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A Frugal Approach Toward Modeling of Defects in Metal 3D Printing Through Statistical Methods in Finite Element Analysis

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Abstract: Metal additive manufacturing has emerged as a revolutionary technology for the fabrication of high-complexity components. However, this technique presents unique challenges related to the structural integrity and final strength of the parts produced due to inherent defects, such as porosity, cracks, and geometric deviations. These defects significantly impact the fatigue life of the material by acting as stress concentrators that accelerate failure under cyclic loading. On the one hand, this type of model is very complicated in its approach, since, even with encouraging results, the complexity of the calculation with these variables makes it difficult to obtain a simple result that allows for a generalized interpretation. On the other hand, using more familiar methods, it is possible to qualitatively guess the behavior that helps obtain results with better applicability, even at limited levels of precision. This paper presents a simplified finite element method combined with a statistical approach to model the presence of porosity in metal components produced by additive manufacturing. The proposed model considers a two-dimensional square plate subjected to tensile stress, with randomly introduced defects characterized by size, shape, and orientation. The percentage of porosity that affects each aspect determines the adjustment of the mechanical properties of finite elements. A series of simulations were performed to generate multiple models with random defect distributions to estimate maximum stress values. This approach demonstrates that complex models are not always necessary for a preliminary practical estimate of the effects of new manufacturing techniques. Furthermore, it demonstrates the potential for the extension of frugal computational techniques, which aim to minimize computational and experimental costs in the engineering field. The article discusses future research directions, particularly those related to potential business applications, including commercial uses. This follows a discussion of the existing limitations of this study.

Keywords: additive manufacturing; porosity; defects; finite element methods; fatigue life; frugal computational techniques

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1. Introduction

Additive metal manufacturing, also known as metal 3D printing, has emerged as a revolutionary technology for the manufacturing of highly complex components [1,2].

Although there is extensive literature on defects in additive metal manufacturing and their impact on fatigue [1,2], this study introduces a simplified and accessible methodology for statistically modeling porosity, combining frugal techniques with the finite element method. The innovative approach presented here addresses a critical gap by providing a cost-effective solution that reduces computational complexity and associated costs, making advanced simulation tools accessible to small and medium-sized enterprises. This enables the broader adoption and practical application of additive manufacturing technologies in diverse industrial contexts.

However, this technique presents unique challenges related to the structural integrity and ultimate strength of parts resulting from such printing operations. Often, additive manufacture of metals causes various defects, pores, cracks, phase segregation, and geometric deviations, due to factors such as rapid solidification, high local temperatures, and residual stresses in manufacturing [3,4]. These defects compromise structural integrity, generate stress points, and thus increase the fatigue of the material. Fatigue is a progressive failure process under cyclical loads, and defects act as initiation and propagation factors of cracks that accelerate component failure [5].

The significant impact of porosity on fatigue strength has historically led to its identification as one of the most common defects in additive metal manufacturing. The effect of porosity reduces the material's mechanical resistance, causing propagation cracks' starting points under cyclic loads. Porosity, number of defects, size, and shape depend on the material and manufacturing technique used. Porosity usually presents a statistical distribution that is difficult to control, since it is inherent in the printing process [6].

To predict the effect of porosities and defects, earlier works [7–12] have developed various numerical approaches to model the formation and propagation of defects, as well as to predict the fatigue life of components manufactured by additive manufacturing. This method allows for the study of the influence of different pore types and sizes on the structural response under cyclic load conditions, providing crucial information for the design and optimization of components. Because the models are complex, they often ignore the statistical distribution, instead focusing on a defect in the worst possible location. In addition to these calculations, enhanced learning processes and machine learning are used together with an experimental database to estimate fatigue life. Therefore, studies in this field are now focused on developing advanced numerical tools to understand and mitigate these effects to improve the quality and reliability of components manufactured using this innovative technology.

Excessive and often unavailable data, along with numerous uncertain assumptions, complicate models, consume time, require computation, and demand energy for both experimental data and the developed numerical models. These factors restrict the practical application of the models in terms of the number of feasible studies. Lately, in the calculations of quantum structures of a problem analogous to that posed here, many parameters are unknown, requiring many resources, both in calculation and computational time. Since this makes experiments difficult to carry out and even economically not always feasible, approximate methodologies, such as frugal techniques, have increased over the past few years, particularly after rising energy prices. These techniques reduce the calculation time and complexity of the experiment, thus minimizing the economic and environmental effects associated with the energy and environmental cost of the experiments and calculations. Not only does the error in these estimates not affect the result, but it also reduces the study's financial investment.

