

UNIVERSITY OF MISKOLC
FACULTY OF MECHANICAL ENGINEERING AND INFORMATICS



**MULTI-OBJECTIVE OPTIMIZATION OF COMPOSITE
SANDWICH STRUCTURES BY USING ARTIFICIAL NEURAL
NETWORK AND GENETIC ALGORITHM**
PH.D. THESES

Prepared by

Mortda Mohammed Sahib Al-Hamzawi

Engineering of Mechanics (BSc)
Applied Mechanical Engineering (MSc)

ISTVÁN SÁLYI DOCTORAL SCHOOL OF MECHANICAL ENGINEERING SCIENCES
TOPIC FIELD OF DESIGN OF MACHINES AND STRUCTURES
TOPIC GROUP OF DESIGN OF MACHINES AND ELEMENTS

Head of Doctoral School

Prof. Dr. Gabriella Bognár
DSc, Full Professor

Head of Topic Group

Prof. Dr. Gabriella Bognár
DSc, Full Professor

Scientific Supervisor

Prof. Dr. György Kovács
Full Professor

Scientific Co-supervisor

Dr. Szabolcs Szávai
Associate Professor

Miskolc
2025

1. INTRODUCTION

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].

1.1. LAMINATED FRP COMPOSITE MATERIALS AND THEIR STRUCTURAL DESIGN

Composite materials consist of two or more distinct materials, usually referred to as matrix and reinforcement phases [2]. 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.

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 [3]. **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 [4]. The general configuration of an FML laminate is illustrated in Figure 1.2.

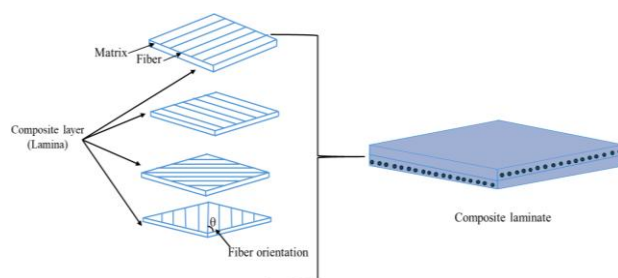


Figure 1.1. Basic concept of composite laminate structure

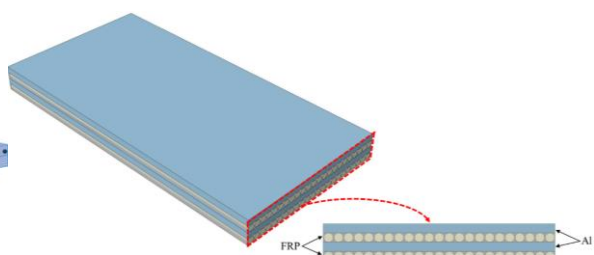


Figure 1.2. FML structure concept

1.2. THE SANDWICH STRUCTURE INCLUDES LAMINATED FACE SHEETS WITH A HONEYCOMB CORE

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) [5]. The purpose of the face sheets is to carry the load, while the lightweight core transfers the load between the

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connected layers. The structure of sandwich composites is shown in Figure 1.3. 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.

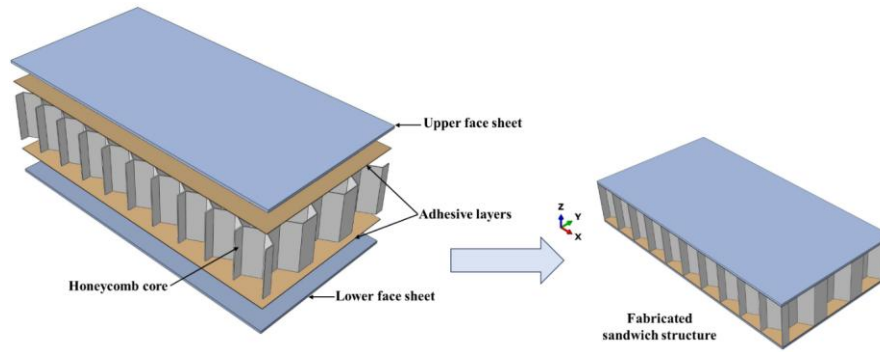


Figure 1.3. Construction schematic of the sandwich panel with honeycomb core

1.3. GOALS OF THE RESEARCH

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

1. to develop an effective approach that can compute the final mechanical properties of stacking composite layers and provide accurate prediction,
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,
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 constraints 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.

2. ELABORATION OF THE OPTIMIZATION PROCEDURE OF THE INVESTIGATED SANDWICH STRUCTURE

This chapter outlines the elaborated methodology for sandwich structure optimization in different scenarios. 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). The mechanical properties of utilized materials in the face sheet and honeycomb core are illustrated in Tables 2.1 and 2.2.

Table 2.1. Mechanical properties of facing materials for sandwich structure [6-8]

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: ν_{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 2.2. Mechanical properties for utilizing honeycomb cores

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

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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
<i>Nomex-Honeycomb</i>						
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 are related to the strength limits of sandwich structure components. The main optimization steps are illustrated in the flowchart in Figure 2.1.

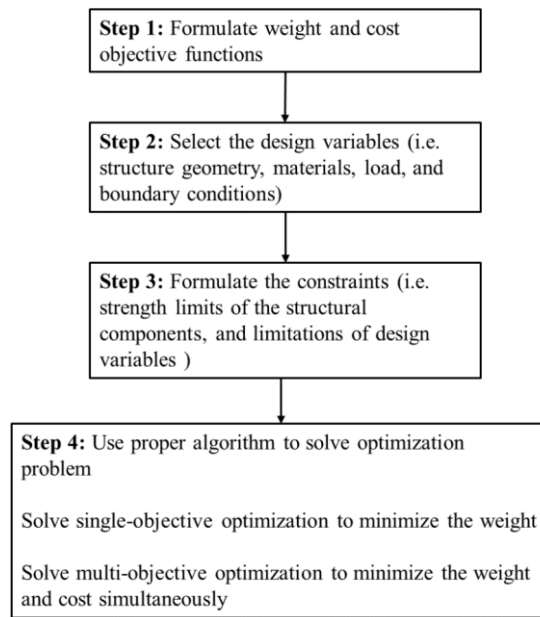


Figure 2.1. The flowchart of the optimization procedure for the sandwich structure

In this research, the optimization process started with a single objective optimization of the sandwich structure for solving the weight minimization problem. 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 the cost of the designed sandwich structure.

The mathematical expressions for the objective functions and constraints of the optimization procedures are illustrated below:

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- Objective functions to be minimized

$$W_t = W_f + W_c = 2l b \sum_{l=1}^n \rho_l N_l t_l + l b \rho_c t_c \quad (2.1)$$

where: W_t is the total weight of the sandwich structure, W_f is the weight of 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, furthermore l is the length, b is the width, n is the total number of constituent layers in the face sheets and t_c is the thickness of the core.

$$C_t = C_{mat} + C_{man} \quad (2.2)$$

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

- Desing constriants to be fulfilled

$$S_{xz} \geq \tau_c = \frac{F}{db} \quad (2.3)$$

where: S_{xz} the ultimate shear strength of the honeycomb core, F is the maximum shear force and d is the distance between the center lines face sheets and which can be caluclated:

$$d = t_f + t_c \quad (2.4)$$

wehere: t_f is the thickness of the face sheet, and t_c is the thickness of the core.

$$\sigma_{fx} \geq \sigma_f = \frac{M_{max}}{dt_f} \quad (2.5)$$

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

$$M_{max} = p \cdot \frac{bl^2}{8} \quad (2.6)$$

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

$$\sigma_{in cr} = \frac{2E_{fx}}{1 - \nu_{xy}^2} \left(\frac{2t_f}{c} \right)^2 \geq \sigma_{fx} \quad (2.7)$$

where: $\sigma_{in,cr}$ is intra-cell buckling of face sheets, E_{fx} is effective modulus of elasticity for the face sheet, ν_{xy} is Poisson's ratio of the face sheet and c is the cell size of the honeycomb core respectively.

$$\sigma_{wr x} = 0,5 \sqrt[3]{E_{fx} E_{zz} G_{xz}} \geq \sigma_{fx} \quad (2.8)$$

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.

$$\delta = \frac{k_b Pl^3}{D} + \frac{k_s Pl}{S} \leq \delta_{max} \quad (2.9)$$

where: δ is the sandwich structure deflection, k_b and k_s 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, D and S are bending and shear stiffnesses of the sandwich structure.

