

Article

Optimization of the Design and Manufacturing Processes for Metal Additive Manufacturing Through Digital Twin

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Abstract

The aim of this study is to develop a digital twin hierarchy that fully examines the design and manufacturing processes of an automotive component for metal additive manufacturing. Initially, a lighter model was obtained that was more resistant to static, dynamic, and fatigue loads under various operating conditions. This step improved product strength and resulted in a 28.5% mass reduction. After the product was validated, the orientation of the part direction and the generation of support structures were performed for the manufacturing process. These processes were implemented with the criterion of minimizing production time. Finally, the manufacturing process was digitally implemented using the selective laser melting method and Ti6Al4V material. The design of the experiment was created using the three most frequently preferred values for each of the three important process parameters. After performing process simulations with thermomechanical analyses, Taguchi and ANOVA were applied to the process parameters. The optimum process parameters for layer thickness, hatch spacing, and scanning speed were found to be 50 µm, 120 µm, and 1200 mm/s, respectively.

Keywords: digital twin; design for additive manufacturing; design of experiment; finite element analysis; metal additive manufacturing

1. Introduction

Additive manufacturing methods, which are no longer considered new, have brought many innovations to manufacturing and co-working areas. One of the areas most affected by this situation was the design for additive manufacturing (DFAM) responsible for structural redesign and structural strength validation of the products. Before we start producing a product with a different manufacturing method, we need to redesign it according to the limitations and extra capabilities of that production method. Only in this way is it possible to acquire the highest efficiency from new production techniques. This is how the workspace called DFAM emerged. In its simplest form, the product prepared for manufacture is topologically optimized with the combined use of CAD and CAE software, brought to appropriate design lines with solid and surface modeling tools, and tested for structural strength with FEA tools. After this process, DFAM software tools are also available in order to be able to manufacture the obtained product geometry in the most appropriate way, to determine the problems that may occur during production and to plan the final operations. Some functions of this software include determining the production orientation, creating



Academic Editors: Yanzen Zhang,
Dege Li and Abhishek Agarwal

Received: 9 December 2025

Revised: 23 January 2026

Accepted: 4 February 2026

Published: 6 February 2026

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support structures and performing process simulations with thermomechanical analyses. Additive manufacturing is not yet a competitive method in the automotive industry, where mass production is common, due to its disadvantage in manufacturing times. For this reason, it is important to make DFAM and production efficient for automotive components.

The suspension system is the automotive component connecting the chassis and wheels of a vehicle. It performs important vehicle-dynamics functions such as providing driving comfort, road holding, balancing the vehicle on rough roads, and damping road vibrations [1]. Types of suspension systems vary according to the place where they are used. They are classified into two primary categories based on the ability of the wheels to move independently. The dependent system is typically used in truck-type vehicles; however, the independent system is preferred in passenger cars. The most common independent suspensions are double wishbones and MacPherson systems [2]. Although the MacPherson system is more compact and lighter, the double wishbone system is preferred in pickup-type vehicles that are longer than cars, as it provides a wider maneuvering capability. It consists of a lower and upper control arm, shock absorber and coil spring [3]. One of the most prominent components of a double-wishbone system is on the front axle; it is the lower control arm that performs important functions such as supporting the vehicle's front weight, guiding the wheel movement and increasing the holding on rough roads [4].

The subject of vehicle dynamics examines the movement of a vehicle and the condition of all its components with this movement. In order to evaluate the properties of an automotive component, such as its strength or durability, it is necessary to determine what kind of loads it is exposed to. Vehicles are used in many different operating conditions due to various factors such as different driving speeds, cornering, braking, or the slope of the road. The more driving scenarios are implemented, the more load cases to which the components are subjected [5].

Structural optimization has an important place in design for additive manufacturing, as it can ensure lightweight and durable geometries. Topology optimization, which is one of the most common methods of structural optimization, is usually performed in finite element analysis. To achieve an efficient geometry through topology optimization, it is crucial to accurately define the objectives and constraints. Since the findings obtained from studies such as static or modal analysis can be used as parameters, these studies are usually performed as preliminary [6].

Patil et al. carried out a weight reduction study based on finite element analysis on the chassis of an auto rickshaw. They calculated the weights of all the components carried by the chassis and the load cases that can occur in different motion variations. With these loading conditions, linear static analyses were performed. By interpreting the obtained results, they decided on the areas that could be mitigated and came up with a new design. They validated their final design by performing the same analyses on it. In the end, they achieved both a strength increase and a mass decrease [7]. Bhat et al. fulfilled generative design for weight reduction on the suspensions of a formula student race car. They showed that they obtained results that would meet their needs with the static and fatigue analyses they applied on the model in which they achieved a mass gain of up to 50% [8]. Kulkarni et al. compared the results by performing static and modal analyses with low carbon steel and Al7075 material on an automobile lower wishbone. They concluded that Al7075 material can be preferred because it has higher strength and lower first natural frequency [9]. Lin and Guo achieved a mass reduction by performing topology optimization followed by size optimization on an automotive lower control arm. The model they attained was subjected to fatigue analysis both with the finite element method and on the test setup. As a result, they validated their model either way [10].