The development of frugal computational techniques, such as those proposed in the present study, will enable companies to implement advanced simulation and modeling solutions without incurring high computational or experimental costs. This point will be especially relevant for organizations interested in efficiently integrating additive manufacturing into the supply chain, thus balancing pragmatic innovation and economic viability [13]. Simplifying the complexity of defect modeling using the proposed techniques will help generate a competitive advantage. This strategic advantage will facilitate rapid adaptation to changes in market demand and allow for more flexible and custom production. It will be key in the decision-making of companies in this sector [11].

Therefore, the analysis aims to use well-established methods so that with simple calculations we can have preliminary results that do not allow qualitative results to decide whether it is cost-effective to carry out the product or to make more detailed calculations or studies. Thus, a preliminary result often matters only for the trend and realism presented. Although the error may be high and its comparison with experimental data or more elaborate models is only qualitative, this approximate method allows quick and cheap studies that justify its usefulness. It provides prior decisions before making complex calculations, experiments, or prototypes. A typical example is the idea of using thin-wall approximations in a pressure vessel to see if the model is needed or comparing data from a model of a thick-walled pressure vessel made into elements.

In addition to the technical challenges posed by metal additive manufacturing, it is crucial to consider the organizational impact that this technology has on enterprises. Transitioning to metal 3D printing production methods requires reconfiguring deep-rooted internal processes and adapting project management strategies [14]. These two elements require sufficient know-how among employees and the implementation of a rigorous quality control system. It sees additive manufacturing as a sort of new control system and, therefore, directly affects the operation of the supply chain. This will generate a learning curve that coexists with change management. Both will need to interact effectively to ensure that the introduction of this new technology improves efficiency and increases the quality of the final product [15,16].

From a business perspective, additive metal manufacturing can offer opportunities for mass customization [6]. This will help companies meet and improve their customers' specific needs. Therefore, the ability of organizations to manage the risks of manufacturing defects in this type of process will be a key element. A predictive model that anticipates and corrects these defects before they become apparent in the final products will undoubtedly make a key difference in competitive markets. Implementing frugal computational techniques, as explained in this paper, can help promote access to advanced simulation and modeling tools. Small and medium enterprises (SMEs) can compete in fair competition despite having fewer resources, thus fostering innovation and not relying solely on available resources.

Using these technologies to produce metal additives poses significant challenges and opportunities in the business and organizational context. It is essential to understand and properly manage the risks associated with implementing these technologies and their production process. The emerging literature on this field highlights the risks of this practice, and the ability to anticipate and mitigate defects through predictive modeling will help optimize operational efficiency and reduce costs. Therefore, the quality of the product will improve substantially and improve market competitiveness [12].

The main objective of this research is to develop and validate a simplified finite element method (FEM) model for statistical modeling of porosity in metallic components manufactured by additive manufacturing techniques. This research aims to analyze the statistical distribution of defects in metallic components manufactured by additive manufacturing (i.e., porosity). Therefore, this article not only contributes to the field of engineering and materials science but also provides valuable implications for business management and economics, specifically in sectors where the precision and reliability of products are a fundamental element. In the business field, this topic has contributed to a strategic tool that helps decision-makers reduce production costs and improve operational efficiency without compromising quality standards [8].

Therefore, the adoption of this approach can be decisive for organizations looking to lead in the era of advanced manufacturing with the best technologies and minimum errors. The two key pieces will be the ability to integrate technology effectively into their business models and the ability to predict and reduce defects. This will open the door for a larger number of industries to adopt these technologies, promoting diversification and competitiveness in the global marketplace. The intersection between advanced engineering and efficient business management will find the best opportunities for growth and differentiation in an industrialized, digitized, and constantly developing world.

The importance of additive manufacturing extends to several sectors. For example, in the aerospace industry, it is very important to minimize the carbon footprint, thus achieving ways for the fossil fuel economy. A major step towards this goal is that of aerodynamic optimization of the wing surface. In this regard, Karkoulias DG et al. [15] bet on an experimental procedure with 3D-printed wing models. Specifically, in terms of 3D printing for aerospace propulsion, there are expected advances in the use of other technologies, such as artificial intelligence (AI) or the Internet of Things (IoT) [16]. Similarly, in the automotive industry, there have been significant advances in additive manufacturing techniques to create deformable parts that absorb energy when impacts occur between vehicles since this would prevent damage to carried goods or individuals [17]. Another well-known industry that uses additive manufacturing is the railway industry, whose experimental case studies have been carried out to evaluate the vibrations induced by railway traffic through a model using the 3D finite element method [18].