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2.1. 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. The design of the bottom panel (as illustrated in Figure 2.2). The original design consists of an aluminum honeycomb core with a density of 80 kg/m^3 and an aluminum face sheets [9]. The geometrical parameters and applied loads are presented in Table 2.3. 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).

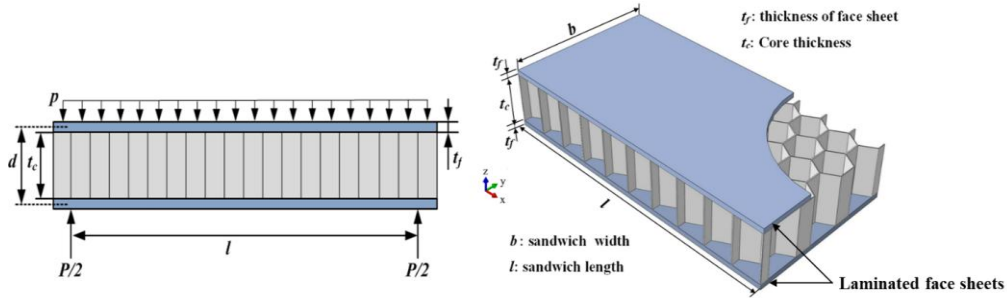


Figure 2.2. Dimensions and boundary conditions of the bottom panel for a heavy duty truck

Table 2.3. Technical data for the investigated bottom panel of a heavy truck

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

Three design variables are considered in this study, which are listed with the associated ranges in the Table 2.4.

Table 2.4. 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	$-90^\circ \leq \theta_{FRP} \leq 90^\circ$	continuous variable, integer values
Thickness of the honeycomb core	$1 \leq t_c \leq 100$ [mm]	continuous variable

The design constraint are included: 1.) core shear strength, 2.) face sheet strength, 3.) face sheet intra-cell, 4.) face sheet wrinkling and 5.) maximum deflection.

2.1.1 SINGLE-OBJECTIVE OPTIMIZATION RESULTS FOR SANDWICH STRUCTURE OF A BOTTOM PANEL IN A HEAVY TRUCK

Figure 2.3 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.

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Figure 2.4 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. A lighter structure of approximately 92 kg can be achieved by carefully balancing core thickness and the number of face sheet layers.

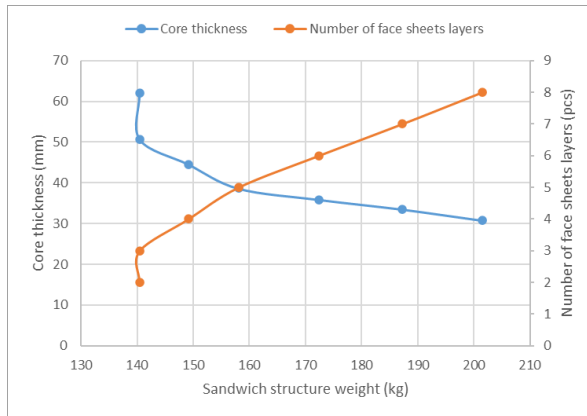


Figure 2.3. Weight of the sandwich structure versus core thickness and face sheets' layer number in case of WGFRP face sheets and Al honeycomb core

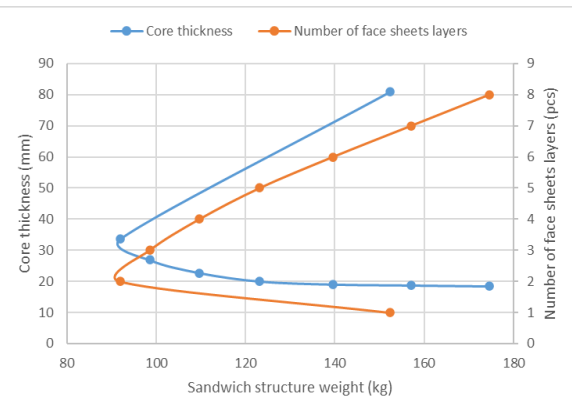


Figure 2.4. Weight of the sandwich structure versus core thickness and face sheets' layer number in case of WCFRP face sheets and Al honeycomb core

As can be seen in Figures 2.3 and 2.4, the optimal values for the number of face sheet layers for both glass WGFRP and carbon WCFRP were two layers.

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.

Figures 2.5 and 2.6 offered a comparative analysis of WCFRP and WGFRP layers used in the face sheets of the investigated sandwich structure. Figure 2.5 illustrated the weights for the sandwich structure designs using eight different configurations, each representing a different number of face sheet layers. Figure 2.6 presented the corresponding thickness for the same configurations.

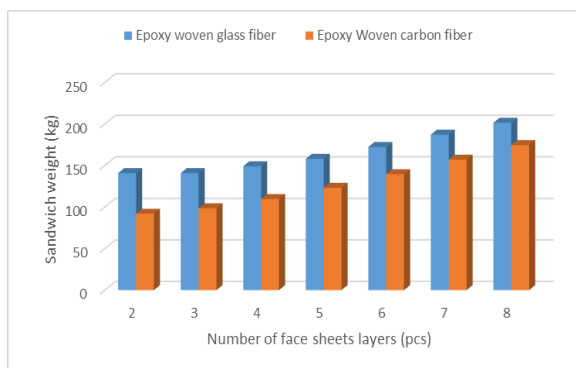


Figure 2.5. Compassion of weight for the structures with WCFRP and WGFRP face sheets and Al honeycomb core

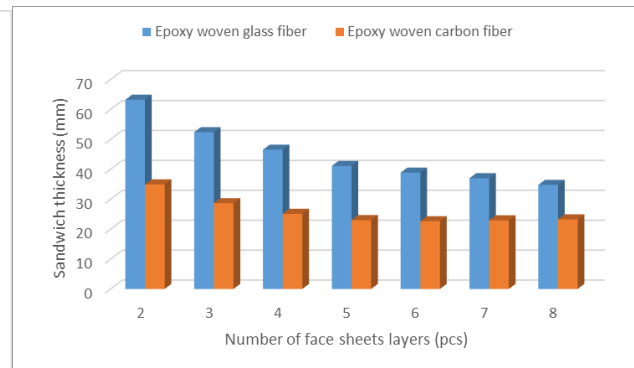


Figure 2.6. Compassion of the total thickness for the structures with WCFRP and WGFRP face sheets and Al honeycomb core

A comparison between the original design of the bottom panel in a heavy truck, which included an aluminum honeycomb core with aluminum face sheets [9] and the optimum designs was performed in Table 2.5.

Table 2.5. 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 [9]	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 optimization highlighted that replacing aluminum face sheets with composite layers significantly reduced the overall weight of the sandwich structure.

2.1.2 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 and two WCFRP layers, which provided the minimal weight. Figure 2.7 shows the deflection contour that resulted from the numerical modeling.

