

Generative Design of the Car's Front Suspension Lower Control Arm

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Abstract

This study applies Generative Design with Artificial Intelligence (GDAI) to the front suspension lower control arm (LCA) to achieve weight reduction while preserving structural integrity and performance. Traditionally, LCAs are manufactured from stamped steel for economy and standard passenger cars, or from cast aluminum for premium vehicles. In this work, GDAI is applied to Aluminum AlSi10Mg to address excess weight while ensuring equivalent mechanical performance. The generative design framework integrates finite element analysis (FEA) with AI-driven geometry optimization to produce lightweight and structurally efficient solutions. Optimization results indicate a potential weight reduction of 17.5% compared with the baseline model, alongside stress distribution improvements of up to 10% under identical load cases. Additional benefits include optimized geometry, reduced material consumption, and enhanced load path continuity. Furthermore, the approach reduces design iteration time by 50% compared to conventional CAD-based methods. The findings highlight the capability of AI-driven generative design to deliver high-performance suspension LCAs with reduced mass, improved durability, shorter development cycles, and accelerated additive manufacturing outcomes. These results contribute to improved vehicle efficiency, lower production costs, and enhanced sustainability.

Keywords

Generative Design AI, Car's front suspension, lower control arm (LCA), Optimization and Shape design.

1. Introduction

The integration of Artificial Intelligence (AI) with Generative Design (GD) has become an important approach in mechanical engineering and component design for achieving optimized mechanical structures (Peckham et al. 2025). Generative design techniques enable rapid design iteration and automated optimization, typically aiming to reduce structural mass while maintaining required mechanical performance (Wang et al. 2023). For certain applications, mass reductions in the range of 40% to 60% have been reported (Shrestha et al. 2021; Ntintakis et al. 2022). The application of AI-driven generative design has been widely explored for various mechanical components, particularly in the automotive sector, including suspension system components and, more specifically, control arms (Lee and Kang 2025; Bhat et al. 2023; Tkachenko and Wang 2024; Sadiq A. Pachapuri et al. 2021). One of the key components suitable for such studies is the control arm, which is a critical element of a vehicle's suspension system. It functions as a hinged linkage between the chassis and the wheel, enabling controlled vertical wheel motion in response to road surface irregularities (Bhat et al. 2023; Tkachenko and Wang 2024; Sadiq A. Pachapuri et al. 2021). Control arms are essential for maintaining proper tire-road contact and wheel alignment, thereby contributing directly to vehicle stability, handling, and overall safety (Lee and Kang 2025). One effective approach for mass reduction is the use of additive manufacturing, which enables weight minimization while preserving mechanical performance through the incorporation of lattice-based designs. Such lattice structures allow material to be strategically distributed,

significantly reducing weight without compromising structural integrity. Several mathematically defined lattice geometries, including triply periodic minimal surfaces (TPMS), gyroid, diamond, and honeycomb structures, have been shown to offer enhanced mechanical performance, improved stress distribution, and high surface-area-to-volume ratios (Barbieri and Muzzupapa 2022; Li, J., et al. 2025; Li, Y., et al. 2024).

Another effective strategy is the application of Generative Design with Artificial Intelligence (GDAI). When combined with additive manufacturing, this approach enables high fidelity translation of optimized geometries directly from the design stage to fabrication (Briard et al. 2020). Generative design tools, such as Fusion 360, typically produce multiple design alternatives that differ significantly in shape, geometry, and mechanical performance (Hossain et al. 2025). While this design diversity expands the solution space, it also introduces a new challenge for designers in selecting the most suitable option. To address this, several selection methodologies have been proposed, including AI-based decision-making frameworks (Hossain et al. 2025; Coulthard and Wang n.d.; Nordin 2018). However, traditional ranking and rating approaches are often subjective, dependent on designer preference, and may fail to capture true multi-criteria performance, leading to potentially suboptimal design selection (Hossain et al. 2025).

AI-driven generative design employs computational algorithms to automatically create and assess design alternatives based on engineer-defined objectives, constraints, materials, manufacturing routes, and cost limits (Peckham et al. 2025). This process typically produces a large set of candidate geometries that achieve significant mass reduction, enhanced structural efficiency, and part consolidation beyond the capabilities of conventional manual design. The methodology builds on techniques such as topology optimization and bio-inspired growth strategies to explore design spaces that are rarely intuitive to human designers. When combined with additive manufacturing, these complex and highly optimized geometries become practically realizable, despite being unsuitable for traditional fabrication methods. This synergy is particularly impactful in metal additive manufacturing, where geometric freedom can be fully exploited; however, fully integrated AI-based generative design and metal AM workflows remain an emerging and underdeveloped area of research (Koul 2024).