To know what is achievable both in economic terms and in terms of know-how on the issue, therefore, it is very necessary to analyze the inherent risks and associated uncertainties to highlight the impact of 3D additive manufacturing on sustainability risk management and financial impact. However, the previous literature is scarce, leading the earlier study to imply a long-term perspective [19].

For some years now, many sectors have been implementing additive manufacturing practices, making it an extremely important field. Therefore, ideally, a system should be in place to evaluate the technical and economic feasibility, as well as the quality and risks faced by organizations. There have been attempts to shed some light on this issue by proposing a framework that establishes the essential steps, thus aiming to achieve a systematic implementation and validation of PBF-LB/M (powder metal fusion of additive manufacturing technology with a laser beam) in two structured phases [20]. They seek to monitor key performance indicators related to the process to ensure reliable product manufacturing and a structured system solution for holistic decision-making about technical and economic feasibility, as well as quality and risk-oriented process management.

This paper aims to apply a simple finite element model for designing an approach to studying material behavior through a two-dimensional domain that statistically incorporates defects without altering the mechanical properties of the relevant elements. This approach, along with some considerations of the fatigue life of the components involved, allows a first approximation of an estimate of the variation in the fatigue life of the material. To answer these issues raised by such an approach, this paper will address the following research questions:

- Is it possible to obtain a simple method to approximate the behavior of the process and control the loss of mechanical properties for design?
- How does the size affect the final strength?
- How does the distribution or density affect the final properties?

- What should be controlled in the process?

2. Background

2.1. Theoretical Framework

The dimensions, location, and configuration of defects in additive manufacturing depend on the specific material and fabrication process employed. A normal statistical distribution [9] is widely accepted to govern the size, shape, and direction of these defects. The fatigue life of the material depends on the aforementioned factors, with the position of the defect having the greatest influence [21–26]. The most critical defects to study to determine fatigue life are surface defects. The Kitagawa–Takahashi diagram, which relates the defect size to the expected maximum stress or fatigue life, is often used to consider the influence of pores (internal defects). The Murakami approach provides an approximation of the stress intensity factor based on the size of the pores. Fracture studies typically address internal gaps or cracks.

Many studies employ both experimental and numerical simulation techniques, using C-scan technology or direct observation of material sections. Furthermore, predictions are made using reinforcement learning techniques, such as machine learning or neural networks, based on the data obtained [27]. To include defects in numerical studies, it is often necessary to employ complex finite element meshes. However, an investigation confined to a single crystallographic or microscopic plane is insufficient to account for the statistical nature of the defect distribution. Consequently, more experiments and increasingly complex calculations that utilize advanced techniques, such as machine learning, are required. These methods require a substantial degree of mathematical expertise and resources that may restrict their applicability.

Due to the presence of pores, a finite element model with a high density of elements is required to accurately represent their probabilistic variability. Furthermore, many pores can cause intricate phenomena such as cracks, crack coalescence, and shielding between them. This makes the results more dependent on the defect configuration than on the precise size of each pore. This complexity requires the utilization of more intricate calculations or the compilation of extensive experimental databases.

A novel approach to programming and problem-solving has recently emerged. The term “Frugal” refers to a set of methods developed by Gutiérrez-Finol et al. [28]. These methods involve the use of streamlined models that require minimal computational time and resources, thereby facilitating the democratization of complex system calculations and reducing the need for extensive resources to achieve satisfactory results. This approach allows for the deferral of more complex and resource-intensive calculations to instances where they are indispensable. This study proposes a methodology to adhere to the frugal concept to approximate the effect of existing pores on fatigue resistance in additive manufacturing. Progress in the topic has increased so far by applying complex approaches to the modeling from experimental databases [21]. Despite growing interest in broadening the knowledge of such a critical matter in theoretical terms, earlier developments have not always proven to be useful in studying certain matters concerning the design of a particular part, as they are expensive or even difficult to carry out. The present study introduces an approach that, as can be seen from the comparison of experimental and numerical data with other articles, allows for the approximation of the effect of the presence of defects on the mechanical properties of the material but keeps it at a low difficulty level and without need for a long and expensive computation (i.e., according to the frugal approach).

2.2. Review of the Literature

Metal additive manufacturing has emerged as a revolutionary technology for fabricating complex components [29]. Figure 1 shows the main earlier works identified in the Web of Science (WoS) database since 2008. In particular, from 2017 onwards, related literature has increased to more than 35 publications per year.