Increasing additive manufacturing efficiency requires optimizing both the part's geometry and the manufacturing process. Scanning speed, hatch spacing, and layer thickness are among the most frequently studied process parameters. This is primarily because each of these parameters, whether high or low, has advantages and disadvantages regarding production time, surface quality, strength, etc. Therefore, it is important to optimize these parameters and ensure the fastest production time with the best mechanical and surface properties [11]. Residual stress is one of the most frequently observed outcomes in SLM experimental studies, as it significantly influences the need for postprocessing. Because residual stress can be calculated as a function of strain, FEA studies typically consider either plastic strain or total strain [12].

Although digital twins have emerged as an important topic of study recently, there is no complete consensus on their definition [13]. Digital twin studies addresses a product's design, manufacturing process, process monitoring, production management, parameter optimization, and more [14]. Typically, tools like simulation, machine learning, and product lifecycle management carry out these functions. These tools have enabled digital workflows to produce cost-effective and performance-optimized products [15].

Studies in the literature on improving the efficiency of additive manufacturing for automotive components have largely focused on either optimizing geometry via DFAM or optimizing manufacturing parameters. This study aimed to develop a digital twin hierarchy that optimizes all processes, from product design for traditional manufacturing to final product production. As shown in Figure 1, the DFAM process was initially implemented, which included vehicle dynamics analysis, structural strength and fatigue behavior calculations, and the determination of manufacturing orientation and support structures. Furthermore, design of experiments and thermomechanical analyses were conducted to simulate the manufacturing process. Optimum manufacturing parameters were obtained using Taguchi and ANOVA methods.

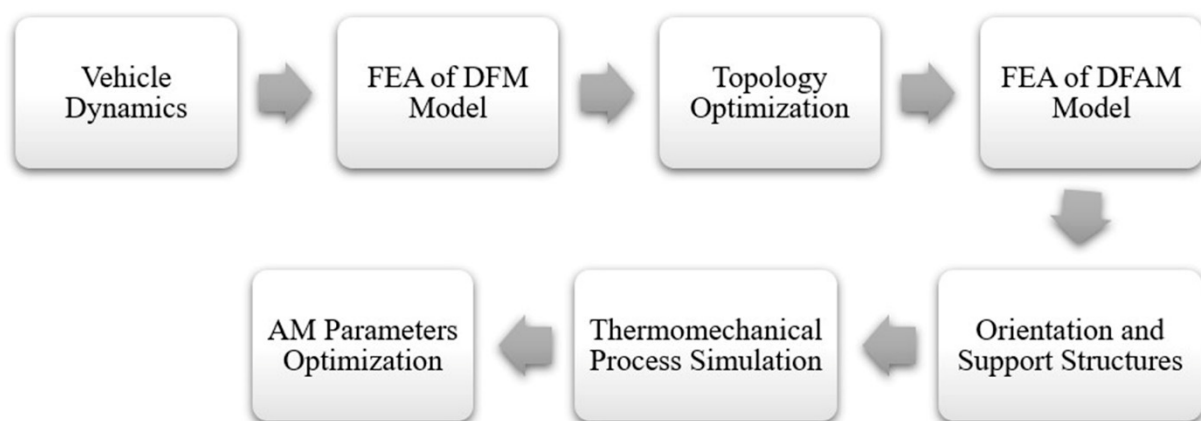


Figure 1. Workflow of digital twin organization in this study.

2. Design for Additive Manufacturing

2.1. Motion Analysis of the Control Arm

Motion simulation is an important method for observing the mechanical effects on the components according to the driving pattern of a vehicle. If parameters such as vehicle models, moving mechanisms, material properties and driving inputs are defined correctly, they can provide results that are very close to reality. In this respect, it is widely used both in the automotive sector and in academic studies [16].

A multitude of factors, such as the activities of the driver and the surrounding environment, can affect vehicles. Ansys Motion 2022 R1 vehicle dynamics software was utilized to

create a dynamic model of the vehicle in order to figure out the forces exerted on the front suspension. Factors affecting the vehicle are taken into account during motion simulation through the parameters included in the motion equations as below [17,18].

$$F = m \cdot \ddot{x} \quad (1)$$

$$F = k \cdot x + c \cdot \dot{x} + m \cdot \ddot{x} \quad (2)$$

$$m_s \cdot \ddot{x}_1 = -k_s(x_1 - x_2) - c_s(\dot{x}_1 - \dot{x}_2) - u \quad (3)$$

The longitudinal stiffness coefficient of a braked axle's tires is denoted by k , the coefficient of inelastic resistance of an axle with brakes is denoted by c . Spring mass, damping coefficient and suspension stiffness are m_s , c_s and k_s , respectively, where x_1 and x_2 are the displacements of the spring and springless masses.

