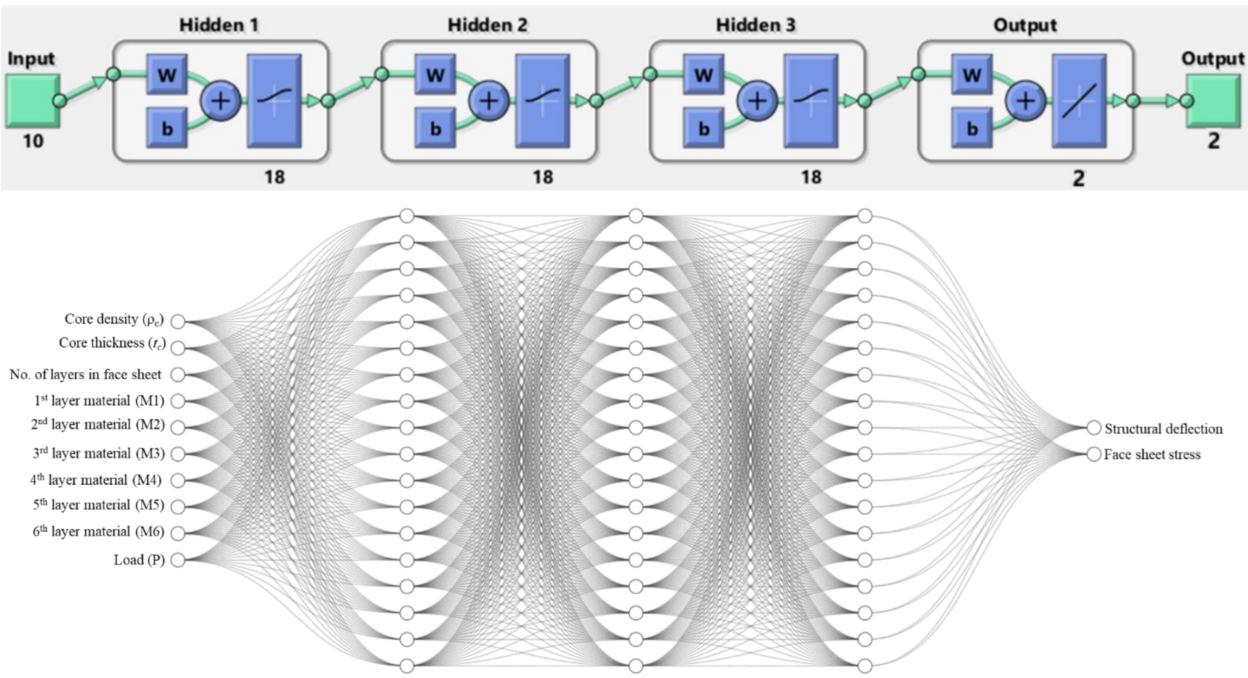


Figure 9.3. Neural network structure for the investigated sandwich structure

The ANN model is evaluated by the *MSE*, which measures the prediction accuracy. Additionally, the R^2 coefficient is utilized to evaluate the fitness accuracy between the predicted values and the actual data. It is worth noting that the model with a higher R^2 (typically $R^2 > 0.98 \sim 0.99$) indicates strong predictive ability, while a lower *MSE* signifies better accuracy.

9.3 Numerical modeling of the investigated sandwich structure

Due to the difficulty of modeling all the design alternatives by FEM, some of the investigated structures are simulated numerically to compare the FEM with the ANN prediction related to the flexural behavior of the composite sandwich structure. Abaqus Cae software is used to model the three-point bending configuration.

To simulate the experimental test, four structural configurations were modeled numerically, which included the structures consisting of 3, 4, 5 and 6 layers of WCFRP laminae in the face sheets. For all structures, a Nomex honeycomb core with a density of 48 kg/m³ and thickness of 8 mm was specified in the FEM simulation. These models represented the test specimens used in our validation. The dimensional parameters were 250 mm x 50 mm in length and width, respectively. The face sheets were modeled as continuum shell elements (S4R) and from the composite module, the number of layers in the face sheets' laminate was specified. Meanwhile, to improve the computational efficiency of the FEM model, the honeycomb core is represented as a homogeneous solid layer with consistent mechanical properties, which serves as a detailed representation of the actual honeycomb structure.

The supports of the investigated structure are modeled to be simply supports and a Reference Point (RP) is created for applying the load at the upper face sheet. The tie interaction is specified for the mating surfaces (i.e. face sheets and core), while the kinematic coupling constraint is defined between the reference point and the loading region in the upper face sheet. This constraint makes the motion of the reference point coupled to the motion of the corresponding regions on the structure, which in turn allows the applied load to be effectively transferred from the reference points to the modeled structure. The interaction, loading and boundary conditions are illustrated on the right side of Figure 9.4. To solve the numerical model, the meshing process is conducted with 27555 elements for the core, while approximately 8500 shell elements are used to mesh the face sheets, as depicted in the meshed structure in the left side of Figure 9.4. It's worth mentioning that the mid-span deflection is evaluated as a function of the applied load. Therefore, only the stresses within the elastic portion are considered in these analyses.