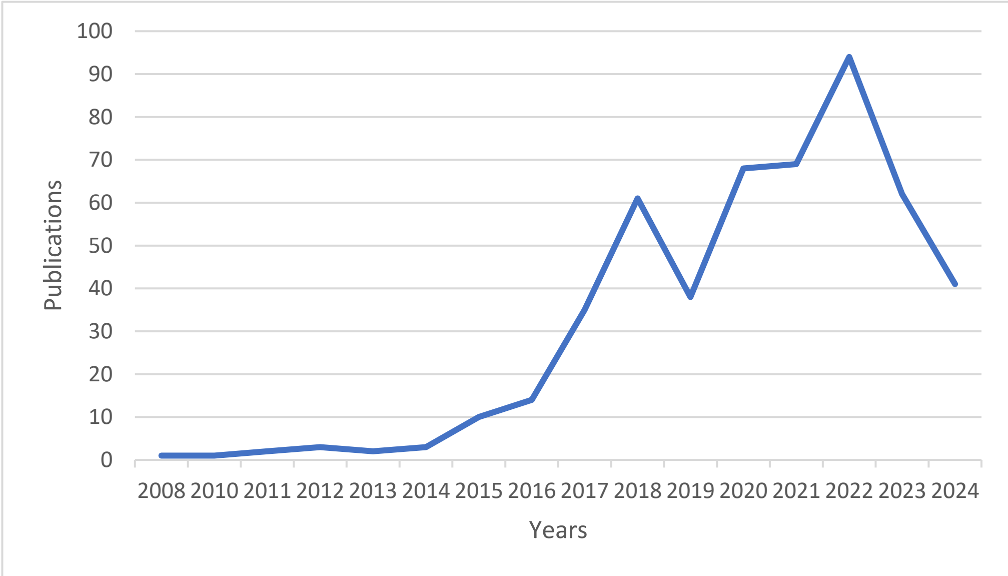

Figure 1. Overview of relevant scientific production focused on the research topic between 2008 and 2024 (as of 8 August 2024). Source: own elaboration based on data collected from WoS.

It is therefore an emerging field in which many questions arise that the literature must cover. In their research, Ren et al. [30] proposed a strategy focused on transforming the part model into the combinations of 2D layers subsequently deposited to use different fabrication methods, particularly those relating to a process planning for metal deposition of three main modules (spatial decomposition, part cutting, and tool path generation for each cutting layer). However, not only are such techniques noteworthy, but their further applications are also extraordinary, such as laser fusion, electron beam fusion, and laser metal deposition [31]. Furthermore, Saheli et al. [32] suggest additive metal manufacturing based on inkjet. Today, these techniques are continually being improved. In this regard, Kimme et al. [33] considered the use of induction melting with pulsed generator powers for additive manufacturing of metal structures. This is a new technique for this type of additive manufacturing. Furthermore, Bhat et al. [34] analyzed the issue by summarizing the results of related studies on metal–ceramic composites made by additive manufacturing. Despite several manufacturing processes identified in the research, the topic presents many problems ranging from the economic effects of frugal computational technique in minimizing computational and experimental cost and thus contributing to efficient 3D printing activities within the economically viable and competitive metals industry based on additive manufacturing [35]. Furthermore, the impact of defects on the compressive mechanical properties in additively manufactured lattice structures has been extensively analyzed in [27].

Moreover, Yue et al. [36] focus the study on hybrid metal–laser additive manufacturing, which includes: multi-process hybrid laser additive manufacturing, additive–hybrid manufacturing subtraction, multi-energy hybrid additive manufacturing, and multi-material hybrid additive manufacturing. This also brings the principles of laser additive manufacturing technology into the picture with the concept of hybrid manufacturing. This brings together several technological advantages. Some authors, such as Azam F.I et al. [37], noted that the additive manufacturing revolution has developed rapidly over the past 30 years. The addition of the term "metals" related to previous scientific production, as shown in Figure 1, clarifies that this is an emerging field with many questions on which future research should focus.

2.3. Conceptual Framework

The model is a 2D square plate subjected to lateral tension or compression, given by σ_0. The approximate percentage of porosity in the material, defined by parameters that characterize the porosity size, determines how random defects are introduced into the plate. Reducing the mechanical properties of an element by the same percentage as the area of the element affected by the pore represents porosity. A number N of models is created with randomly distributed pores, and the maximum stress value, σ_{max}, is extracted from each finite element model. This value is the maximum sigma in the model in any direction causing the maximum effect. The goal is to calculate the stress concentration factor, K, which is critical in fatigue life studies and is used, for example, by M. Seifi [38]. This is done by calculating as follows:

$$K_{med} = \left| \frac{\sigma_{max}^{mean}}{\sigma_0} \right| \tag{1}$$

$$K_{max} = \left| \frac{\sigma_{max}^{N}}{\sigma_0} \right| \tag{2}$$

where σ_{max}^{mean} and σ_{max}^{N} are the median and maximum values of σ_{max} from associated models. It is therefore necessary to consider, in addition to the nominal value of applied tension on the sides, σ_0, the existence of clusters of defects that cause early failure. Furthermore, K-related values divide the maximum stress, maximum strain, or fatigue life estimation of the material. This can be seen as a reasonable approximation for the issue considered. Similarly, on the one hand, the calculation of K_{med} provides an estimation of how defects will be affected in a generic statistical way. On the other hand, the calculation of K_{max} may include the effect of the existence of clusters. In any case, both are needed for preliminary study.