Motion analyses were conducted in three different scenarios using rigid body dynamics. These analyses are carried out according to Newton's second law and the equations derived from it as below. With this law, Newton defines the relationship between the motion of a rigid body and the forces and torques acting on it [19].

$$m \cdot (\dot{v}_z - v_x \cdot \omega_y + v_y \cdot \omega_x) = F_z \quad (4)$$

$$m \cdot (\dot{v}_y - v_z \cdot \omega_x + v_x \cdot \omega_z) = F_y \quad (5)$$

$$I_x \cdot \dot{\omega}_x + (I_z - I_y) \omega_z \cdot \omega_y = T_x \quad (6)$$

In the equations above, v_x is the longitudinal velocity, v_y is the lateral velocity, ω_x is the roll rates, ω_y is the pitch rates, ω_z is the yaw rates.

Figure 2 shows the velocity–time graphs applied in each scenario, along with the corresponding force diagrams occurring on the X, Y, and Z axes.

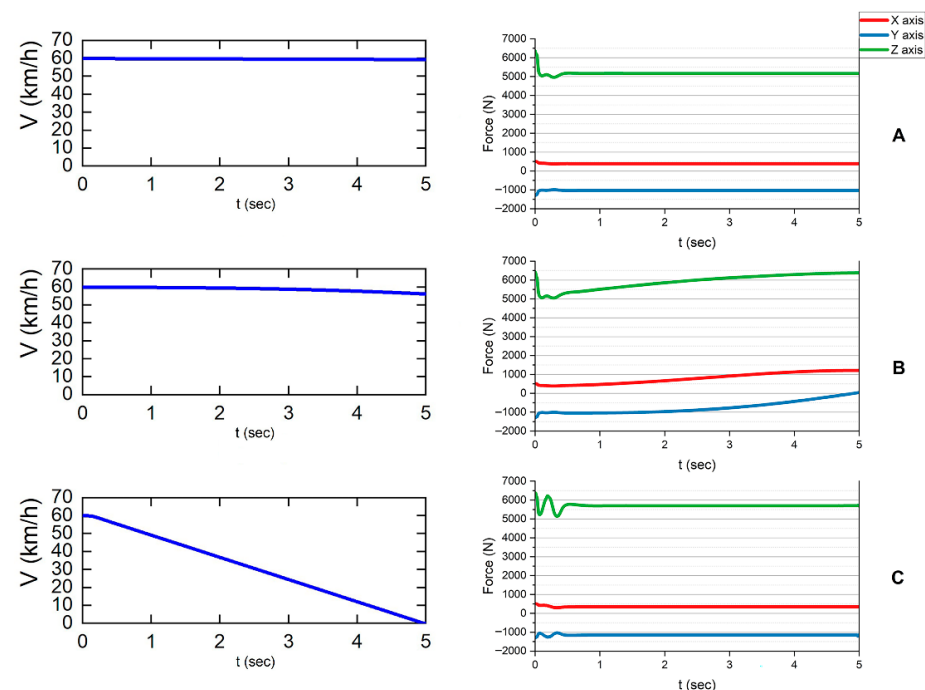


Figure 2. The velocity and force diagrams of the front LCA under different dynamic conditions ((A): steady state 60 km/h, (B): ramping 30° with constant speed 60 km/h and (C): Braking 60 to 0 km/h).

2.2. Structural Analysis and Optimization

For numerical analysis, firstly the material suitable for the production method and place of use was determined, and the material properties given in Table 1 were assigned to the part [20]. For the finite element analysis, the lower control arm boundary conditions were applied according to the working principles of the motion analysis performed in Section 2.1. The part was fixed using control arm bushings. Loads were applied to the ball joint area connecting the wheel. Three linear static analyses were performed using the loading values obtained for the three different cases in Section 2.1. Mesh convergence was done by looking at the von Mises stress results, leading to a finite element mesh that provides accurate results without greatly raising computing costs [21]. Thus, a tetrahedral mesh with 235,271 elements and 336,845 nodes was generated. As a result of the structural static analysis, the highest von Mises stress occurred in the constant speed ramp climbing scenario, as seen in Figure 3.

Table 1. Mechanical properties of Ti64 material at room temperature.