In this study, a generative design approach based on artificial intelligence is applied to the development of a lower control arm (LCA) by integrating mechanical design principles, numerical simulation, and algorithmic optimization. A multi-simulation workflow is employed within generative design software, where AI-driven algorithms automatically generate lightweight and structurally efficient design alternatives that satisfy predefined performance constraints. The resulting optimized solutions are subsequently evaluated and integrated using a Python-based decision framework, which ranks the candidates according to multiple criteria. Based on this scoring process, three optimal LCA designs are selected as the final outcomes of the study.

2. Materials and Methods

This study adopts an AI-assisted generative design workflow to produce and select a lightweight, structurally optimized lower control arm (LCA). The methodology combines commercial generative design software for automated solution generation with a custom Python-based framework for multi-objective evaluation and design ranking. The overall approach is organized into four sequential phases, as illustrated in the workflow shown in Figure 1.

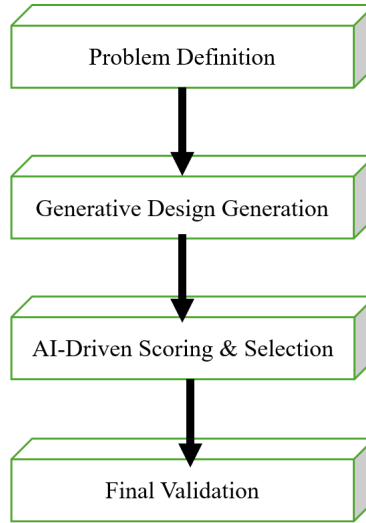


Figure 1. Design Workflow for Low control Arm (LCA) Optimization

- **Phase 1: Problem Definition and Prescription**

This phase defines the constraints and objectives of the generative algorithm. The initial design space is set as the maximum bounding volume of a conventional steel LCA. Preserved geometry and obstacle regions are specified, including hard points for bushings and ball joints, as well as required clearance zones for adjacent assemblies. Structural requirements include a minimum safety factor of 2 under defined multi-load-case conditions. The manufacturing scenario is additive manufacturing AM. The objective of optimization is to minimize mass while satisfying all structural and manufacturing constraints.

- **Phase 2: Generative Design Generation**

The defined design problem is addressed using AI-driven generative design software, which produces multiple lower control arm design alternatives through simulation-based optimization. The algorithm systematically explores the design space by redistributing material, removing it where unnecessary and reinforcing it along critical load paths to satisfy the imposed constraints. This process results in a set of viable design solutions, each with a distinct geometry that meets the specified mechanical performance and manufacturing requirements.

- **Phase 3: AI-Driven Scoring and Optimal Design Selection Custom Python Framework**

A custom Python script is developed to evaluate and rank the generated design outcomes beyond the built-in objectives of the software. Key performance metrics, including mass, maximum stress, displacement, and safety factors, are extracted for each design. A weighted scoring function is then applied to reflect the relative importance of competing performance criteria. Based on the resulting composite scores, the designs are ranked and the solution with the highest overall score is selected as the optimal configuration.

- **Phase 4: Validation and Finalization**

The selected optimal design undergoes final engineering validation. Its geometry is reconstructed as a solid model and analyzed using a high-fidelity, independent finite element analysis within a dedicated simulation environment to confirm structural performance and compliance with all requirements.

The lower control arm (LCA), illustrated in Figure 2, is a critical metal component of the independent suspension system, key to vehicle handling, comfort, and stability. While lightweighting of a standard-shaped LCA could be attempted using honeycomb or TPMS lattice structures, such approaches risk creating weak joints and potential failure points. Generative design (GD) offers a superior solution by simultaneously reducing mass and preserving structural performance.