To study porosity, as shown in Figure 2, a reference model of $L \times L$ with regular 2D square finite elements and an element size of $h = \frac{L}{100}$ has been used. L is chosen such that the element size is of the order of the pore size, $\sqrt{\Omega} \approx h$, ensuring no gaps appear. The plate is subjected to lateral tension σ_0 and assumed to be in the elastic regime. The material selected is Ti-6Al-4V with a Young's modulus of 113 GPa and a Poisson's ratio of 0.3, to use the defect density per mm^2 and statistical data (mean and standard deviation) for the size, shape, and orientation of pores [39]. From these data, a function generates the dimensions and orientation of the defect, assuming a normal distribution.

Practically, the defect is considered an ellipse where the aspect ratio is given by the defect's shape factor ($0 < f < 1$), so $a = fb$, where a is the major axis and b is the minor axis, and the area is that of the pore. The Young's modulus of each element containing or affected by a pore is adjusted according to the ratio of the pore area affecting the element to the element area, reducing its mechanical properties proportionately (simplified to 10 values between 0% (element removal) and 100% of resistance (intact element), as shown in Figure 3). The pore shape differs from a square, so it can affect multiple elements. The element is therefore subdivided into smaller sub-elements with known areas, allowing numerical determination of whether they belong to the defined elliptical area of the pore. The number of subdivisions for each element is the square of the number of Young's modulus divisions; in this case, 10×10 regular sub-elements, as seen in Figure 4.

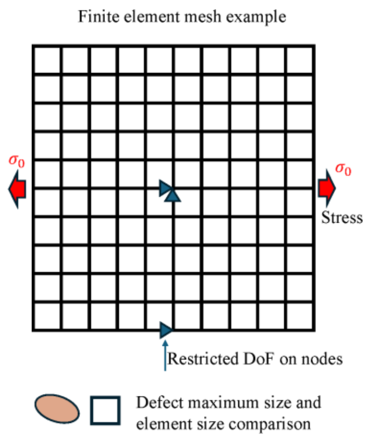

Figure 2. Diagram of the finite element model and its boundary conditions. Source: own calculation based on experimental results.

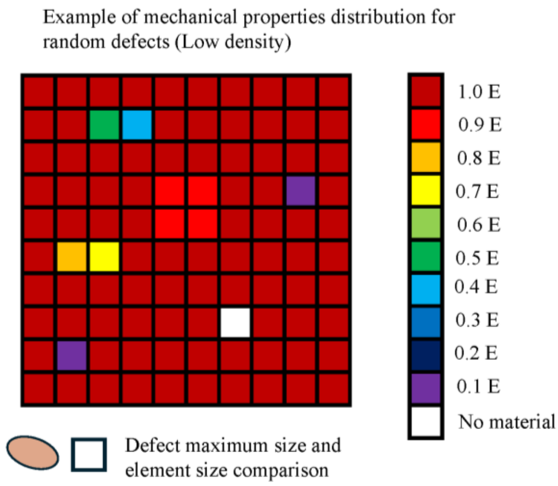

Figure 3. This figure shows an example of mechanical properties, where variations in mechanical properties correspond to the presence of defects. Source: own formulation according to the proposed research design.

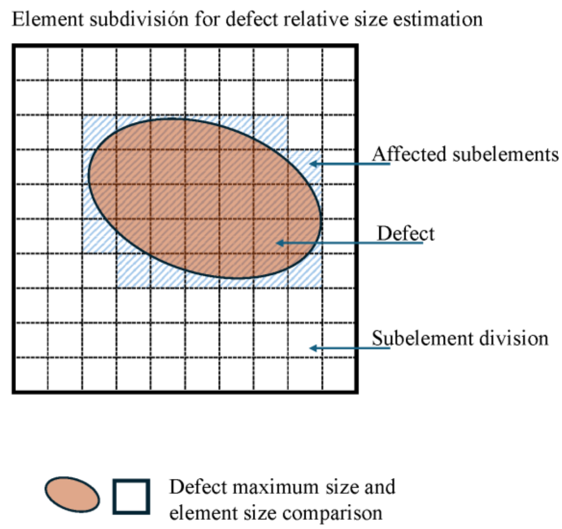

Figure 4. Example of an area comparison to obtain the final mechanical properties. The original properties are multiplied by affected sub-elements and divided by the total number of sub-elements (simplified in 10% range). Source: own formulation according to the proposed research design.