Young's Modulus	Poisson's Ratio	Yield Strength	Tensile Strength
107 GPa	0.323	1098 MPa	1200 MPa

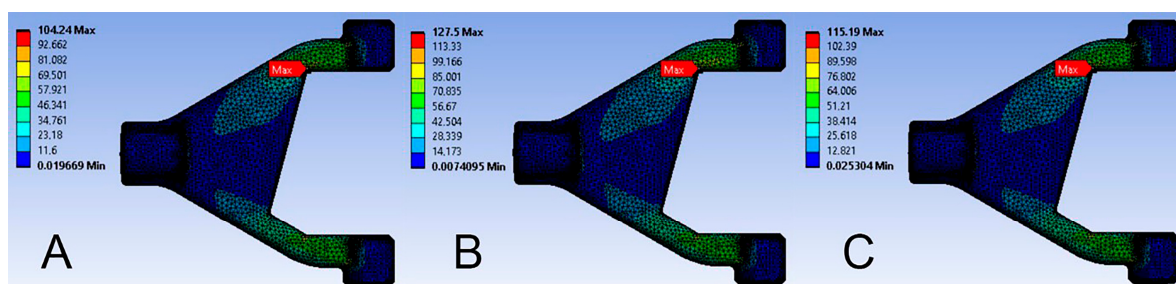


Figure 3. The von Mises stress results in different dynamic conditions ((A): steady state 60 km/h, (B): ramping 30° with constant speed 60 km/h and (C): Braking 60 to 0 km/h).

Finite element analysis has widely adopted the SIMP method due to its suitability for use. The SIMP method performs a finite-element-based iterative solution by assigning values of 0 or 1 to each element, with a function dependent on the modulus of elasticity. In order for the SIMP method to work efficiently, attention should be paid to creating a thinner and lighter transition-finite-element mesh than in static or modal analysis. In the solution principle in Equation (7), E_0 represents the initial elastic modulus of the material, ρ_e indicates the density factor and p indicates the penalty factor [22].

$$E(\rho_e) = \rho_e^p \cdot E_0 \quad (7)$$

The fixture and loading regions were excluded from the optimization region for the manufacturing constraint. Additive manufacturability and symmetry constraints were also implemented. The optimization goal was set to minimize compliance. A response constraint was defined to prevent an increase in the von Mises stress. The result shown in Figure 4 was obtained in the 16th iteration. The graphical result includes marginal regions where the ρ_e value is between 0 and 1. By smoothing these regions with CAD, a new model was obtained with a 28.48% volume reduction.

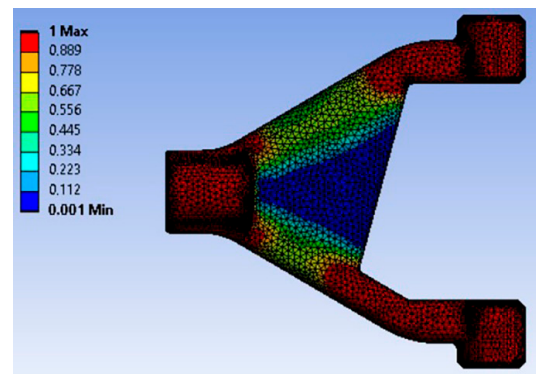


Figure 4. The topology optimization result under multiple load cases.

The optimized new model was subjected to structural analysis using the same boundary conditions as the initial model. The results in Figure 5 show that the new model exhibited less stress under all loading conditions.

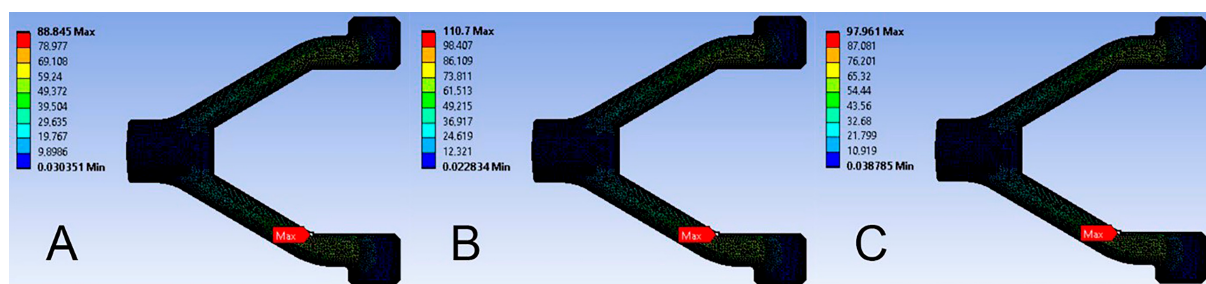


Figure 5. The von Mises stress results of topology optimized model in different dynamic conditions ((A): steady state 60 km/h, (B): ramping 30° with constant speed 60 km/h and (C): Braking 60 to 0 km/h).

It is important to consider natural frequencies in product development to ensure the part does not present resonance risks. Modal analyses, the results of which are shown in Table 2, were performed to validate the model's dynamic behavior. To avoid resonance, a natural frequency value close to or higher was generally expected [23]. Satisfactory results were obtained with this application. Most natural frequencies were measured either close to or higher than those in the initial model.