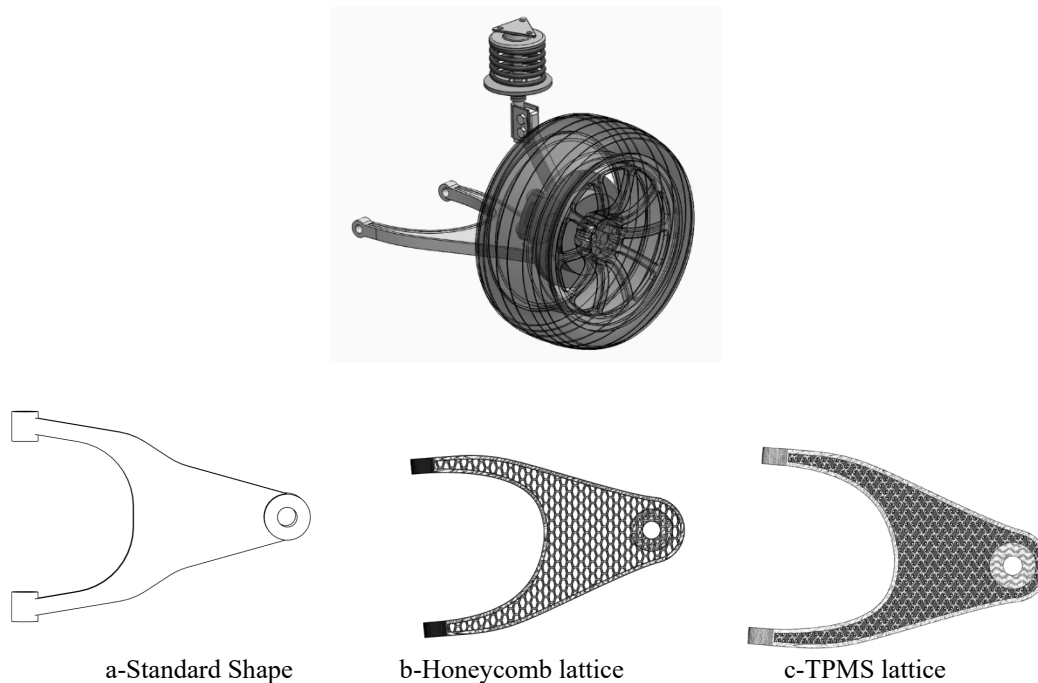


Figure 2. CAD Design without GD of Lower Arm Control with standard shape, Honeycomb and TPMS lattice

The automotive industry widely adopts aluminum alloys for control arms to reduce weight. High-performance variants like 6082-T6 and AlSi10Mg are particularly favored for LCAs due to their strength and heat-treatability. Typical properties include tensile strength (340-460 MPa), yield strength (280-300 MPa), Poisson's ratio (0.33), density (2.70 g/cm³), and Young's modulus (70-75 GPa) (Song 2022; Ye et al. 2023), confirming their suitability.

During Geometry and Topology (GD) optimization, multiple load cases are applied simultaneously. For a single front lower control arm (LCA) (Tkachenko and Wang 2024; Sadiq A. Pachapuri et al. 2021), these loads include:

- A static vertical load of 4,250 N.
- A cornering load of 13,280 N in the lateral direction.
- A bump force of 18,760 N.
- An acceleration force of 2,580 N in the horizontal direction.
- A braking force of 1,300 N with a moment of 49.4 Nm.
- A combined load of ~7,682 N when the vehicle traverses a hump at 75 m/s.

For the MacPherson strut connection (point A in Figure 3), the maximum loads are approximately 549 N (X-direction), 2,519 N (Y-direction), and 480 N (Z-direction), with the LCA mass being 4.717 kg (Zhang et al. 2025).