The study has been carried out using a software suite for finite element analysis (FEA) and computer-aided engineering, namely Abaqus [40], with linear quadrilateral plane stress elements to simulate the interior of the material. The von Mises-related stress field is shown in Figure 5. Because the statistical approach is not based on any real issue, it made little sense to perform a convergence study. The model must give an approximation to an unknown result, relying on the parameter variation of an approximation to the real microstructural behavior.

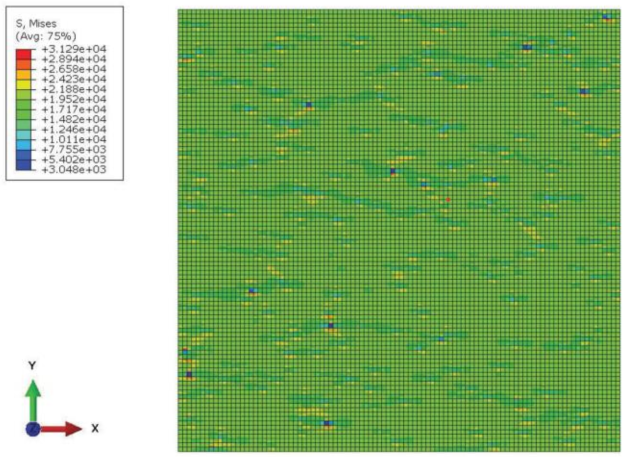

Figure 5. Detail of the von Mises stresses from a result with specific parameters (ξ = 11 mm^2, Ω = 250 µm^2, f = 0.7) under a mesh of 100 × 100 elements.

In the study, 25 simulations were carried out for each variation of the parameters considered to obtain a statistical approximation of the existing situation. This is an acceptable realistic model, which favors simplicity rather than precision. Through calculations on the model of Figure 5, it is possible to obtain a detailed approximation of the real case. This demonstrates the importance of frugal techniques, thus making a comprehensive approach for FEM-related calculations without modest resources at the computational level.

3. Research Methodology

The parameters of the model are $L = 20$ mm and element size $h = L/100$, so $h = 0.2$ mm. The Table 1 presents the model parameters that have been taken into account during this research project.

Table 1. Summary of parameters.

Parameters [1]	Mean	Standard Deviation
Defects ξ (mm^2)	10	n/a
Area Ω (µm^2)	770	250
Shape factor f	0.7	0.1
Orientation (degree)	0	15

[1] Source: own calculation according to Poudel [31].

The pores are defined by diameter D_q, where D_q can take values of 10, 20, 30, 40, 50, 60, 70, and 80 µm. The area Ω of each pore is calculated using the following relationship:

$$\Omega = \pi \left(\frac{D_q}{2} \right)^2$$

A normal distribution relative to the parameters in Table 1 has been used under a first hypothesis according to Poudel et al. [38].

The results obtained from this model can be compared with those of Akgun [41]. This modeling approach allows analysis of how different pore sizes affect the mechanical properties of the material, particularly in terms of stress concentration and fatigue life.

The main advantage is that no micromechanical modeling or special techniques are employed, only with an approximation for the mechanical properties based on the relative size between pores and elements, and with a probabilistic approach some insight of the final mechanical properties and expected problems can be gained. Therefore, it could be used as a first decision on which additive process and characteristics of the procedure (time, temperature, etc.) can be used for a specific goal.

4. Results

This section presents the findings of the numerical simulations. Figure 6 illustrates the maximum stress concentration factor (K_{max}) as a function of size defect Ω for the various pore concentrations ξ under consideration. The total area of the defect for all solid pores defines the defect concentration parameter. As illustrated in Figure 5, the maximum stress concentration factor increases with defect concentration, with this effect becoming more pronounced for a defect concentration of 70 mm^2, even at lower area values. Furthermore, an increase in the size defect only affects K_{max} when the defect concentration is 55 mm^2. No significant variation in K_{max} with area is observed for other defect concentrations. This analysis suggests that controlling defect concentration is a more critical factor than controlling defect size.