Table 2. The modal analysis results of the non-optimized and optimized model.

Mode	Frequency (Hz)	
	Non-Optimized Model	Optimized Model
1	396.27	406.92
2	1547.10	1276.50
3	1998.60	1896.70
4	2190.80	2310.70
5	2868.70	3083.30
6	3415.20	3203.00

2.3. Fatigue Analysis

Fatigue, one of the most likely causes of damage to mechanical structures, occurs when cyclic loads expose the structure. Stress life fatigue calculations are performed using SN curves. These graphs exhibit the number of cycles in which the damage occurs and the stress amplitude that causes it. It is important to know the endurance limit of the material

for which fatigue analysis will be made. The structure is assumed to be undamaged at values below the endurance limit determined by the SN curve. Since a material that is assumed isotropic and homogeneous in structural analysis software cannot actually carry the same ideal conditions, scaling factors are used according to the type of material used and the type of loading applied when performing fatigue analysis [24].

The results in Figure 6 were acquired in the high cycle fatigue analyses performed by assuming $R = -1$ and a fatigue strength factor of 0.7 [24]. Considering the 300 MPa value accepted as the fatigue limit of the Ti64 material, it was determined that the model was resistant to high cycle fatigue [25].

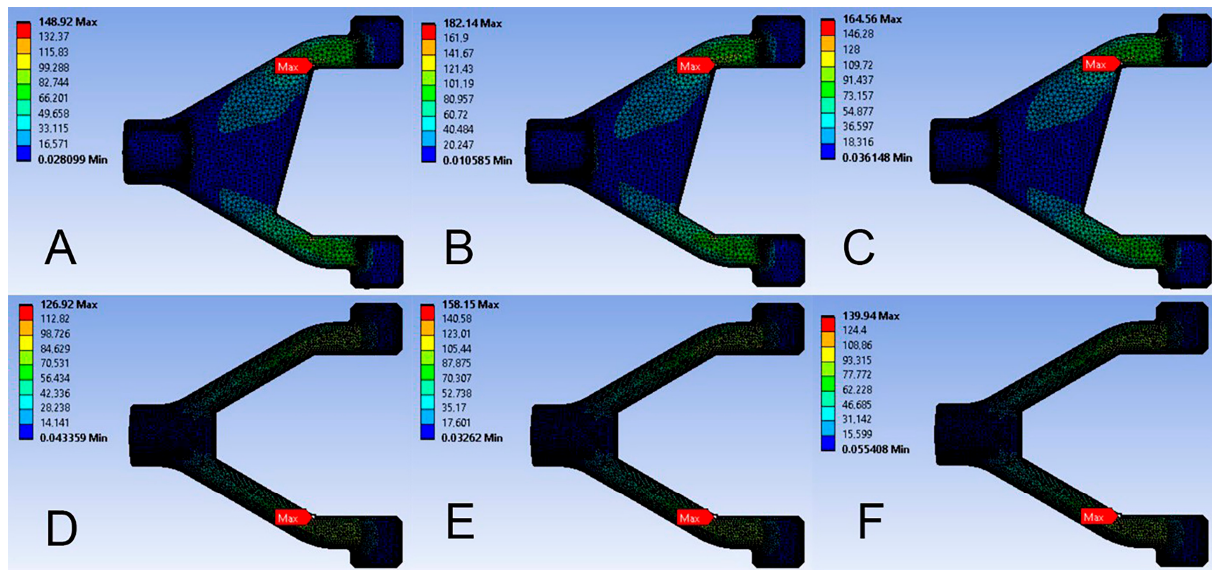


Figure 6. The fatigue alternating stress results in different dynamic conditions ((A–C): non-optimized model, (D–F): optimized model).

In high-cycle-fatigue analyses, the new model performed better under all dynamic conditions. Furthermore, it achieved approximately twice the safety factor compared to the fatigue limit. The results demonstrated that the structure was in the infinite life region.

3. Additive Manufacturing Process

3.1. Define Orientation and Support Structures

In additive manufacturing, determining the manufacturing orientation and generating the support structures are often carried out simultaneously because these processes are directly related. The orientation must be determined based on multiple criteria, such as part complexity, size, production time, and cost [26]. However, one of the most important criteria to consider when determining the orientation is to minimize the need for support structures. This saves both material costs and production time. In this study, the orientation was determined based on the criterion of minimizing the need for support structures [27].