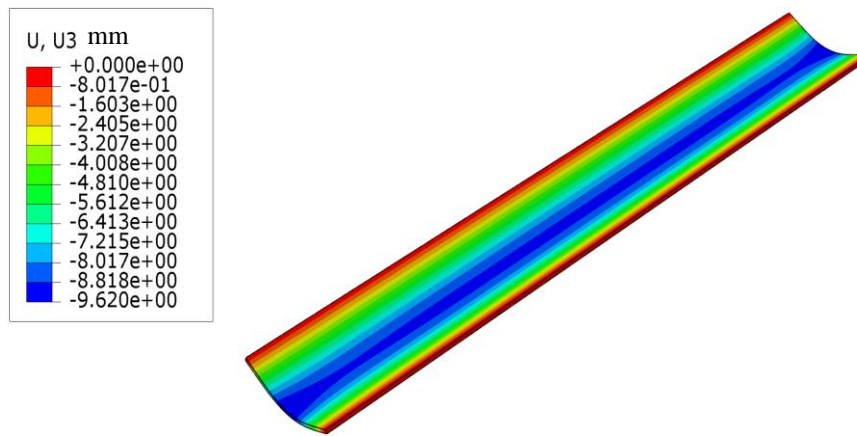


Figure 2.7. The numerical results of the structure consist of laminated WCFRP face sheet with honeycomb core for the bottom panel

The obtained deflection from the numerical solution was compared with the optimization results. The deflection value of the numerical model was 9.62 mm, as shown in Figure 2.7. While, deflection constraint was fixed to be 10mm. 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.

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

Figure 2.8 illustrates the floor structure of a high-speed train. 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

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investigated sub-panel, which is considered a sandwich structure (inner floor) with a lightweight honeycomb core and two face sheets, as shown in Figure 2.9.

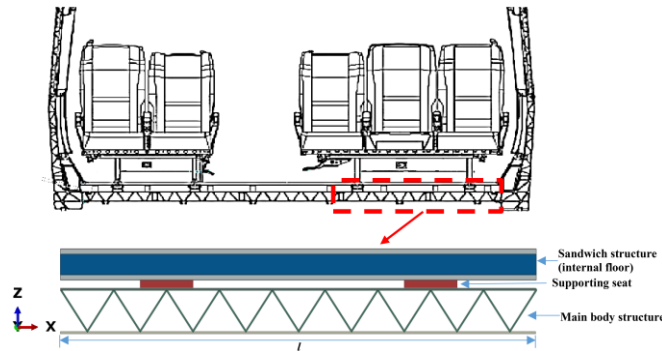


Figure 2.8. Structure of sub-panel of the high-speed train floor

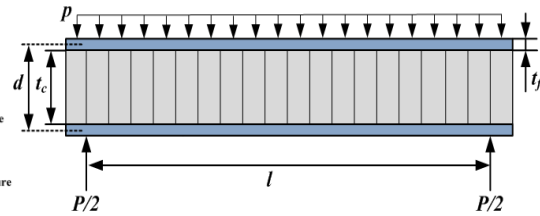


Figure 2.9. Loading and boundary conditions of the investigated sandwich structure

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. The value of the load (p) acting on the floor is estimated to be 4.142 kPa [10].

In this case study, the design variables include face sheets and honeycomb core are defined in the Table 2.6.

Table 2.6. 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	$\theta_{FRP} = 0^\circ, 90^\circ, +45^\circ, -45^\circ$	discrete variable
Core density	ρ_c [kg/m ³]	discrete, as specified in the Table 2.2
Core thickness	$5 \leq t_c \leq 20$ [mm]	continuous value

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.

2.2.1 MULTI-OBJECTIVE OPTIMIZATION RESULTS FOR SANDWICH STRUCTURE OF A HIGH-SPEED TRAIN FLOOR

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. The changes in weight and cost for the optimized alternatives are shown in Figures 2.10-2.11. 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.

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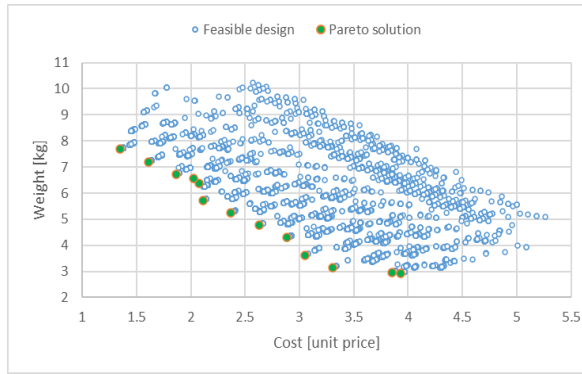


Figure 2.10. Feasible design points for the investigated sandwich structure

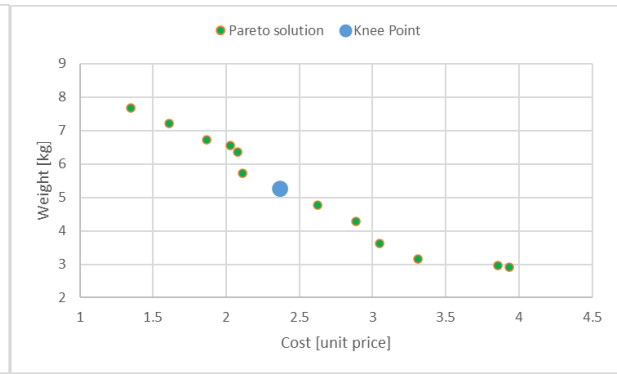


Figure 2.11. Pareto optimal points and the knee point of the investigated sandwich structure

The Pareto curve of the optimized sandwich structures plots the relationship between cost (unit price) and weight (kg). 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.

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 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.

2.2.2 FINITE ELEMENT METHOD RESULTS AND OPTIMIZATION VALIDATION FOR THE INVESTIGATED SANDWICH STRUCTURE

The 3 points of pareto curve were choice to represent numerically 1.) the structure which provides minimal weight, 2.) the structure which provides minimal cost and 3.) the knee point that provides a compromise between cost and weight minimization. The related data have been listed in the Table 2.7 for FEM modeling.

Table 2.7. The design parameters for FEM simulation

Face sheet layup	Face sheet materials and fiber orientations	Number of layers in the laminate [pieces]	Core thickness t_c	Face sheet thickness t_f	Core density ρ_c	Remarks
	CFRP layer: No. 1 GFRP layer: No. 2 Aluminum layer: No. 3		[mm]	[mm]	[kg/m ³]	
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

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Figures 2.12-2.17 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.

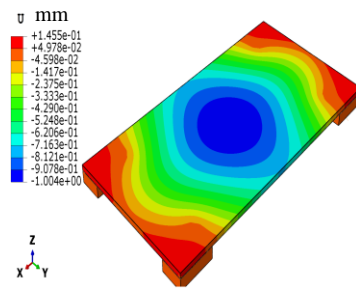


Figure 2.12. Deflection of the structure – minimal weight

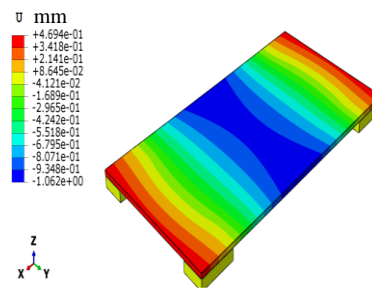


Figure 2.13. Deflection of the structure – minimal cost

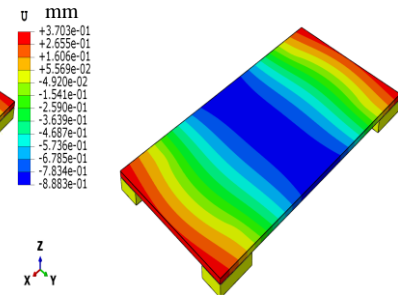


Figure 2.14. Deflection of the structure – knee point design

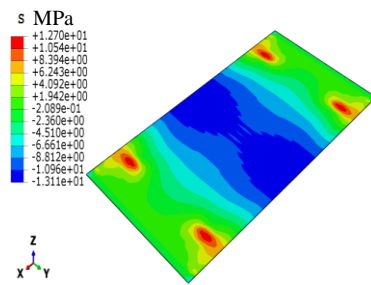


Figure 2.15. Stress in the structure's face sheet – minimal weight

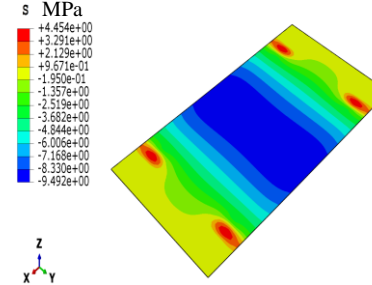


Figure 2.16. Stress in the structure's face sheet – minimal cost

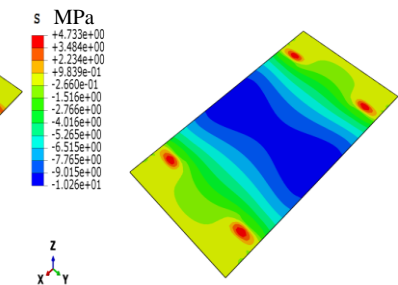


Figure 2.17. Stress in the structure's face sheet – knee point design

To evaluate the optimization procedures accuracy, a comparison of the optimization results and the FEM simulation outcomes was conducted and presented in Table 2.8.