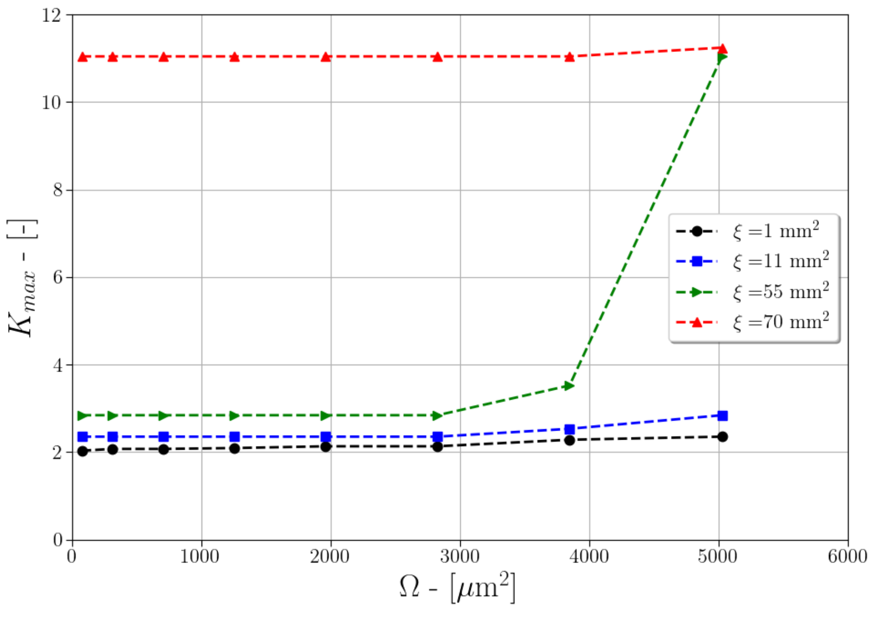

Figure 6. Maximum values of K for each Ω. Source: own calculation from study results.

Figure 7 shows the mean stress concentration factor (K_{mean}) as a function of area size for each pore concentration considered. It can be seen that as the defect size increases, K_{mean} also increases for all defect concentrations. However, there can be no guarantee that with smaller defect area values, K_{mean} shows minimal variation. This difference becomes more pronounced as the defect size area increases. Based on the mean stress concentration factor, it is more important to control the defect size than the defect concentration, at least for lower area values. Similarly, the results have compared behaviors by qualitative validating data for Akgun [41].

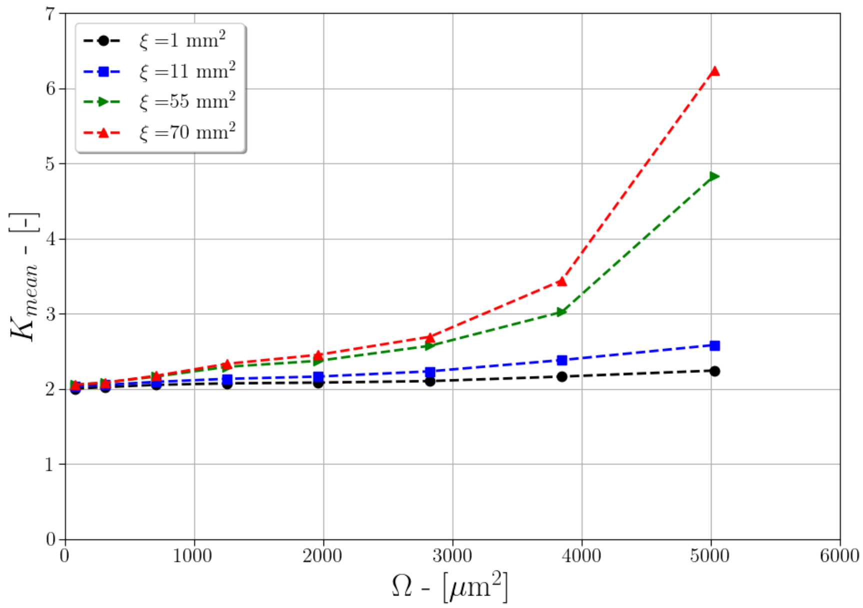

Figure 7. Mean values of K for each Ω. Source: own calculation from study results.

With all this, the enhancement of K_{max} and K_{mean} with rising porosity can be ascribed to the interplay among pores. In that regard, ref. [33] ascertained that defect interaction transpires exclusively when the separation between pores is less than their diameter, with the consequence becoming particularly pronounced when the separation is diminished to less than half a diameter.

5. Discussion

The results presented in the preceding section indicate a notable finding: Low defect concentrations, specifically at 11 mm^2, exert no significant impact on the maximum or mean stress concentration factor, regardless of the pore size. This observation remains valid as long as the pore sizes and concentrations remain within the typical ranges encountered in the additive manufacturing processes evaluated in this study.