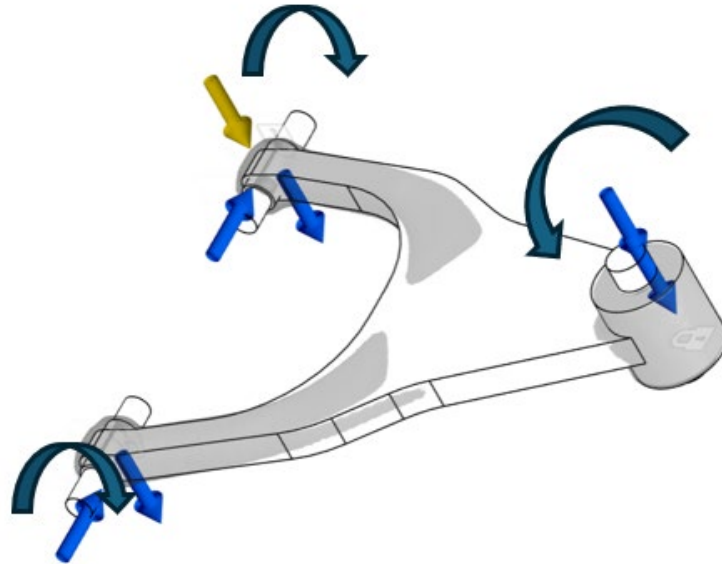


Figure 3. Principal load points in the LCA

Setting up the lower control arm (LCA) for the Generative Design process involves defining preserve and obstacle geometries, specifying load cases and directions, and selecting the material and manufacturing constraints (Tkachenko and Wang 2024; Sadiq A. Pachapuri et al. 2021). Manufacturing methods were specified as either fully unrestricted or additive manufacturing with a 45-degree maximum overhang angle in the X and Y directions. The baseline LCA weight is approximately 2.868 kg.

3. Results and discussion

The configuration for the generative design process comprised a starting geometry, three preserved regions, and three obstacle volumes. Manufacturing constraints were also defined to reflect the capabilities of additive production. The complete setup is visualized in the software interface, as shown in Figure 4.

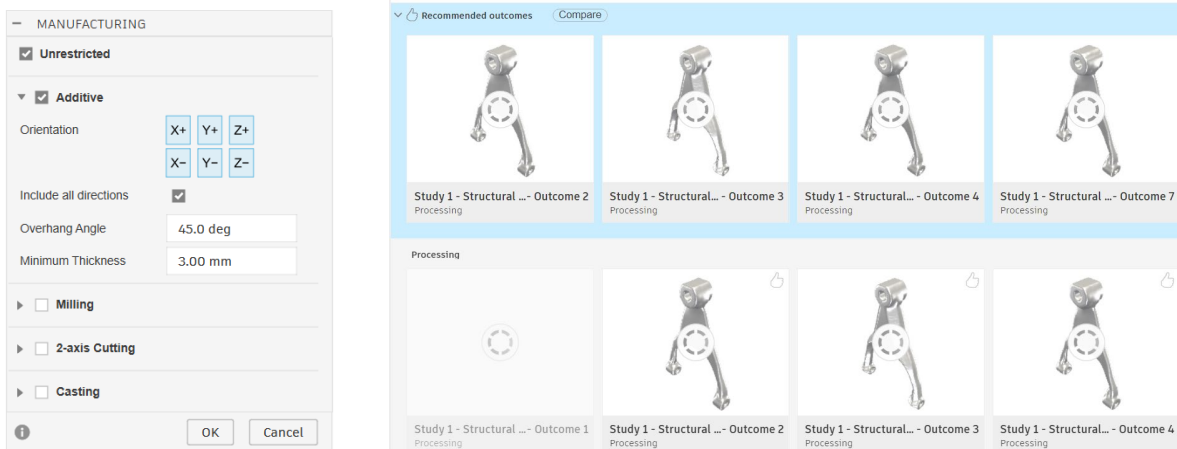


Figure 4. Screenshot of the generative design software setup

Figure 5 illustrates the three optimal design configurations selected by the GDAI system via a multi-criteria scoring process. From a vast set of generated geometries, these designs were chosen for their superior combined performance

in minimizing mass, maximizing stiffness, and adhering to additive manufacturing constraints, forming the basis for the subsequent comparative study.

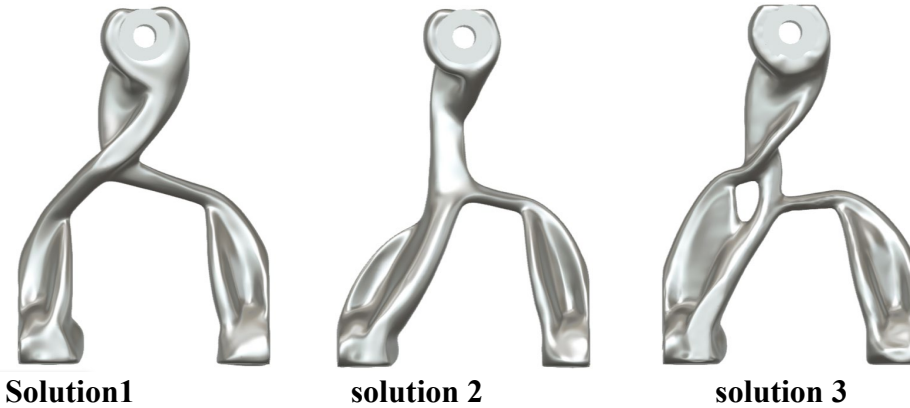


Figure 5. Generative design models of the lower control arm showing different manufacturing outcomes Table 1 summarizes the resulting geometries and their key performance metrics, including von Mises stress, safety factor, and mass.