Table 2.8. Comparisons of optimization and FE solutions

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

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

3. USING ARTIFICIAL NEURAL NETWORK FOR MODELING OF SANDWICH STRUCTURES

Artificial Neural Networks (ANN) are 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 [11]. For modeling sandwich structure, the ANN undergoes through several steps.

- Data generation for the Artificial Neural Network model

The core densities (as shown in Table 2.2), 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.

- Normalization of acquired data

In this process, the input data is transformed into a standardized range to prevent certain features from dominating the learning process. In this research, the generated data are normalized to the range [0.1, 0.9] as detailed in [12].

- Creating an Artificial Neural Network model for sandwich structure

In this research, the Back-propagation Feedforward Network (BFFN) technique was chosen as the modeling approach for the sandwich structure design due to its effectiveness in addressing complex problems.

- ANN performance in the modeling sandwich structures

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. The coefficient of determination (R^2) and Mean Square Error (MSE) can be computed as detailed in [13].

3.1. ELABORATION OF A REVERSE DESIGN METHODOLOGY FOR THE SANDWICH STRUCTURES 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.

3.1.1 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. A commercial 3003 aluminum (Al) honeycomb core manufactured by Hexcel in various densities is used as the core of the sandwich panel. Figure 3.1 illustrates the considered structure under a distributed load (p) with simply supported edges.

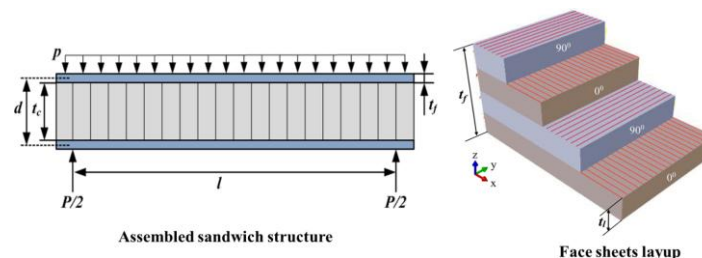


Figure 3.1. Sandwich structure and face sheet configurations

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

The design variables are taken across a wide range of values, as listed in Table 3.1. While, 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.

Table 3.1. 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 obtained data are normalized to the range [0.1, 0.9] by using the related equation. The data is 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.

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 3.2 defines the input and output data used in the creation of the ANN.

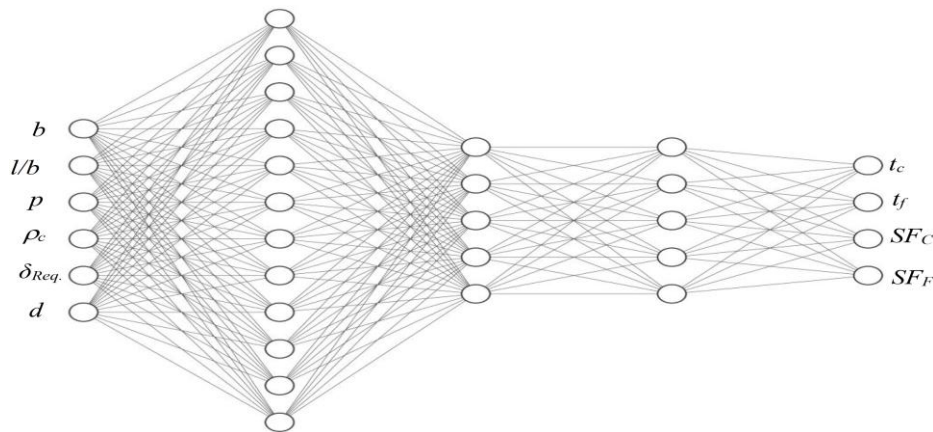


Figure 3.2. Neural network structure for reverse design model

3.1.2 RESULTS OF THE ELABORATED REVERSE ANN MODEL

The ANN prediction was assessed using MSE and R^2 values as depicted in Figures 3.3-3.6.

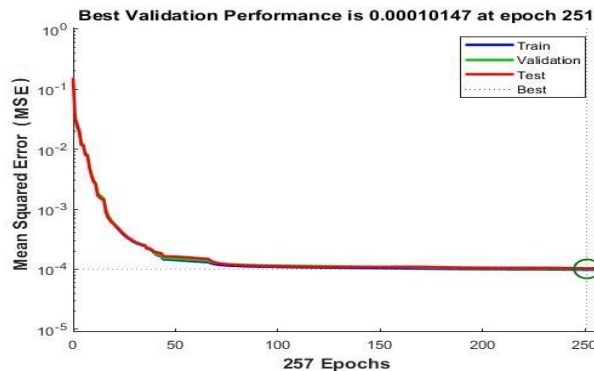


Figure 3.3. Neural network (MSE)

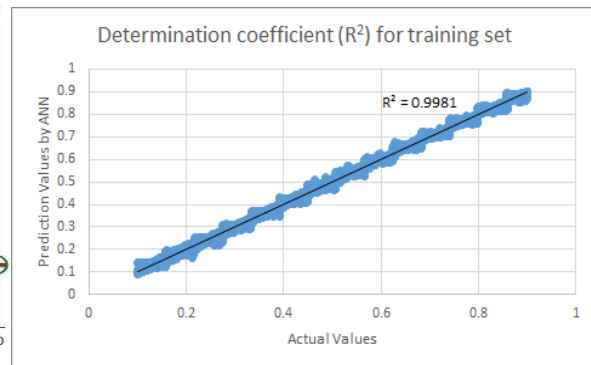


Figure 3.4. Neural network (R^2) – training set

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

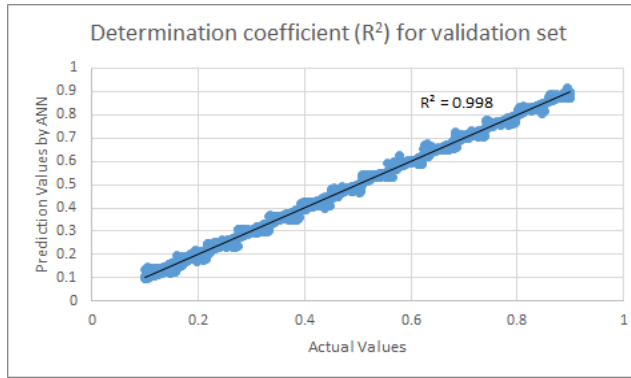


Figure 3.5. Neural network (R^2) – validation set

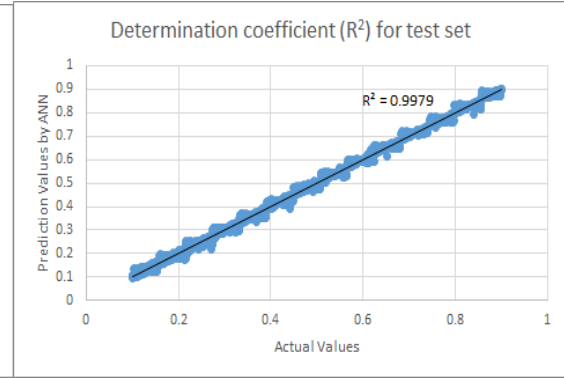


Figure 3.6. Neural network (R^2) – test set

Figures 3.3-3.6 showed the MSE curves and R^2 for the ANN, where the best ANN performance occurred at epoch 251, with a MSE of 10^{-4} , marked by the green circle, while 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.