Support structures are designed to prevent deformation of the part during production, ensure proper temperature distribution, and provide easy post-production removal. It is noted that the need for support structures increases on surfaces with angles less than 45° , and that supports play a critical role in both temperature distribution and mechanical stability in these areas [28]. Support structures include different types such as block, point, line, volume, and contour. These types offer advantages over each other depending on their intended use [29]. In this study, the volume method was chosen because the surfaces requiring support structures were mostly circular. Figure 7 shows the support structures and manufacturing orientation obtained using the volume method, with a 45° overhang

angle, minimizing support structures and production time. The volume method has a volume of 204,084 mm³ and a surface area of 46,643 mm².

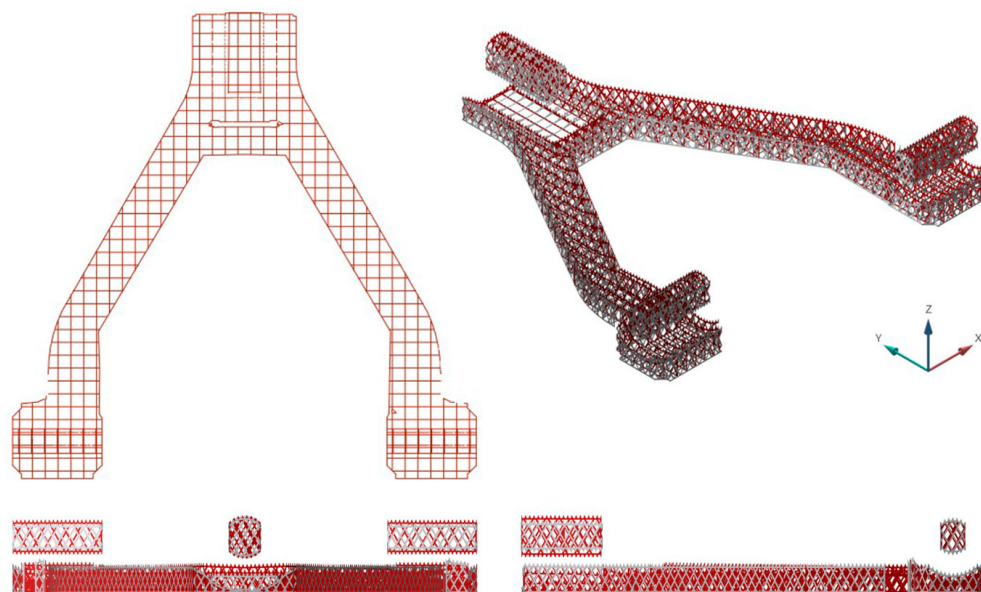


Figure 7. Support structures and building orientation.

3.2. Thermomechanical Process Simulation

The methodology for thermomechanical simulation of laser powder bed fusion requires a multi-scale and multi-disciplinary approach. The accuracy of numerical models depends on a precise definition of process parameters and material properties. The integration of simulation-based methods for process control and optimization forms the basis for methodological advances in this field. These methodological approaches enable L-PBF processes to become more predictable, repeatable, and optimized [30]. Additive manufacturing process simulation is performed by combining transient thermal and mechanical analyses. In this study, the ambient temperature was 24 °C and the preheat temperature was 150 °C. Thermal stresses were obtained as a function of time between the melting temperature of Ti64 material, 1605 °C, and room temperature, 24 °C. The thermal stress value induced on the surface by the melted material as a function of temperature was obtained from Equation (8) [31].

$$\sigma(T) = \sigma_0 + \frac{d\sigma}{dT}(T - T_L) \quad (8)$$

σ_0 : Surface tension at melting, T_L : Melting temperature, $\frac{d\sigma}{dT}$: Gradient of the surface tension.

An FEM-based computer-aided solution was used for thermomechanical process simulation. This solution utilizes the layer lumping method, which combines multiple powder layers into a single mesh element [32]. Because the mesh size significantly impacts the calculation time of a simulation, which typically lasts for hours, it is important to find the largest size that will not affect the results using mesh refinement. In preprocessing for this study, analyses were performed with lumped layers 10 and 20 times the powder layer thickness. Considering that both mesh sizes did not affect the results, the process was continued with a mesh size 20 times the powder layer. Since mechanical analyses will rely on the results from the transient thermal analysis, all the material's mechanical properties were added to the engineering database, covering the range from room temperature to the melting point, as shown in Figure 8 [33].