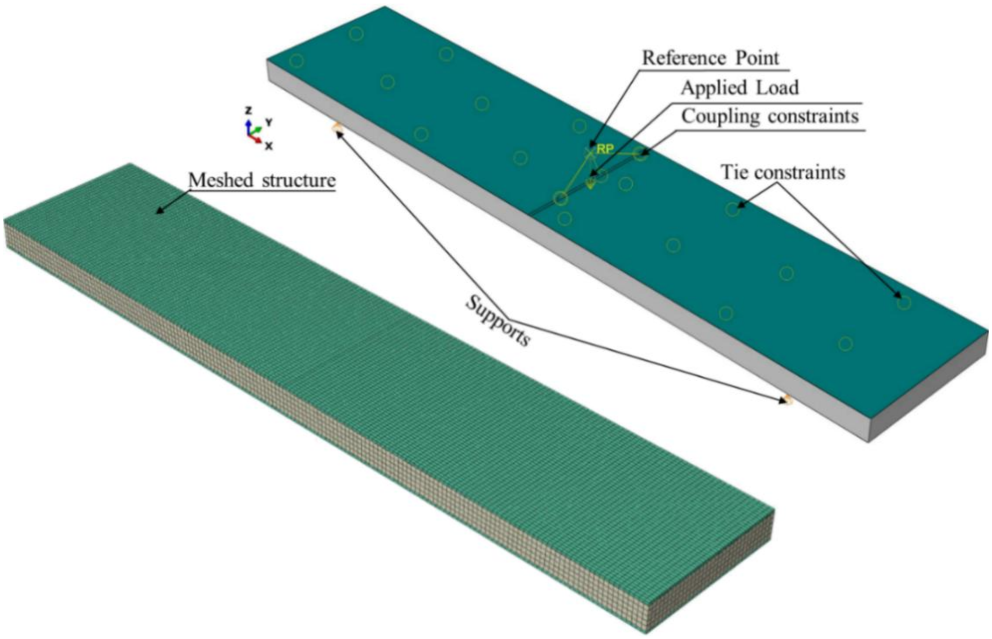
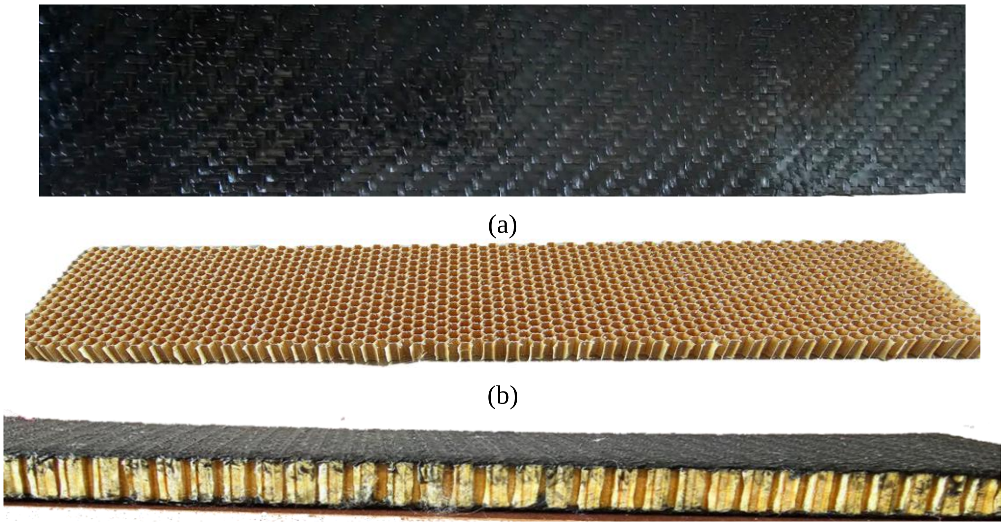


Figure 9.4. FEM modeling of the investigated sandwich structure

9.4 Experimental setup of the investigated sandwich structure

The investigations focused on sandwich structures under out-of-plane loading conditions. This is due to an extensive range of engineering applications such as the components of trains, airplanes and vehicles experience this loading mode. The central structural requirements for these applications are stiffness, weight and cost. Given this, the goal of these investigations was to ensure the necessary validation for the ANN and FEM modeling techniques, which is also offering insights into sandwich structures from an experimental perspective.

As shown in Figure 9.5, the sandwich structure consisting of WCFRP laminated face sheets combined with Nomex honeycomb core was investigated. To provide the required strength in the core-face sheet connection regions, an epoxy adhesive layer between the core and face sheets was applied.



(a)

(b)

(c)

Figure 9.5. The investigated sandwich structure's components (a) face sheet, (b) honeycomb core, (c) assembled final structure

9.4.1 Manufacturing of the investigated test specimens by vacuum bag technique

A vacuum bag technique is a commonly used approach for creating laminated composite structures. Vacuum bag components include releasing film, breather, nylon bag sealant tape and vacuum valve, as illustrated in Figure 9.6. Release film covers both sides of the composite structure to prevent it from being stuck to the breather or the mold. The breather or bleeder texture helps in distributing the vacuum and absorbing the excess resin, which may result during the autoclave process. The last part is a flexible nylon, which is sealed perfectly to prevent leakage and attain the required vacuum.

The sandwich structure components (i.e. laminated prepreg face sheets, core and adhesive) were sliced into the standard dimensions with a length of 250 mm and width of 50 mm according to ASTM C393/C 393M standard [135]. The laminated face sheets are made from laying-up layers of woven carbon fiber prepreg and then attached to the Nomex honeycomb core. Then after, the assembled parts were placed in the vacuum bag.

By applying a vacuum inside the bag through a vacuum pump, a uniform pressure acts over the assembled sandwich structure. This, in turn, helps in removing the excessive trapped gases and improving the stacking quality of both the face sheets layers and the face sheets with the core. After confirming no bag leakages, the assembled sandwich structure was cured in an autoclave.