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

A novel optimization method for weight and cost minimization has been developed an Artificial Neural Network and Genetic Algorithm (ANN-GA) integration technique. In this modeling technique, the 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 was 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 structure under consideration is a footbridge deck. The practical and equivalent analytical models of the investigated structure are illustrated in Figure 3.7 [14].

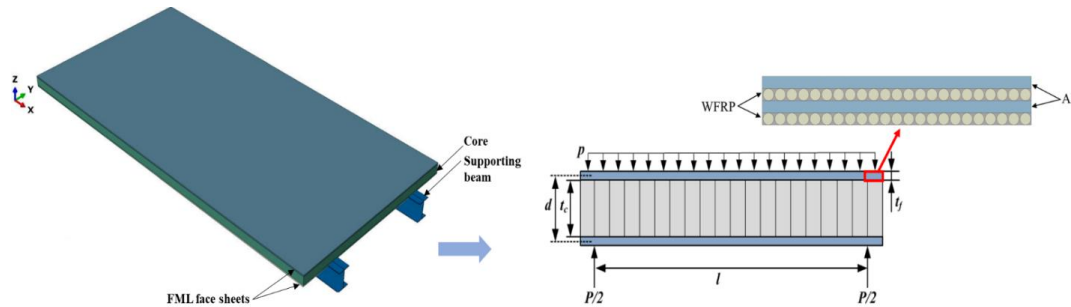


Figure 3.7. Footbridge deck geometry and configuration

The analytical model is considered as a simply supported beam under a distribution load. The investigated sandwich structure has a longitude length (l) of 1800 mm, a transverse length (b) of 5000 and distribution load (p) of 0.006 MPa.

The variations in design parameters are performed to involve a broad spectrum of structural designs. Table 3.2 illustrates the main design parameters used for generating the required data.

Table 3.2: Design parameters used for generating ANN data

Core density ρ_c [kg/m ³]	Distribution load p [MPa]	Core thickness t_c [mm]	Number of layers N_l [pieces]	Possible face sheet materials
Al and Nomex cores in Table 2.2	0.001-0.006	15-200	3-6	Al, WCFRP, WGFPR

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The Monte Carlo simulation under the isight software framework is used to generate the required data. 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.

Figure 3.8 depicts the architecture of the developed ANN for the investigated sandwich structure, along with the corresponding input and output data utilized in the model.

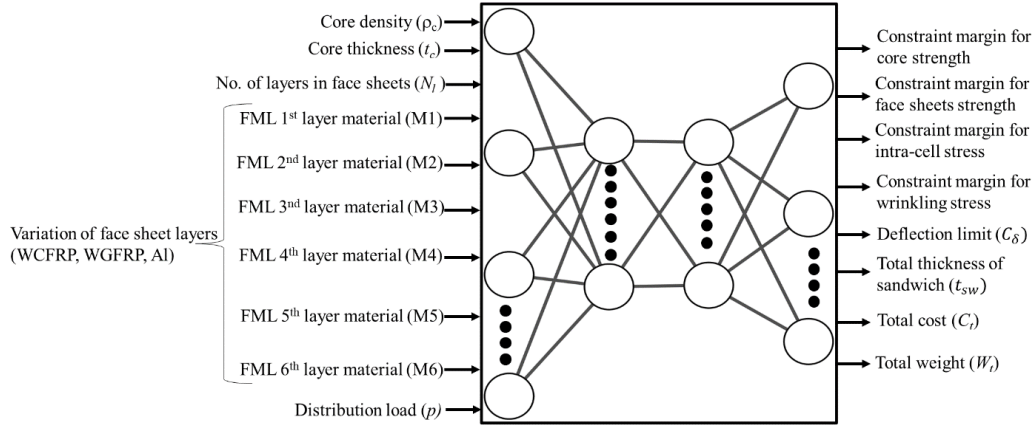


Figure 3.8. Neural network structure model for the investigated sandwich structure

3.2.1 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 3.9. Initially, a model of the sandwich structure was developed based on the Classical Lamination Theory and Beam Theory. This model is used to create a 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.

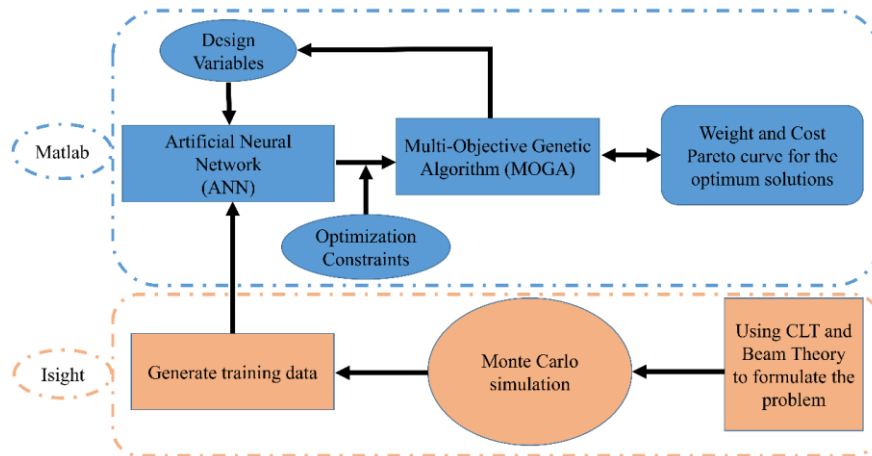


Figure 3.9. Newly developed optimization framework for the proposed structures

The main aim of the optimization phase is to minimize weight and cost simultaneously for the investigated sandwich structure. 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 design variables play a critical role in determining the key properties of an optimal sandwich structure. The design variables for this study are summarized in Table 3.3.

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

Table 3.3. 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 2.2
Core thickness	$30 \leq t_c \leq 200$ [mm]	continuous value

To ensure a successful optimization procedure, it is crucial to determine the sandwich alternatives that meet a specific purpose and those that do not. The constraints can be acquired from the output of the ANN model are: (1) core shear strength, (2) face sheet strength, (3) Face sheet intra-cell, (4) face sheet wrinkling, (5) maximum deflection, (6) overall thickness of the sandwich panel.

3.2.2 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 3.10-3.12 illustrate the *MSE* and *R*² throughout the model training process.

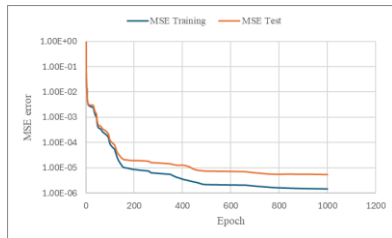


Figure 3.10. Neural network (*MSE*)

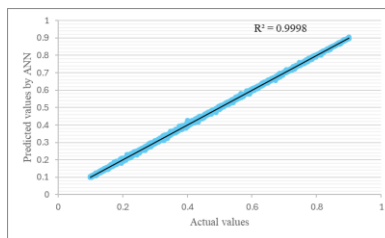


Figure 3.11. Neural network (*R*²) – training set

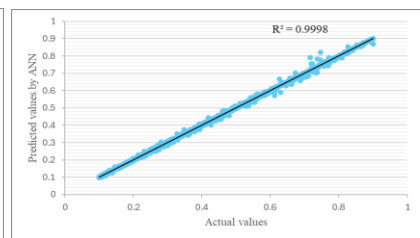


Figure 3.12. Neural network (*R*²) – test set

The lower *MSE* values and the *R*² values approach unity indicated a higher predictive ability of the ANN, highlighted its effectiveness in capturing the relationships between input variables and their corresponding outputs.