Table 1. Selected seven results from the LCA–GDAI analysis

GD model	Mass (kg)	Max von Mises stress (MPa)	Min safety factor
1	2.366418332	30.12524406	7.966740436
2	2.389668223	30.48835392	7.871858239
3	2.365959595	29.53397517	8.12623423
4	2.365290096	30.67318792	7.824423095
5	2.377553612	30.17282576	7.954177111
6	2.364568632	29.77220377	8.061210444
7	2.370619335	30.0086966	7.997681579

Figure 6 compares seven generative design outcomes using mass, maximum von Mises stress, and safety factors.

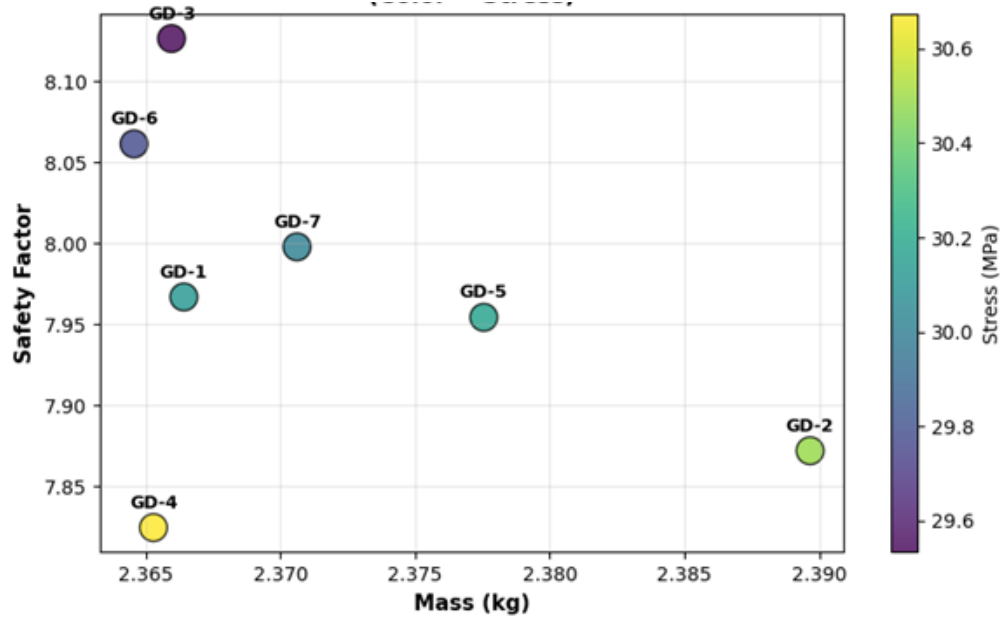


Figure 6. Results in GD of LCA

The results highlight the performance of trade-offs achieved through topology optimization. All optimized designs show a significant mass reduction from the baseline value of 2.868 kg, with weights ranging between 2.365 kg and 2.390 kg, corresponding to a reduction of approximately 16.7–17.5%, exceeding the initial optimization target. GD-4 and GD-6 achieve the lowest mass at 2.365 kg, while GD-2 is the heaviest among the optimized variants. An inverse relationship between mass and safety factors is observed, where lighter designs such as GD-3, GD-6, and GD-4 exhibit higher safety factors, indicating efficient material redistribution rather than mass-driven strength. Among all cases, GD-3 demonstrates the best overall performance, combining the lowest maximum stress of 29.53 MPa, the highest safety factor of 8.13, and near-minimum weight. GD-6 provides an excellent alternative, achieving the lowest weight with a safety factor of 8.06, while GD-1 and GD-7 offer balanced mid-range performance. Compared to the baseline, all generative designs show improved stress distribution, with maximum stresses reduced by approximately 8–10% and clustered within a narrow range of 29.5–30.7 MPa, indicating consistent structural optimization. Overall, the results define a clear Pareto frontier, validating the effectiveness of the generative design approach and supporting GD-3 as the optimal candidate, with GD-6 as a strong alternative when minimum weight is the primary objective.