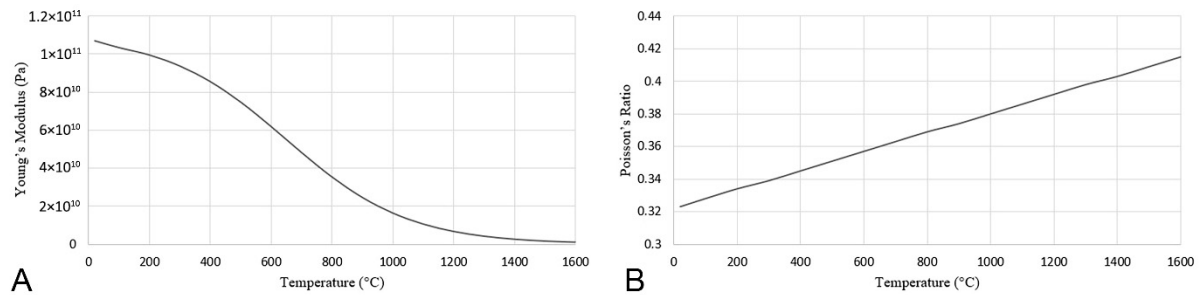


Figure 8. Thermomechanical properties of Ti64 Alloy ((A): Young's modulus, (B): Poisson's ratio).

The geometry, baseplate, and support structure with an STL file extension were successfully transferred to the application, as seen in Figure 9. The process parameters to be compared were determined to be layer thickness, hatch spacing and laser scanning speed, which we found to have the greatest impact on the results in the literature [34]. Three commonly used values were selected for these parameters as a result of the literature review [35–37]. To find the optimum values of these parameters, the Taguchi L9 design of experiment method was chosen. Input factors for the Taguchi are given in Table 3.

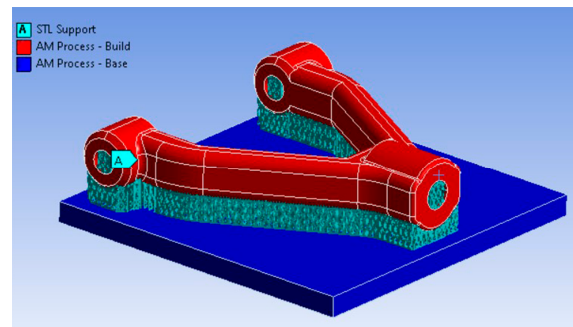


Figure 9. The printed model defined for process simulation.

Table 3. Input factors and levels for design of experiment.

Level	Layer Thickness (Micron)	Hatch Spacing (Micron)	Scanning Speed (mm/s)
Level 1	30	80	800
Level 2	40	100	1000
Level 3	50	120	1200

Making a production method more efficient is generally measured by producing more durable products in a shorter time. Simulations took into account build time, a key output in additive manufacturing. The production time also included the time required to cool the part to room temperature and separate it from the baseplate and supports. The time needed to print a part with SLM is calculated by adding the time spent on scanning and coating. Production time calculations are given in Equations (9)–(11). To observe the changes in results on a large scale, production times were measured in seconds [38]. Additionally, the total strain value was examined as a deformation-related result. The calculation of the total strain value is given in Equation (12). In some studies, only plastic strain was observed because the change in elastic and thermal strain values was negligible compared to the change in process parameters [39,40].

$$T_{\text{scanning}} = \frac{\text{Part Volume}}{LT \times HS \times SS} \quad (9)$$

$$T_{coating} = \frac{Part\ Height}{LT} \quad (10)$$

$$T_{total} = T_{scanning} + T_{coating} \quad (11)$$

$$\varepsilon_{total} = \varepsilon_e + \varepsilon_p + \varepsilon_{th} \quad (12)$$

4. Optimization of AM Parameters

Thermomechanical analysis results were analyzed using Taguchi's design of experiments. The L9 design for inputs consisting of three factors and three levels is presented in Table 4. Nine process simulations were performed based on this design, and the effects of process parameters on the results were examined. When analyzing production time and total strain results, the signal-to-noise (S/N) ratio was calculated using the smaller-is-better option. The S/N ratio is calculated using Equation (13). Here, n represents the number of experiments and y_i represents the resulting value [41].

$$\frac{S}{N} = -10 \times \log \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right) \quad (13)$$

Table 4. Process parameters and their responses of thermomechanical simulations.

Runs	Layer Thickness (Micron)	Hatch Spacing (Micron)	Scanning Speed (mm/s)
1	30	80	800
2	30	100	1000
3	30	120	1200
4	40	80	1000
5	40	100	1200
6	40	120	800
7	50	80	1200
8	50	100	800
9	50	120	1000

Analysis of variance (ANOVA) was performed at a 95% confidence level. Taguchi and ANOVA were used to specify the optimum process parameters and their contribution to the results [42]. Thus, as shown in Figure 10, it was observed that as layer thickness, hatch spacing, and scanning-speed values increased, both build time and total strain results were minimized. Layer thickness had the highest impact on build time, at 43.97%, while scanning speed had the lowest impact, at 26.54%. In terms of total strain, layer thickness had the least effect at 27.53%, while hatch spacing had the largest effect at 34.6%.