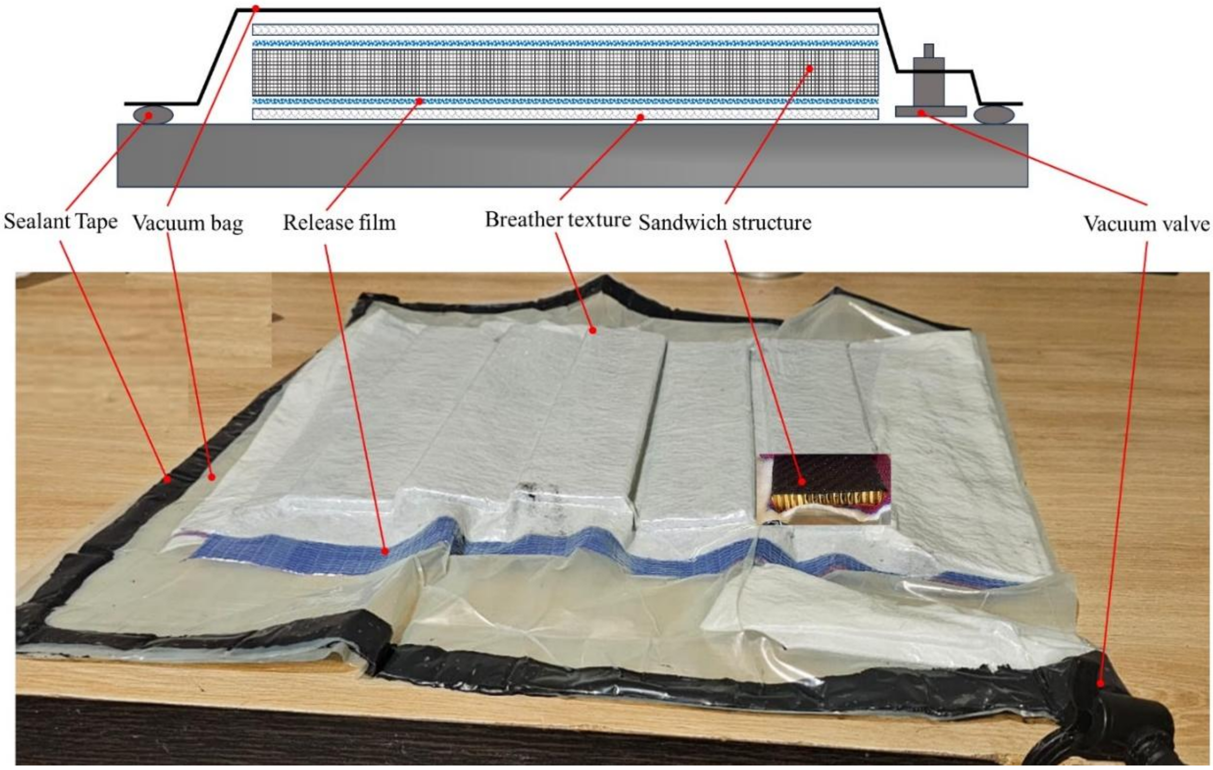


Figure 9.6. Vacuum bag applied during the manufacturing of the test specimens

In the case of the applied prepreg (W245-TW2/2-E323) WCFRP material, the curing time was 150 minutes, with the highest temperature reaching 123 °C according to the manufacturer's protocol. The applied autoclave was equipped with a temperature control system. The required elevating curing temperatures for processing the sandwich structure were commonly conducted via electrical heating. After closing the autoclave door, the curing cycle was initiated. The implemented curing profile for the applied prepreg is illustrated in Figure 9.7. The epoxy viscosity rapidly decreases proportionally as the temperature increases, indicating the initiation of a chemical reaction within the resin.

After approximately 70 minutes of pre-heating, the main curing phase begins, which includes holding the temperature at 123°C for 60 minutes. At this point, the resin viscosity reaches a minimum as the resin transforms into a solid phase. Importantly, the vacuum is applied through all curing stages to provide a uniform pressure on the composite structure to remove any generated volatiles. After completing the main curing step, the autoclave is switched off to enable a gradual cooling.

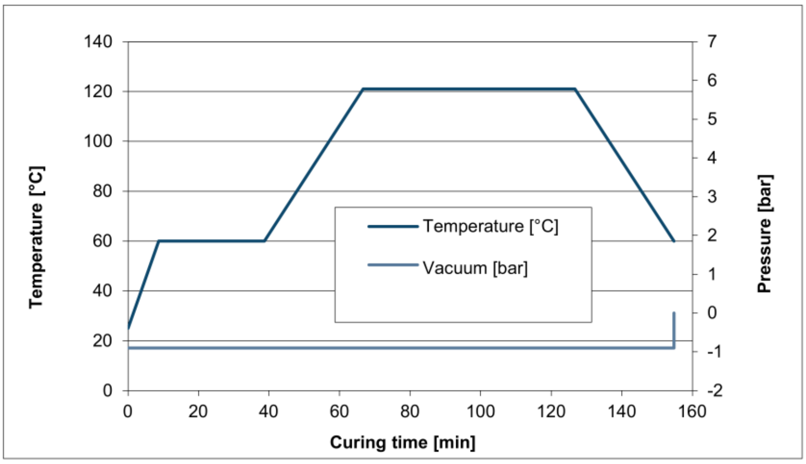


Figure 9.7. Curing cycle for the prepreg of the face sheets (manufacturer's protocol)

9.4.2 Experimental work configuration

The manufactured test specimens, produced by vacuum bag technology as described in 9.4.1, were used in three-point bending tests. The test aimed to investigate the flexural behavior of the designed sandwich structure and compare the results with ANN predictions. This can be assessed by analyzing the established load-displacement curves.

Based on the layers' number in face sheets, four groups of sandwich structure test specimens were manufactured: 1.) 3 layers, 2.) 4 layers, 3.) 5 layers and 4.) 6 layers, respectively. Each group included three test specimens. A Nomex honeycomb core with a density of 48 kg/m³ and 8 mm thickness was used as the core material for all specimens. Based on the ASTM standard, the specimens' length was specified to be a working span of 200 (*l* on Figure 9.2) mm plus 50 mm [135]. While the width of the specimens was fixed at 50 mm.

The three-point bending test was carried out using a universal testing machine, Instron 5566 (Instron, Canton, MA, USA), as shown in Figure 9.8. The test was conducted at a crosshead rate of 3 mm/min. Each sandwich specimen was loaded until reaching the peak load that the manufactured sandwich structure could sustain. During the test, the load data and the derived deflections were recorded by the machine's data acquisition system.

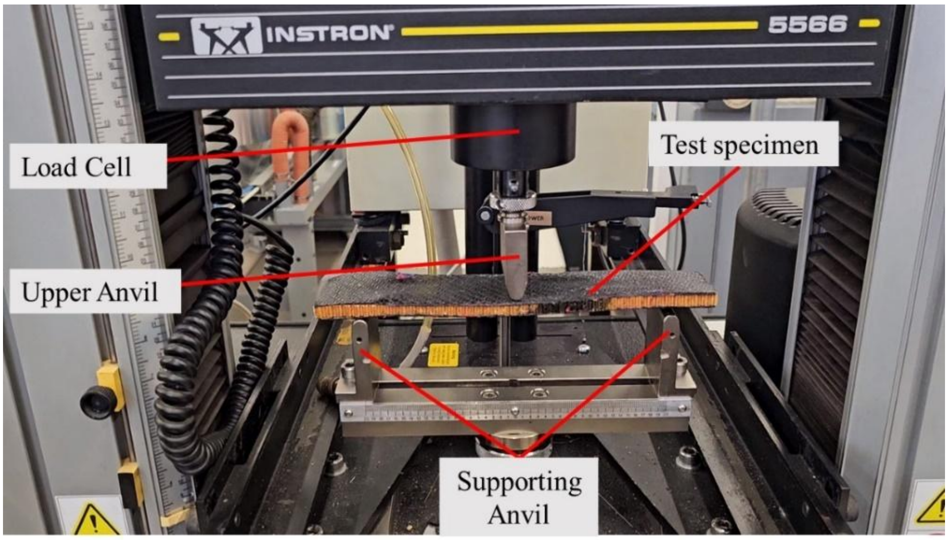


Figure 9.8. The three-point test set-up to obtain force-displacement of sandwich test specimens

Figure 9.9 illustrates the load-displacement curves obtained for the respective test specimens. These curves provide an in-depth understanding of the flexural behavior of the investigated sandwich structures. By analyzing these curves, the effect of varying the number of composite layers in the face sheets on the overall structural performance can be evaluated. Generally, the specimens exhibited similar behavior, with the curves showing a linear increase in load and displacements in the first part. However, the structure rapidly deteriorated after reaching a certain load value due to face sheet and core failures. As can be noticed in Figure 9.9, adding more composite layers to the face sheets would result in a stiffer structure.