3.2.3 OPTIMIZATION RESULTS FOR THE INVESTIGATED FOOTBRIDGE DECK

After creating an accurate ANN model to predict the structural performance of the sandwich footbridge deck, the focus shifted to the optimization procedures using the MOGA combined with ANN. The design variables in Table 3.3 considered to achieve the final objectives.

Figure 3.13 demonstrates optimization results of the Pareto curve. For instance, if weight reduction is prioritized, a combination of lighter materials should be considered. As a result, the total cost would be increased. Considering cost as the primary objective would lead to a weight increase.

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

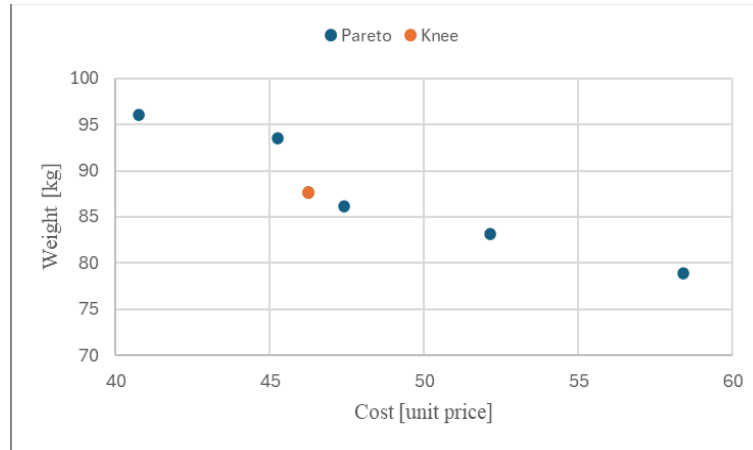


Figure 3.13. Pareto and knee points of the investigated structure's optimal solutions

The selection method to determine the most satisfactory solution, commonly known as the IMDSM method, was used to determine the "knee point". In Figure 3.13, 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. 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. We have separated relevant data for these design points to be utilized for further analysis, as listed in Table 3.4.

Table 3.4. Parameters of single- and multi-objective optimized structures

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

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). The **knee point** was identified as the most satisfactory solution (Design 3). 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 [14]. 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 Design 1, Design 2 and Design 3, respectively. In contrast, the costs were increased by 23.4%, 40% and 76.9% for the same alternatives.

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3.2.4 VERIFICATION OF THE ELABORATED OPTIMIZATION PROCEDURE BY FEM

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 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 Figures 3.14 - 3.19.

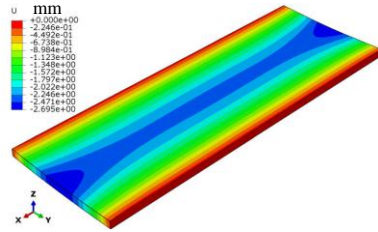


Figure 3.14. Deflection of the structure – minimal weight

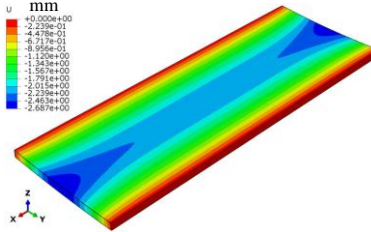


Figure 3.15. Deflection of the structure – minimal cost

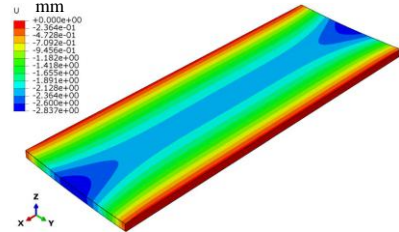


Figure 3.16. Deflection of the structure – knee point

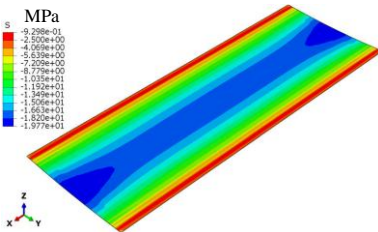


Figure 3.17. Stress in the face sheet of the structure – minimal weight

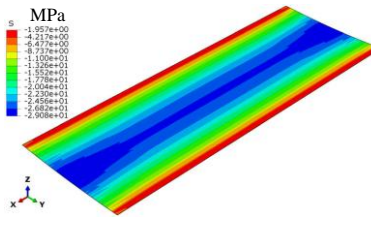


Figure 3.18. Stress in the face sheet of the structure – minimal cost

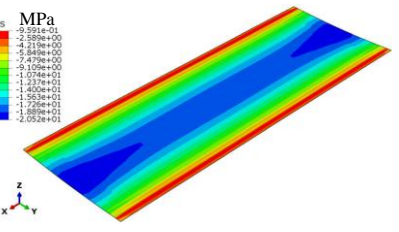


Figure 3.19. Stress in the face sheet of the structure – knee point

A comparative analysis was performed between the obtained optimization results and the corresponding results obtained from the simulations using the FEM models. The summarized results, presented in Table 3.5, show good agreement between the two sets of results, indicating the reliability and accuracy of the optimization process with minor observed differences.

Table 3.5. 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 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.

4. 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 to identify the impact of different face sheets configurations on the mechanical behavior of the entire sandwich structure.

The investigations in this chapter involved modeling composite test specimens using the ANN technique to predict structural deflection and face sheet stress. The same sandwich structures were simulated using FEM to predict the structural deflection and face sheet stresses.

4.1. 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 loading and boundary conditions for the considered structure are illustrated in Figure 4.1, where a span length (l) between the supporting rollers is 200 mm, with a fixed width of the test specimen (b) at 50 mm.

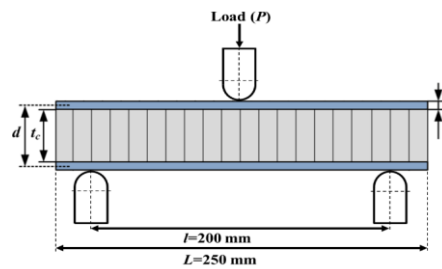


Figure 4.1. Loading configuration of the investigated sandwich structure

The structural responses in terms of the maximum deflection of the total sandwich structure (δ) and maximum stress (σ_f) in the face sheets are considered. Hence, the related mathematical expressions are provided by the following equations [9]. Based on Beam Theory calculations, the mathematical expression can be formulated as follows:

$$\delta = \frac{Pl^3}{48D} + \frac{Pl}{4S} \quad (4.1)$$

$$\sigma_f = \frac{M_{max}}{dt_f} \quad (4.2)$$

4.2. ARTIFICIAL NEURAL NETWORK MODELING OF THE INVESTIGATED STRUCTURE

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. The design variables utilized in this study are illustrated in Table 4.1.

Table 4.1. 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

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Core density	ρ_c [kg/m ³]	Al and Nomex cores in Table 2.2
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 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.

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. Accordingly, the data are randomly divided into two subsets, with 60% allocated for training and 40% for testing. Figure 4.2 illustrates the ANN structure of the investigated sandwich structure.