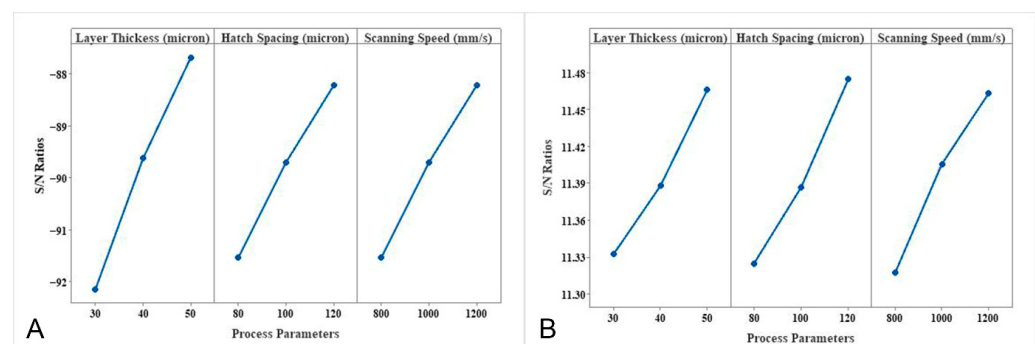


Figure 10. Signal to noise ratios versus process parameters ((A): Build Time, (B): Total Strain).

The study using Taguchi and ANOVA found that the best results occurred when the layer thickness, hatch spacing, and scanning speed, which were not part of the L9 design, were set to 50, 120, and 1200, respectively. When this setup was tested, the optimized design showed a build time of 16,833 s and a total strain of 0.25.

5. Discussion

Recently, there has been a significant increase in studies on the digital twin of additive manufacturing. These studies generally focused on monitoring the process in physics-based manufacturing, controlling data measured by sensors in a digital environment, or training a given manufacturing parameter with machine learning [43–45]. Thus, the literature in this field has mostly focused on identifying and solving a specific problem in the manufacturing process. This study, however, addressed all stages from the design for additive manufacturing to the final product under a digital-twin hierarchy for additive manufacturing. In this way, a model was developed that optimized the structural design, support structures, and manufacturing parameters of a product that was to be manufactured using metal additive manufacturing.

The implementation of design of experiments methodologies is essential for conducting experimental investigations more efficiently, yielding more productive results, and analyzing those data [46,47]. This study employed the Taguchi approach, which identifies optimal parameters with minimal experimental trials. Upon defining the factors and levels of the parameters for simulation-based thermomechanical tests, the sequence of operations was determined through the design of experiments methodology. Taguchi identified the optimal experimental combinations to figure out the optimal parameters [48]. Upon completion of the tests and subsequent analysis of the results, the optimal parameters were validated at a 95% confidence level utilizing ANOVA.

The literature on metal additive manufacturing generally encompasses experimental investigations, process monitoring assessments or optimization of process parameters. This work proposes a FEM-based digital-twin hierarchy that integrates the optimization of all processes and parameters. However, this model possesses some limitations. Although thermomechanical simulations yield significant insights into production time and structural performance, surface characteristics remain indeterminate due to the lack of prototype fabrication. Consequently, surface integrity and surface roughness, commonly addressed in metal additive manufacturing research, could not be incorporated in this study.

6. Conclusions

In this study, all procedures required for the production of an automotive component using additive manufacturing, starting with its design for traditional manufacturing, were carried out in the digital-twin system.

- From the three motion simulations (driving at a constant speed of 60 km/h, climbing a 30° ramp at a constant speed of 60 km/h, and braking to a stop from a speed of 60 km/h within 5 s), it was calculated that the highest force affected the lower wishbone during the ramp climbing motion.
- Optimization was performed for lower von Mises stress, higher natural frequencies, and a more fatigue-safe topology. The emerging part was revised to a smoother geometry, resulting in a 28.5% mass reduction.
- The production orientation and support structure generation were designed to minimize production time without negatively impacting post-production strength values. By setting the production orientation horizontally along the Z axis and using a 45° overhang angle, the minimum material quantity was achieved. This resulted in a support structure of 204,084 mm³.

- Process simulations in the framework of DOE were performed using an ANOVA with a 95% confidence level. Taguchi analysis revealed optimum parameters for layer thickness, hatch spacing, and scanning speed as 50 μm , 120 μm , and 1200 mm/s, respectively. The simulation using these parameters yielded a build time and total strain of 16,833 s and 0.25, respectively.
- In the parameter optimization, it was established that the maximum value for all factors produced better results. Nevertheless, employing values exceeding the current three levels could not be considered beneficial for enhancing the results. The parameters, comprising three elements and three levels, were carefully chosen from experimental studies to prevent defects like porous structures and poor surface properties.

Author Contributions: Conceptualization, H.B.; Methodology, H.B.; Software, H.B.; Validation, H.B.; Investigation, H.B.; Writing—original draft, H.B.; Writing—review and editing, C.Ö.; Visualization, H.B.; Supervision, C.Ö. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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