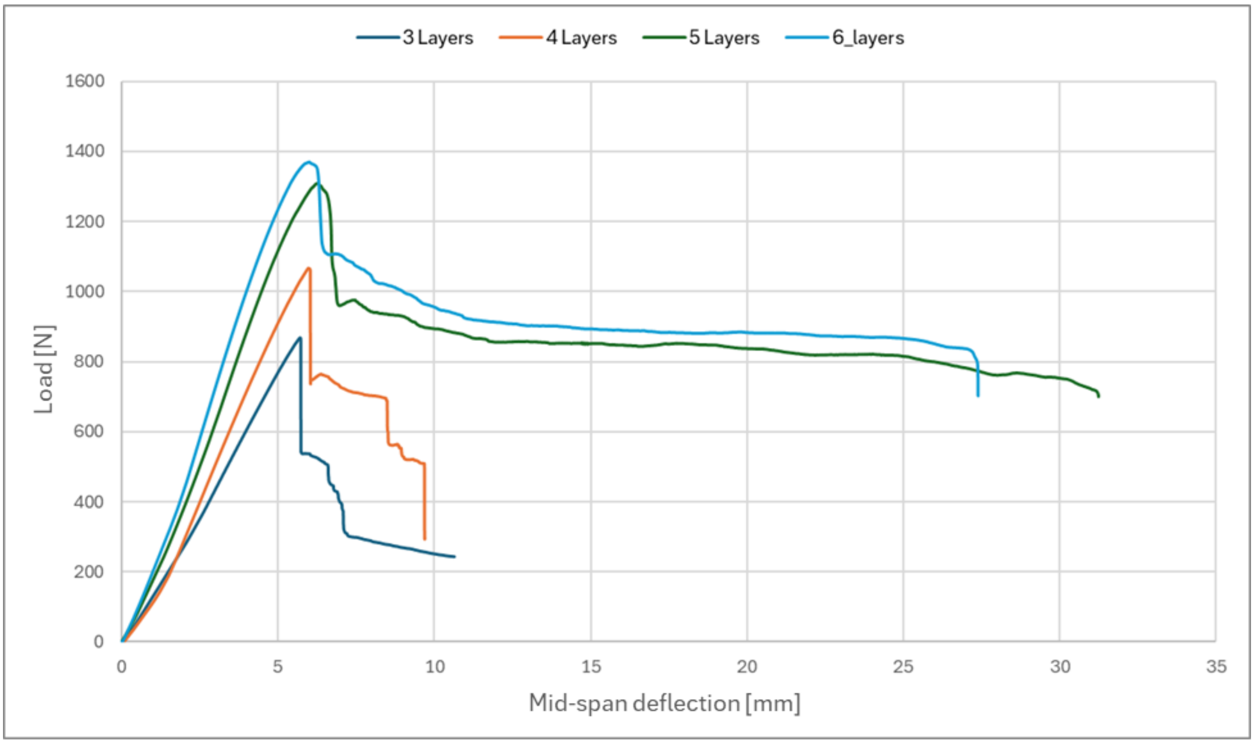


Figure 9.9. Force-displacement curves for the tested sandwich structures

9.5 Results of ANN and FEM analysis on the investigated sandwich structures

This section provides an overview of the results obtained from the ANN and FEM analyses, which were performed on the investigated test specimens of the sandwich structures. We will first discuss the performance metrics and findings of the ANN, followed by the outcomes of the FEM simulations that evaluate structural behavior under various sandwich structure face sheet alternatives.

9.5.1 Artificial Neural Network performance of the investigated sandwich structure

The *MSE* evaluated the performance of the ANN model. Additionally, R^2 was also utilized to evaluate the fitness between the predicted values and the actual data. Initially, both training and testing errors began with high values, indicating a big difference between the ANN prediction and actual values. With further training iterations (Epochs), the *MSE* showed a rapid decrease in its values. This, in turn, indicated that the ANN was learning effectively to provide a better fit with the training data. The final ANN model exhibited a very low *MSE* value of about 1×10^{-7} after 1000 epochs, as can be seen in Figure 9.10.

The linear relationship of the determination coefficient (R^2) indicates strong predictive ability and signifies better accuracy. Figures 9.11-9.12 depicted the training and test sets correlation between the predicted values by ANN and the targeted values that were used to create the ANN model. Based on the performance results, it can be concluded that the trained ANN acquired the ability to model the considered sandwich structure.

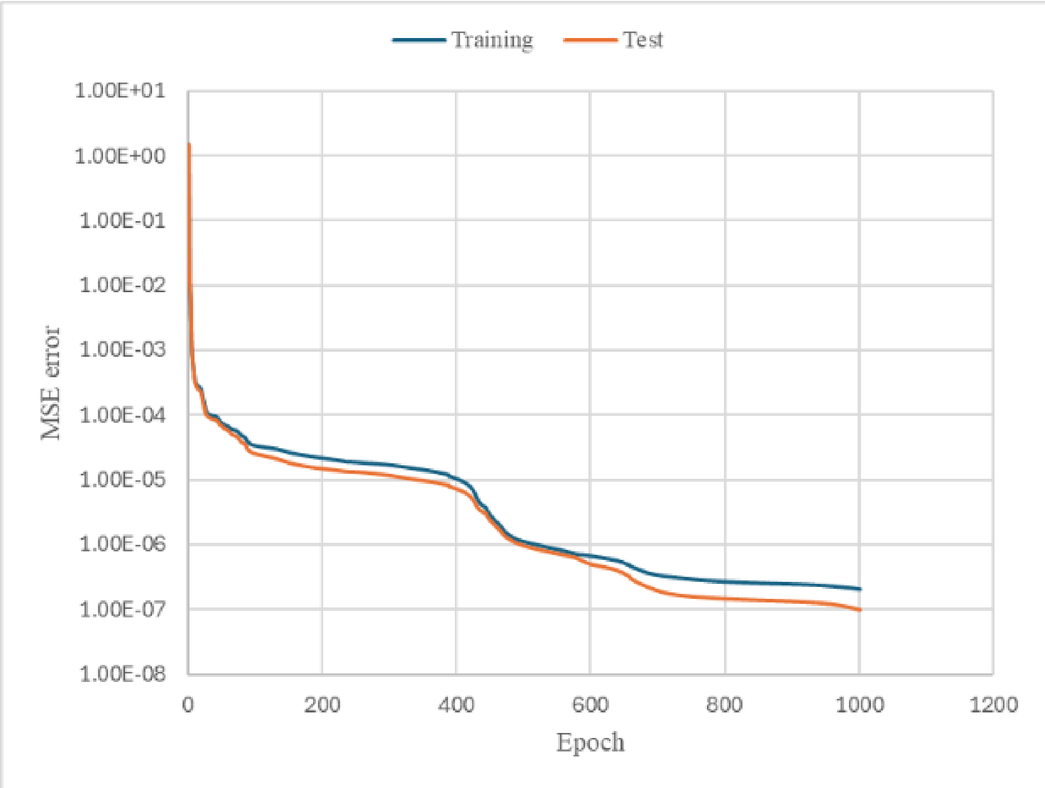


Figure 9.10. Mean Square Error (MSE) for the ANN in case of investigated structures