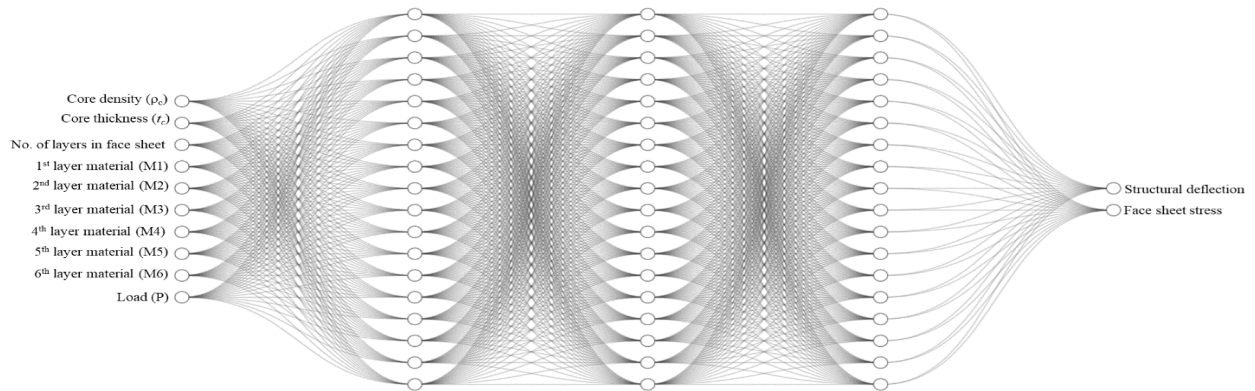


Figure 4.2. Neural network structure for the investigated sandwich structure

The ANN model is evaluated by the *MSE* and the *R*² coefficient which measures the prediction accuracy. As shown in Figure 4.3, 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.

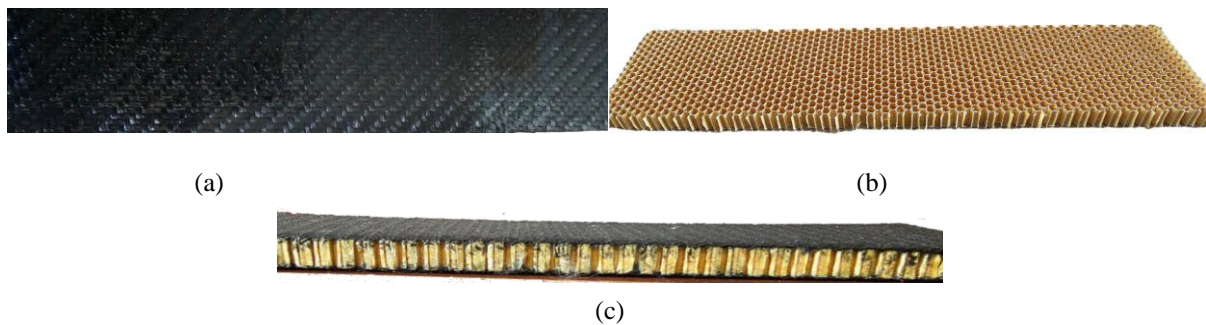


Figure 4.3. The investigated sandwich structure's components (a) face sheet, (b) honeycomb core, (c) assembled final structure

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

4.3. 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 4.4. 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 [15]. 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.

In the case of the applied prepreg (W245-TW2/2-E323) WCFRP material, the curing time was 150 minutes. The implemented curing profile for the applied prepreg is illustrated in Figure 4.5. 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.

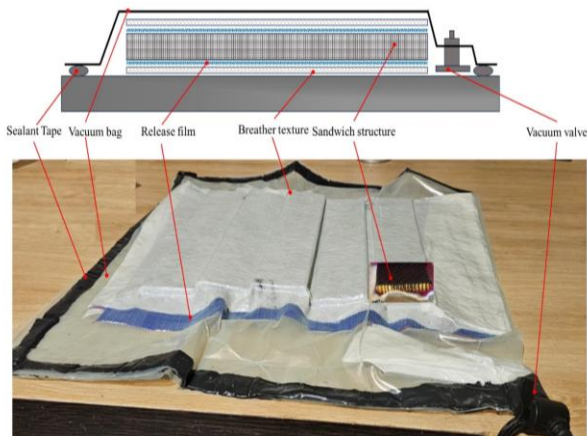


Figure 4.4. Vacuum bag applied during the manufacturing of the test specimens

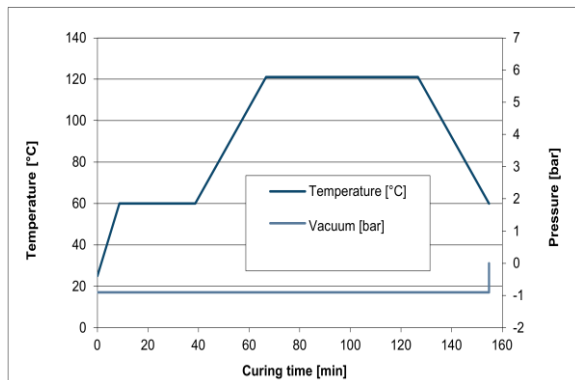


Figure 4.5. Curing cycle for the prepreg of the face sheets (manufacturer's protocol)

4.4. EXPERIMENTAL WORK CONFIGURATION

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 mm (*l* on Figure 4.1) plus 50 mm [15]. While the width of the specimens was fixed at 50 mm.

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The three-point bending test was carried out using a universal testing machine, Instron 5566 (Instron, Canton, MA, USA), as shown in Figure 4.6. 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 4.7 illustrates the load-displacement curves obtained for the respective test specimens.

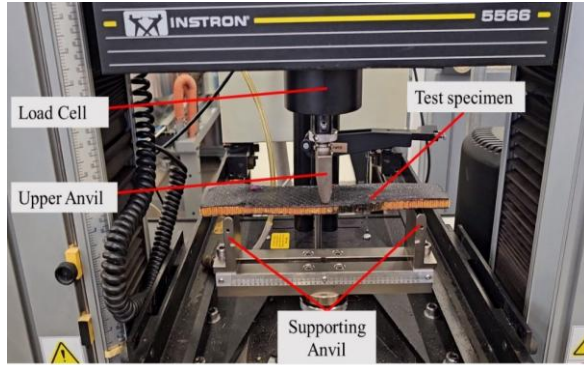


Figure 4.6. The three-point test set-up to obtain force-displacement of sandwich test specimens

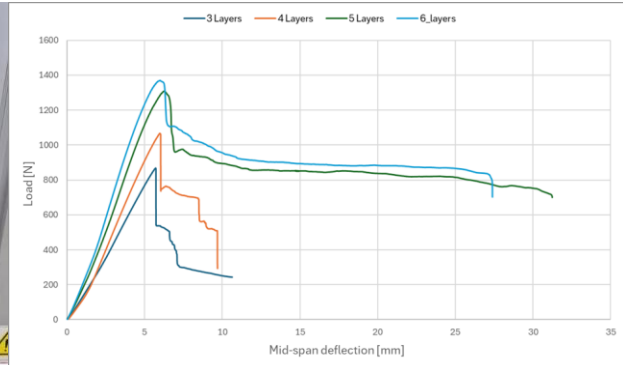


Figure 4.7. Force-displacement curves for the tested sandwich structures

4.5. 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. The Figures 4.8-4.10 indicated that the ANN was learning effectively to provide a better fit with the training data.

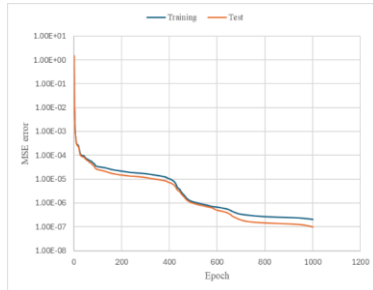


Figure 4.8. Neural network (*MSE*)

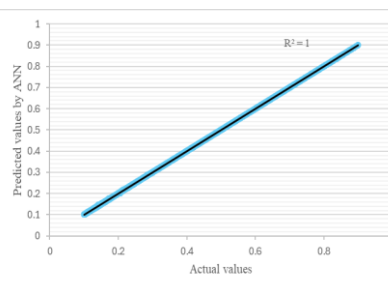


Figure 4.9. Neural network (R^2) – training set

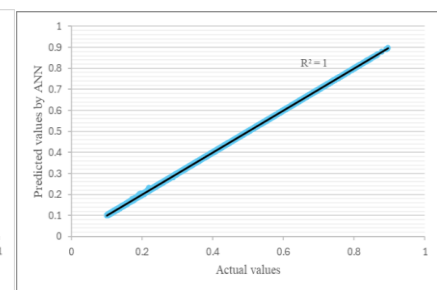


Figure 4.10. Neural network (R^2) – test set

4.6. VALIDATION OF THE ELABORATED ANN MODEL WITH EXPERIMENTAL MEASUREMENTS AND FEM

The FEM simulations primarily aimed to evaluate two critical aspects: the maximum deflection of the structure and the maximum stress in the face sheets. The contour patterns in Figures 4.11-4.18 depicted the deflection at the test specimens' structure and the stress distribution on the upper face sheets which simulated numerically.