This leads to a significant conclusion regarding the influence of pore characteristics on material performance: controlling pore concentration is more critical than managing pore size to maintain structural integrity. The data indicate that, at low pore concentrations, variations in pore size do not result in significant alterations to the stress concentration factor. Once the concentration of defects falls below a certain threshold, the effect of increasing the pore size on the stress concentration becomes inconsequential.

These findings highlight the importance of defect concentration management in manufacturing processes in optimizing the mechanical properties of the materials produced. By prioritizing the minimization of the number of defects in their dimensions, manufacturers can improve the overall reliability and performance of components produced through additive manufacturing techniques.

More research is required to gain a more complete understanding of the implications of varying pore concentrations and sizes across different materials and manufacturing processes. This could result in the development of improved defect control strategies, which in turn would facilitate the advancement of additive manufacturing technologies.

In summary, this article proposes a simple method to obtain an approximation of the behavior of the process analyzed in the study and to control the loss of mechanical properties applied in the design. Additionally, this method is used to evaluate how size affects ultimate strength. Similarly, it has been used to evaluate how the distribution or density affects the final properties. Therefore, the parameters that are necessary to control in order to control the density of defects in the process have been determined.

6. Conclusions

This study presents a simplified statistical model to analyze the effect of porosity on metallic components produced by additive manufacturing. The developed method employs finite element simulations to calculate stress concentration factors and evaluate the influence of defect distribution and size on mechanical behavior.

The methodology, based on a statistical approach and a simplified representation of defects, ensures sufficient accuracy for this investigation. The proportional adjustment of mechanical properties following the pore area and element size, coupled with qualitative validation against previous studies, ensures the reliability of the results. The findings indicate that the porosity concentration exerts a more pronounced influence on fatigue resistance than the size of individual defects, within the typical manufacturing ranges evaluated.

This approach is particularly well suited to industrial applications, as it balances precision and simplicity, thereby reducing the costs associated with computation and experimentation. The robustness of this approach provides an accessible tool for small and medium-sized companies, facilitating the design and optimization of additive manufacturing processes without the need for extensive resources.

It is also advised to extend the approach to three-dimensional components and integrate machine learning techniques to enhance the model's precision and versatility. Future research should investigate the applicability of this approach to other metallic materials and loading configurations to enhance their industrial impact.

Regarding specific commercial applications, especially focused on those sectors where this model could be most impactful, the proposed model offers a practical approach to incorporating defect tolerance criteria into the design of structural components. By considering the size and quantity of pores, it is possible to optimize material usage while maintaining structural integrity. This is particularly advantageous in metal additive manufacturing, where controlled porosity can serve as a design parameter to improve resource efficiency. Such applications provide a robust engineering framework to guide the production of components with tailored mechanical properties, balancing performance and economic considerations.

Finally, the corresponding research questions, which were introduced at the beginning of this paper, can be answered as follows:

- A simple method has been introduced to approximate process behavior and control the loss of mechanical properties for 3D-printing-related design.
- An evaluation of how size affects ultimate strength and how distribution or density affects the final properties regarding final density, which may affect the final properties in comparison with the defect size, has been completed.
- The control of density and defects and a comparison of the estimated importance of each one set the properties for controlling the additive manufacturing process.

7. Research Limitations and Future Directions

Primarily, the principal limitation of the proposed model is its reduction of a three-dimensional phenomenon to a two-dimensional framework. Although this approach is computationally efficient, it may introduce inaccuracies in capturing the complex interactions of real-world scenarios. It is recommended that future research be directed toward extending the model to three dimensions to enhance its accuracy, particularly in regions of stress concentration near boundaries and defects.

In addition, the model's application to materials such as ceramics, resins, and composites, and its performance under varied mechanical loading conditions, represents a valuable avenue for further exploration. Concerning the issue of defects in 3D printing, the findings could facilitate advances in metal additive manufacturing, particularly in the case of aluminum and titanium alloys, using technologies such as powder bed fusion and direct energy deposition.

One advantage of the method described above is modeling regions with different densities in the final prototype, thus statistically limiting the mean and maximum value of property loss. However, it should be borne in mind that this affordable method allows decisions to be made before the expensive experimental phase and even before a complex and costly calculation phase. In short, the technique is a deciding factor in determining whether it is worth taking the risk of undertaking the next phase (more expensive than the previous one).

Finally, the application of machine learning with the aim of error detection and sound-based analysis in 3D printing could provide new insights into the modeling of defects and the analysis of failure. In the future, efforts should be made to prioritize the development of affordable computational strategies to promote the reliability and efficiency of additive manufacturing processes.

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