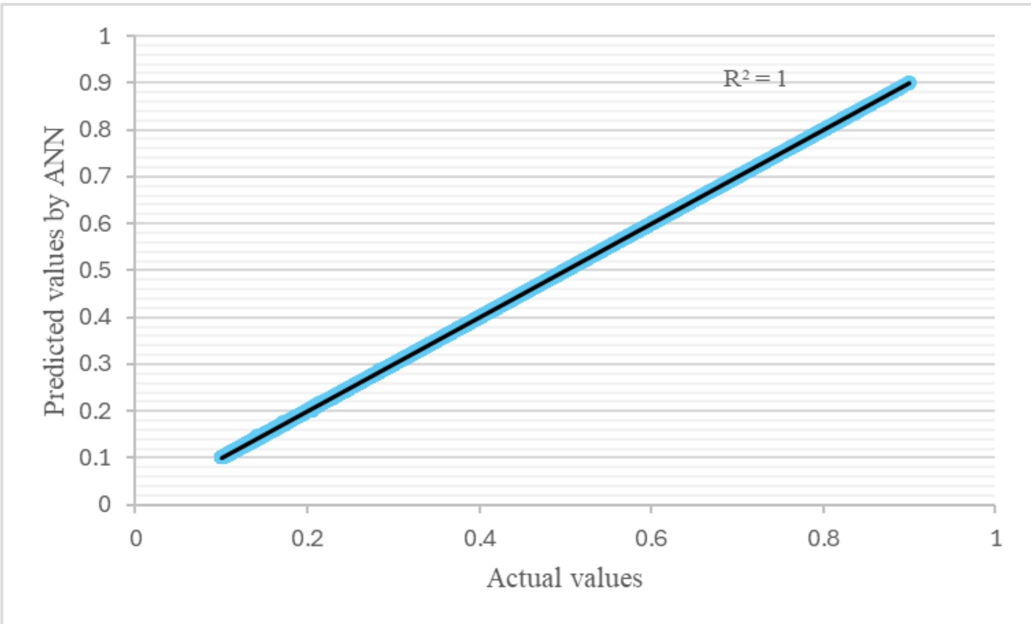


Figure 9.11. ANN prediction vs. actual values (training) in case of investigated structures

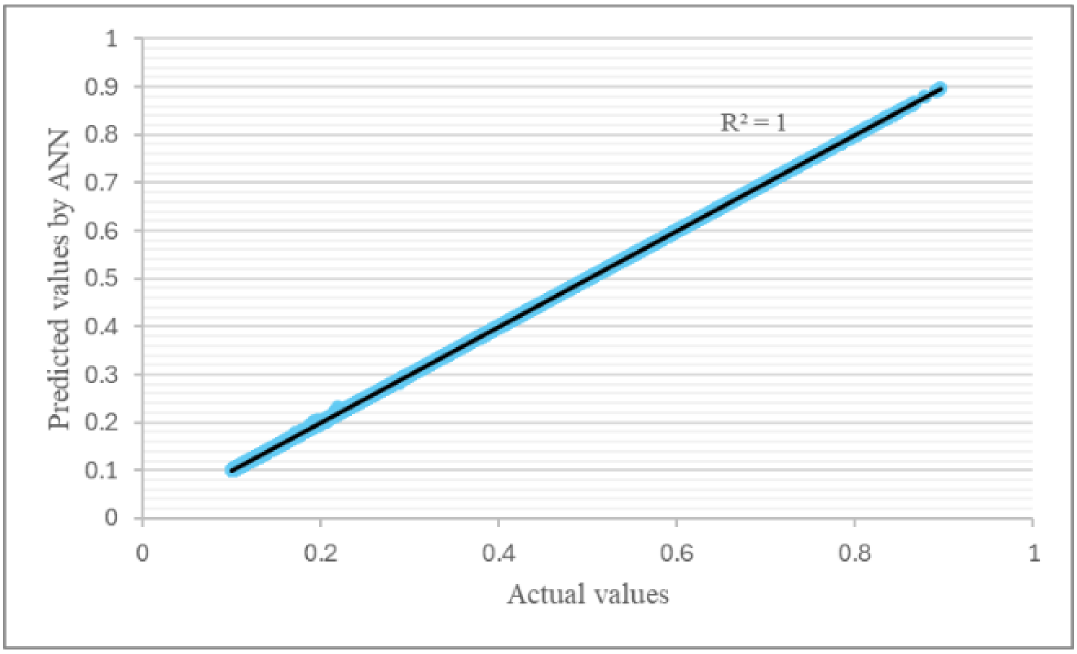


Figure 9.12. ANN prediction vs. actual values (test) in case of investigated structures

9.5.2 FEM modeling of the investigated sandwich structure with WCFRP face sheets

The FEM simulations primarily aimed to evaluate two critical aspects: the maximum deflection of the structure and the maximum stress in the face sheets. Given this, the same experimental test specimens (see in Figure 9.5) were modeled numerically in terms of dimensions, materials, boundary and loading conditions. It is worth noting that the experimental data used in FEM modeling were in the elastic stage of the structural behavior and before the structural failure threshold.

The contour patterns in Figures 9.13-9.20. depicted the deflection at the test specimens' structure and the stress distribution on the upper face sheets.