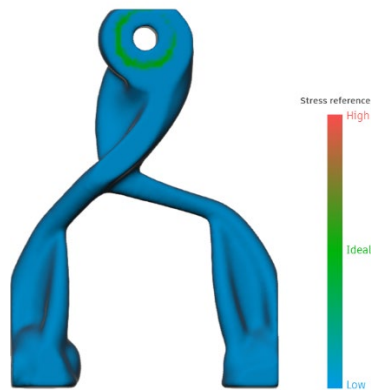


Figure 7. the FE results on LCA

The finite element analysis of the generatively designed component, as visualized in Figure 7, reveals an effective stress distribution that validates the optimization process. Most of the structure operates within an ideal stress range, demonstrating efficient load transfer through the organic topology. The absence of extensive low-stress regions confirms the material efficiency achieved, with minimal underutilized mass, thereby meeting the core objective of LCA lightweight design.

While the generative design process successfully produced a structurally efficient geometry, the selection of both the optimal design variant and the most suitable material for fabrication presents a complex challenge. The multiple alternatives generated often involve trade-offs between mass, stiffness, manufacturability, and cost. Therefore, it is recommended to implement a multi-criteria decision-making (MCDM) framework for material selection (Gherissi, A 2026). Approaches such as the Analytic Hierarchy Process (AHP) or Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) can systematically evaluate and rank candidate materials like AlSi10Mg and 6082-T6 against weighted criteria, including mechanical properties, cost, and additive manufacturing suitability, thereby reducing subjectivity in the final choice.

Furthermore, the current generative design workflow represents a static optimization based on predefined loads and constraints. To enhance the component's performance and longevity under real-world, variable driving conditions, the integration of adaptive design principles is recommended (Gherissi, A et al. 2025).

4. Conclusion

The results of this study demonstrate that Generative Design with Artificial Intelligence is an effective approach for optimizing front suspension lower control arms by simultaneously reducing weight and enhancing structural performance. The application of GDAI to an Aluminum AlSi10Mg LCA achieved a significant weight reduction of up to 16.7–17.5%, while improving stress distribution by approximately 8-10% under identical loading conditions, without compromising structural integrity. The integration of finite element analysis with AI-driven geometry optimization enabled the development of efficient load paths, reduced material usage, and minimized design redundancy. In addition, the reduction in design iteration time highlights the advantage of generative workflows over conventional CAD-based approaches. The successful generation of additive manufacturing-ready geometry and fabrication of a representative prototype further confirm the practicality of the proposed method. Overall, this work confirms the potential of AI-driven generative design to deliver lightweight, durable, and sustainable suspension components, contributing to improved vehicle efficiency, reduced development time, and enhanced manufacturing sustainability.

Upcoming work will prioritize experimental validation of additively manufactured lower control arm (LCA) prototypes through physical fatigue, durability, and service-load testing. The optimization framework can be expanded to incorporate multi-physics performance criteria, including vibration behavior, noise–vibration–harshness (NVH), and crashworthiness.

In addition, embedding cost assessment and sustainability indicators, such as carbon emissions, energy consumption, and material recyclability would strengthen the industrial applicability and environmental impact of the results. Further refinement through the development of a dedicated, component-specific AI model for suspension systems may enhance design convergence, manufacturability, and performance consistency. Finally, large-scale validation through field deployment and fleet-level testing will be essential to transition generative design solutions from numerical simulation to fully validated automotive applications.

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Biographies

Abderraouf Gherissi is an Associate Professor of Mechanical Engineering at the University of Tabuk, Saudi Arabia. He obtained his Ph.D. in Mechanical Engineering from the University of Tunis El Manar, Tunisia, in 2014. His professional background includes industrial and academic experience. He served as Head of the Maintenance Department at Graphic Art Diffusion, Tunisia, before moving into academia as a Mechanical and Industrial Instructor at the Industrial Center of Maintenance in Tunis and later at Ruasyl Institute in Muscat, Oman. Since 2015, he has been a faculty member in the Department of Mechanical Engineering at the University of Tabuk, where he was appointed Assistant Professor and subsequently promoted to Associate Professor. His research interests include

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