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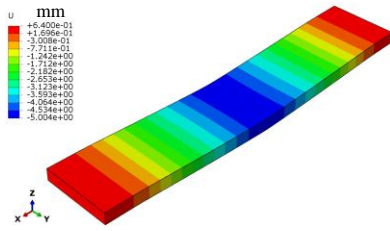


Figure 4.11. Deflection of the structure in case of 3 layers in the face sheets

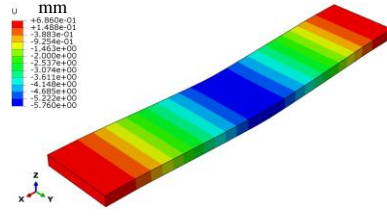


Figure 4.12. Deflection of the structure in case of 4 layers in the face sheets

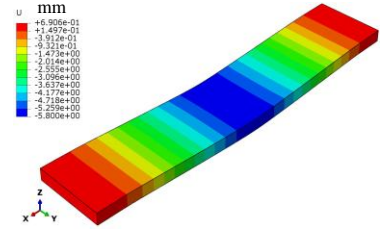


Figure 4.13. Deflection of the structure in case of 5 layers in the face sheets

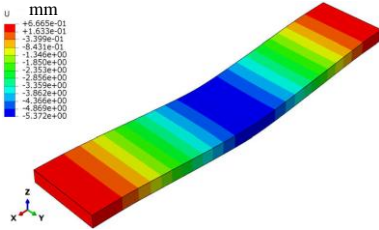


Figure 4.14. Deflection of the structure in case of 6 layers in the face sheets

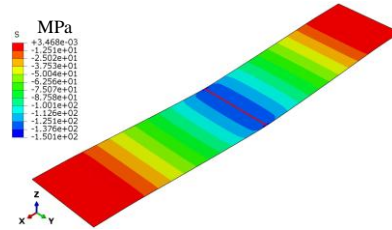


Figure 4.15. Stress in the face sheet in case of 3 layers

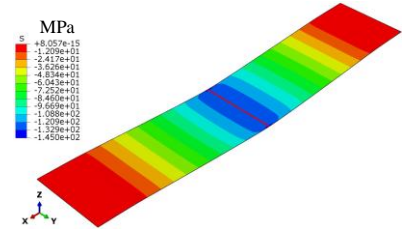


Figure 4.16. Stress in the face sheet in case of 4 layers

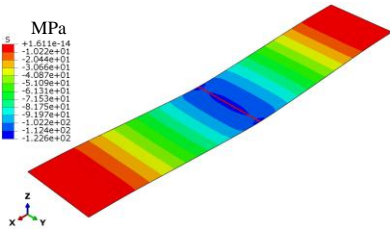


Figure 4.17. Stress in the face sheet in case of 5 layers

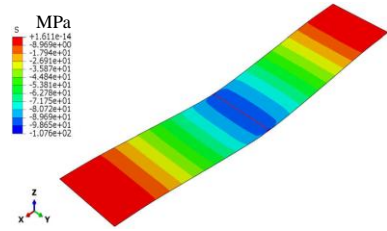


Figure 4.18. Stress in the face sheet in case of 6 layers

A comprehensive validation of the ANN model, FEM and experimental measurements are presented. The ANN predictions were compared with the corresponding experimental measurements and FEM results as illustrated in Figures 4.19-4.22. 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.

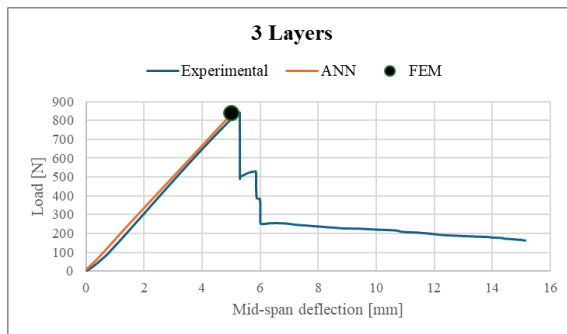


Figure 4.19. Load-deflection curves of the test specimens in case of the structure including 3 layers in the face sheet

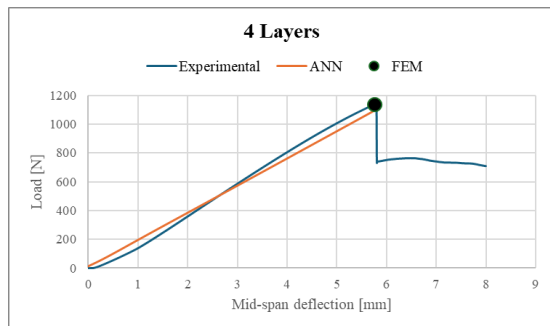


Figure 4.20. Load-deflection curves of the test specimens in case of the structure including 4 layers in the face sheet

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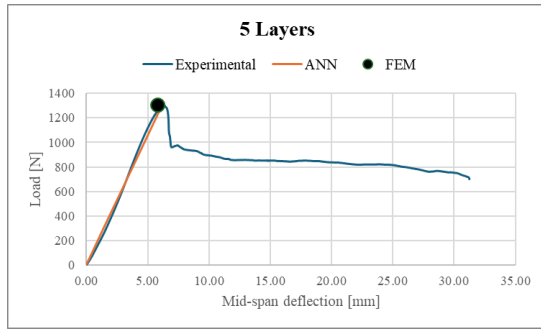


Figure 4.21. Load-deflection curves of the test specimens in case of the structure including 5 layers in the face sheet

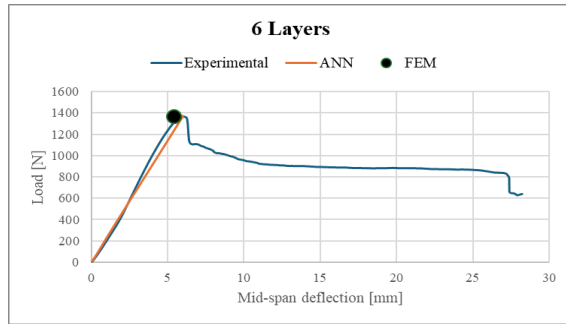


Figure 4.22. Load-deflection curves of the test specimens in case of the structure including 6 layers in the face sheet

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. Table 4.2 summarizes the comparison of the obtained results from the ANN, FEM and experimental measurements.

Table 4.2. Comparison of ANN and FEM results with the experimental measurements

No. of layers in the face sheets	Maximum deflection					Face sheet stress		
	Experimental [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.

5. NEW SCIENTIFIC RESULTS – THESES

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].

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

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].

LIST OF 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)
- [P8] Sahib, M.M.; Szávai, S. *Optimization of weight and elastic properties for unidirectional glass fiber reinforced composites*. Multidisciplinary Sciences, Vol. 11, No. 5, pp. 206–214, 2021. doi: 10.35925/j.multi.2021.5.21.
- [P9] Sahib, M.M.; Kovács, G.; Szávai, S. *Numerical analysis of composite sandwich structures with circular honeycomb core*. Annals of the University of Petroșani, 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.

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