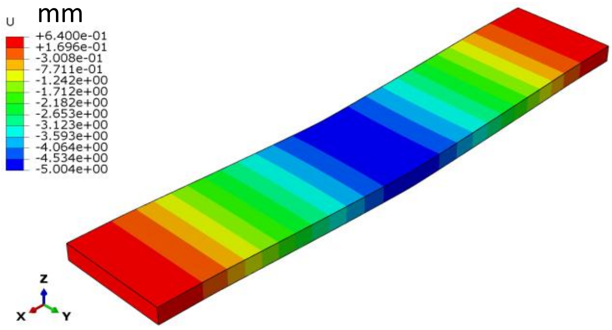


Figure 9.13. Deflection of the structure in case of 3 layers in the face sheets

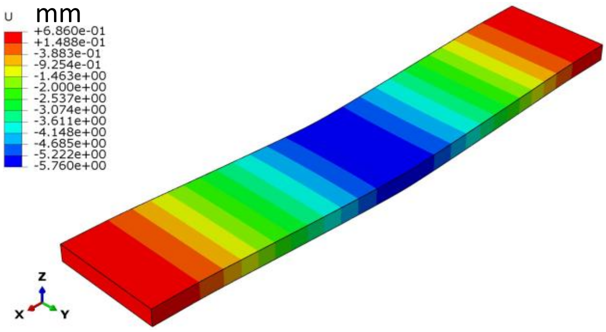


Figure 9.14. Deflection of the structure in case of 4 layers in the face sheets

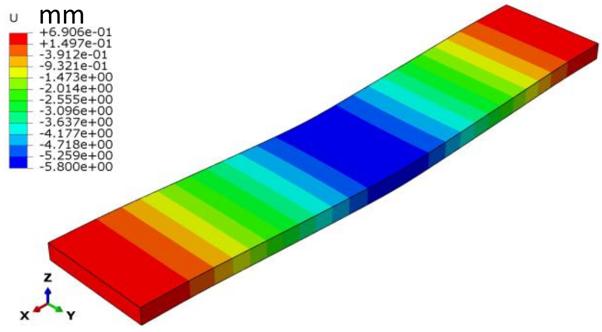


Figure 9.15. Deflection of the structure in case of 5 layers in the face sheets

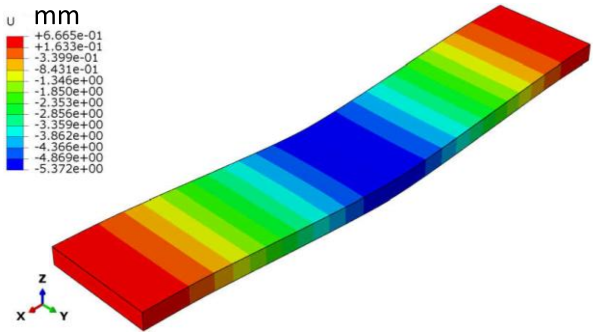


Figure 9.16. Deflection of the structure in case of 6 layers in the face sheets

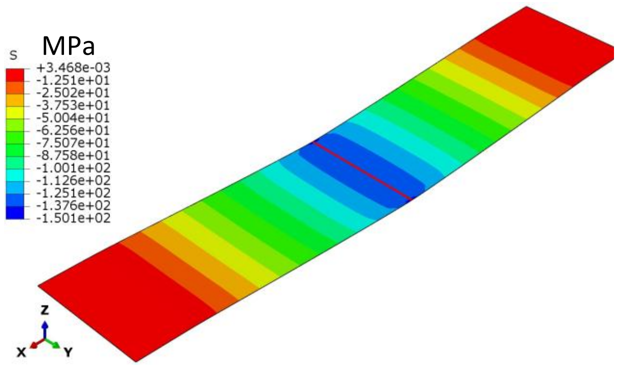


Figure 9.17. Stress in the face sheet in case of 3 layers

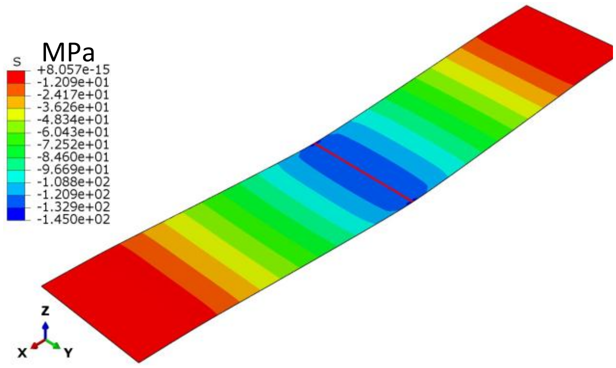


Figure 9.18. Stress in the face sheet in case of 4 layers

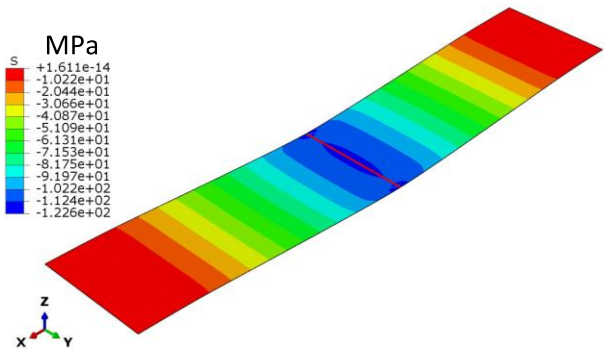


Figure 9.19. Stress in the face sheet in case of 5 layers

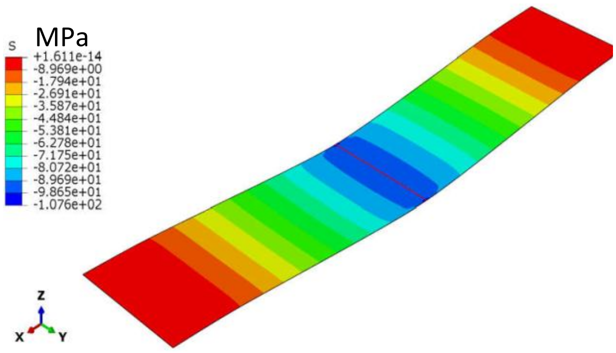


Figure 9.20. Stress in the face sheet in case of 6 layers

Figures 9.13-9.16 illustrate the deflection contour pattern across the investigated structures. The results showed a similar pattern, where the sandwich structures with 3, 4, 5 and 6 layers in the face sheets provided comparable deflections. However, it is important to mention that the maximum applied loads were directly proportional to the number of layers in the face sheets. For instance, as the number of layers increased from 3 to 6, the maximum applied load increased from 842.7 N to 1370.1 N. It can be concluded that the face sheet layup is a key factor in the design of sandwich structures.

Figures 9.17-9.20 depict the stress distribution on the face sheets of the sandwich structures. The results showed a clear correlation between the maximum stress and the number of layers utilized at the face sheets. As the number of WCFRP layers increased, the face sheets became thicker, which resulted in a noticeable reduction in the maximum stress. This stress reduction was due to the enhanced load-carrying ability of the sandwich structure with the additional layers in the face sheets, which distribute the stresses more uniformly across the face sheets. Consequently, thicker face sheets with more layers not only improve the stiffness of the structure but also significantly lower the stress concentrations, thereby minimizing the risk of structural failure under applied load.

9.6 Validation of the elaborated ANN model with experimental measurements and FEM

In this section, a comprehensive validation of the ANN model, FEM and experimental measurements are presented. Regarding the ANN model comparison with the experimental measurements, the experimental load data were fed into the ANN model along with the structure configurations (i.e. 3, 4, 5 and 6 layers in the face sheets) to predict the deflection-load curve. The ANN predictions were compared with the corresponding experimental measurements and FEM results as illustrated in Figures 9.21-9.24. It is worth noting that the experimental data used in ANN predictions were in the elastic stage of the structural behavior and before the structural failure threshold.

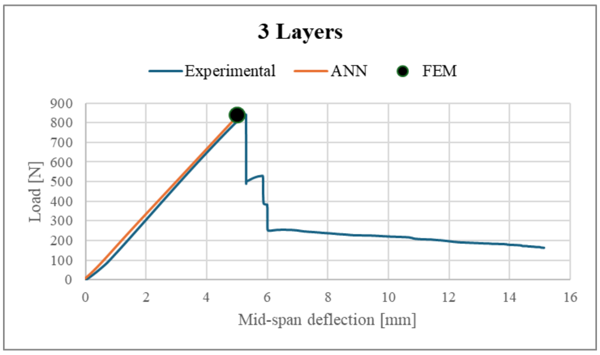


Figure 9.21. Load-deflection curves of the test specimens in case of the structure including 3 layers in the face sheet

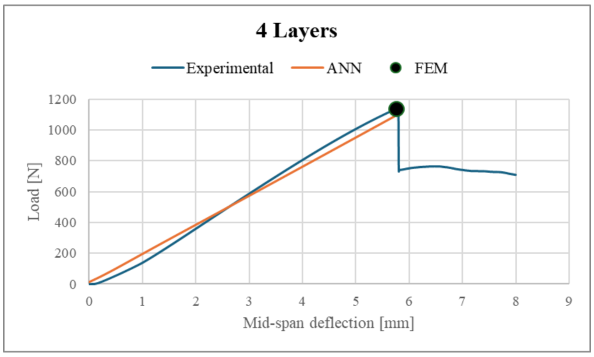


Figure 9.22. Load-deflection curves of the test specimens in case of the structure including 4 layers in the face sheet

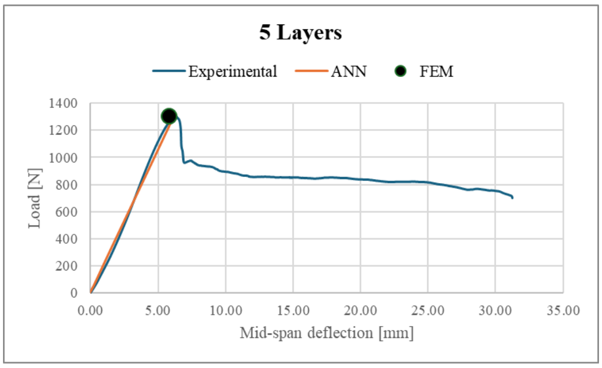


Figure 9.23. Load-deflection curves of the test specimens in case of the structure including 5 layers in the face sheet

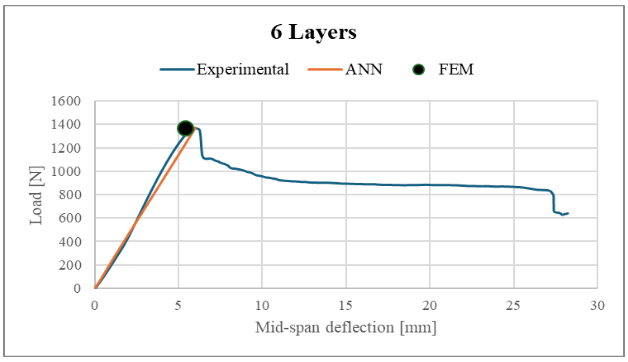


Figure 9.24. Load-deflection curves of the test specimens in case of the structure including 6 layers in the face sheet

The ANN model developed for the investigated structure showed strong agreement with the actual experimental measurements and FEM results. The comparison showed that the ANN predictions accurately captured sandwich structure behavior in the considered loading domain. The close agreement across these key validation metrics provides confidence in the ANN model's ability to predict reliably within the scope of the experimental results.

The ANN predictions and FEM results were compared with the experimental measurements in terms of maximum deflections of the structures and maximum face sheet stresses to assess the agreement among the results for the utilized methods. Table 9.2 summarizes the comparison of the obtained results from the ANN, FEM and experimental measurements.

Table 9.2. Comparison of ANN and FEM results with the experimental measurements

No. of layers in the face sheets	**Maximum deflection**					**Face sheet stress**		
	Experi-mental [mm]	**FEM** [mm]	**Error (FEM vs. Exp. test)** [%]	**ANN** [mm]	**Error (ANN vs. Exp. test)** [%]	**FEM** [MPa]	**ANN** [MPa]	**Error (ANN vs. FEM)** [%]
3	5.28	5.00	5.30	5.064	4.16	150.1	140.7	6.21
4	5.78	5.76	0.35	5.983	3.51	145.0	138.7	4.3
5	6.29	5.80	7.88	6.199	1.54	122.6	124.1	1.26
6	6.00	5.37	10.47	6.006	0.11	107.6	106.0	1.42

The comparison highlighted the accuracy of the ANN model in predicting both maximum deflections and face sheet stresses. For instance, the deflection values from the ANN model are consistently close to the experimental measurements, with errors ranging from 0.11% to 4.16%. This indicates that the ANN model is highly effective in capturing the structural behavior.

Furthermore, the face sheet stress values predicted by the ANN model are also closer to the experimental values, with errors between 1.26% and 6.21%. This trend is consistent across different numbers of layers, underscoring the robustness of the ANN model. Therefore, the ANN model demonstrates reliability, making it a valuable tool for predicting structural behavior in this context.

9.7. Conclusions and new added value of the experimental measurements

The analysis began by solving analytical equations used during the design of investigated structures under three-point bending. The design formulation was organized by the Monte Carlo simulation to obtain the training data set for building the ANN model of the investigated composite sandwich structure. The data generation included different configurations relevant to laminated face sheets, face sheet materials, honeycomb core types and the applied loads. Consequently, the outcomes from the data generation phase were used to train an Artificial Neural Network model. A network model with three hidden layers, a back-propagation algorithm and 18 neurons for each hidden layer showed good prediction performance.

The investigations included the experimental measurements for the sandwich structure under three-point bending. On the other hand, the FEM analysis was also performed for the investigated sandwich structure with totally WCFRP laminated face sheets, The developed ANN demonstrated good agreement with FEM results and experimental measurements.

In summary, the principal added values provided by these investigations can be concluded as follow:

- A comprehensive modeling process was conducted, which involved the use of various techniques and software for data generation, modeling and validation of sandwich structures. Excel, isight, Abaqus Cae and Matlab were utilized, while the Monte Carlo method, ANN and FEM were applied as analysis techniques. Various configurations of laminated face sheets, materials, core types and applied loads were modeled.
- The validation of the ANN model with FEM and experimental measurements was achieved, the integration of ANN modeling with FEM analysis and experimental measurements was performed to ensure reliability by comparing the model with real-world data.
- Theory and practice were bridged, computational models were combined with experimental validation, bridging the gap between theoretical predictions and practical structural behavior and enhancing the applicability of machine learning in engineering.

10. THESIS - NEW SCIENTIFIC RESULTS

T1. A new multi-objective optimization procedure was developed for a lightweight sandwich structure consisting of laminated face sheets and a honeycomb core.

1. Weight and cost objective functions were elaborated for the investigated structures. Five design constraints related to the strength limits of the sandwich structure were taken into consideration. Material type and configuration were the design variables and various optimization algorithms were applied.
2. An integrated framework was developed to solve the structural optimization problem. Excel was utilized for Classical Lamination Theory and Beam Theory calculations, which were integrated with an optimization tool in the isight software environment.
3. The elaborated optimization method was validated through finite element simulation in the case studies, providing confidence in the adopted analysis and optimization procedures.
4. Case studies were conducted to confirm the effectiveness of the elaborated optimization procedure. For single-objective weight optimization of heavy truck bottom panels, weight reductions of 50% and 23% were achieved using different advanced composite materials. During the multi-objective optimization of the high-speed train floors, FML face sheets achieved a 32% weight reduction, while CFRP face sheets achieved a 62% reduction compared to all aluminum face sheets in the investigated sandwich structures.

Published articles relating to T1: [P1] and [P2].

T2. A new model was developed using Artificial Neural Network and the data-driven approach for the investigated sandwich structures.

1. A robust data-driven framework was built by applying related theories such as Classical Lamination Theory and Beam Theory for analyzing sandwich structures. These theories were integrated with the Monte Carlo simulation tool to generate data for the investigated sandwich structures. This data was crucial for developing ANN models to optimize weight and cost for the sandwich structure. Programming scripts were written in Matlab software to perform the generated data that related to the sandwich structure in the ANN model.
2. A new “reverse design” model was elaborated for the investigated sandwich structures using an Artificial Neural Network. A new reverse design aspect related to using the structural response of the sandwich structure (i.e. structural deflection) to predict the design variables (i.e. core and face sheet parameters). The new reverse design results were compared with the traditional analytical results for the same structural designs, which showed good agreement. The comparison highlighted the effectiveness of the utilized technique.
3. The applied Artificial Neural Network model demonstrated accurate prediction related to the flexural behavior of the investigated composite sandwich structure under three-point bending tests.

The ANN model was validated using experimental measurements and FEM simulations. The comparisons between the ANN predictions, experimental data, and FEM results demonstrated strong agreement.

Published articles relating to T2: [P3] and [P4] currently under review.

T3. A new multi-objective optimization procedure (ANN-MOGA) was developed for the investigated lightweight sandwich structure that integrated the Artificial Neural Network technique with Genetic Algorithm.

1. The elaborated ANN model accurately predicted the structural performance and determined the optimal solution to minimize weight and cost objectives for the investigated sandwich structure considering design constraints.
2. The new ANN-MOGA technique integrated isight, Excel and Matlab scripts to link the neural network model with Genetic Algorithm, providing a practical, flexible and time-efficient tool for optimizing the investigated sandwich structures.
3. The effectiveness of the elaborated ANN-MOGA was demonstrated through a case study related to the optimization of a footbridge deck. The optimization procedure for the footbridge deck discovered the utilization of the FML face sheets for obtaining optimum weight and cost while maintaining structural integrity. The application of ANN-MOGA showed a strong agreement between the optimization and the FEM results for the case study under consideration.

Published article relating to T3: [P5].

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LIST OF OWN PUBLICATIONS RELATED TO THE TOPIC OF THE RESEARCH FIELD

P1. Sahib, M.M.; Kovács, G.; Szávai, S. *Optimum design for the bottom panel of a heavy-duty truck by using a composite sandwich structure*. Lecture Notes in Mechanical Engineering, Vehicle and Automotive Engineering 4, 2023, pp. 734–746. doi: 10.1007/978-3-031-15211-5_61. (Q3, Scopus)

P2. Sahib, M.M.; Kovács, G. *Elaboration of a multi-objective optimization method for high-speed train floors using composite sandwich structures*. Applied Sciences, Vol. 13, No. 6, Mar. pp. 1–19, 2023. doi: 10.3390/app13063876. (Q2, IF: 2.5, WoS, Scopus)

P3. Sahib, M.M.; Kovács, G. *Using artificial neural network in the reverse design of a composite sandwich structure*. Structural Engineering and Mechanics: An International Journal, Vol. 85, No. 5, pp. 635–644, 2023. doi: https://doi.org/10.12989/sem.2023.85.5.635; (Q2, IF: 2.2, WoS, Scopus)

P4. Sahib, M.M.; Kovács, G. *Using artificial neural networks to predict the bending behavior of composite sandwich structures.* Polymers, Vol. 17, No. 3, pp. 337, 2025. doi: https://doi.org/10.3390/polym17030337; (Q1, IF: 4.7, WoS, Scopus)

P5. Sahib, M.M.; Kovács, G. *Multi-objective optimization of composite sandwich structures using artificial neural networks and genetic algorithm*. Results in Engineering, Vol. 21, Mar. 2024. doi: 10.1016/j.rineng.2024.101937. (Q1, IF: 6.0, WoS, Scopus)

P6. Sahib, M.M.; Kovács, G.; Szávai, S. *Weight optimization of all-composite sandwich structures for automotive applications*. Lecture Notes in Mechanical Engineering, Vehicle and Automotive Engineering 4, 2023, pp. 720–733. doi: 10.1007/978-3-031-15211-5_60. (Q3, Scopus)

P7. Sahib, M.M.; Szávai, S.; Kovács, G. *Optimization of elastic properties of composite honeycomb core by finite element method*. Academic Journal of Manufacturing Engineering, Vol. 19, No. 4, pp. 1–6, 2021. (Q4, Scopus)

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P9. Sahib, M.M.; Kovács, G.; Szávai, S. *Numerical analysis of composite sandwich structures with circular honeycomb core*. Annals of the University of Petroşani, Vol. 23, pp. 79–86, 2021.

P10. Sahib, M.M.; Szávai, S. *Prediction of unidirectional composite materials by using artificial neural network*. In *XXIV.* Tavaszi Szél Konferencia, Miskolci Egyetem, May 28-30, 2021, pp. 233–238.

P11. Sahib, M.M.; Szávai, S.; Kovács, G. *Analysis of fiber reinforced plastic composite honeycomb structure's mechanical properties using finite element method.* In: Abstract Book for the 17th Miklós Iványi International PhD & DLA Symposium: Architectural, Engineering, and Information Sciences, Pécs, Hungary, Pollack Press, p. 120, 2021.

P12. Sahib, M.M.; Kovács, G.; Szávai, S. *Using Artificial Neural Network in the design of composite sandwich structures*. In: Homolya, M.; Mankovits, 8th International Scientific Conference on Advances in Mechanical Engineering (ISCAME 2022), Debrecen, Hungary, pp. 68–69, 2022.