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Evaluation of Topological Modification on Gear Wheel Bodies

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Abstract: Paper was devoted to introduction of various methods regarding the possibilities of optimization of gear wheel body shape. Evaluation was done by a finite element analysis, which gave a deformation results of a gearing, and also by comparison of weight loss. This optimization was performed by modeling 5 models of gear wheel bodies of which, one was reference one and other four had relieve elements modeled. Each model was compared to the reference one in first step by weight loss and deformation values. In the second step the analysis was conducted taking into account both evaluations, which result was a choice of best variant.

Keywords: Weight loss; deformation; topology; body shape; gearing; analysis

1. Introduction

Engineers and designers create and evaluate multiple design alternatives in order to find the most optimal solutions during the conceptual design phase of the product development process. All subsequent steps of product development, including areas such as manufacturing, production, testing, cost, and others, are heavily influenced by the procedures chosen and decisions made during this phase [1]. Anderson [2] claims that by the end of the design phase, up to 80% of a product's cost can be determined. As a result, multiple requirements must be considered during the design phase to avoid additional costs later in the development process.

Various design programs have been developed to support creativity, to enable faster production and testing of concepts, and to speed up the process. The development of intelligent design automation tools has been aided by technological advancements, particularly in computing power, machine learning, and related algorithms. Complex optimization calculations and iterations that were previously impossible to perform are now possible thanks to high-performance computing power available via the cloud. This allows designers to run complex simulations in a short period of time to test different product configurations in a wide range of conditions, providing valuable information for making the best design decisions possible. The fast development of additive manufacturing technology, on the other hand, is causing considerable changes in component production and design. They enable for the creation of complicated geometries that would otherwise be impossible to achieve using regular manufacturing processes [3]. Furthermore, new materials with improved characteristics and compatibility with modern production processes are being developed.

The use of CAD systems is increasingly being implemented into the design process, and this implementation is being bolstered by the systems' increasing scope and capabilities [4]. Users followed a traditional design workflow in which CAD programs were only used to implement design ideas, not to develop them, until the introduction of programs that can generate designs in CAD using algorithms. As a result of the aforementioned technological advancements, there was a surge in interest in digital

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design generation and optimization programs, which typically resulted in lightweight structures built as complex organic shapes. Engineers began developing CAD-based topology optimization (TO) programs capable of generating optimal designs for given structures. Such programs can modify existing designs, incorporate explicit features into the design, and create entirely new designs; however, this has primarily been appreciated by designers and engineers, rather than the wider field of product design [5]. The introduction of generative design (GD) programs in CAD software has recently solved this problem. The main goal of these programs is to encourage designers' creativity by generating a variety of design solutions.

2. Methods of design

The traditional design process begins with the development of functional specifications based on user requirements, which are then incorporated into the modeling phase. CAD systems are used to convert these into geometric shapes. CAD systems are primarily used to create a detailed 3D model of the final product as well as to generate precise engineering drawings. The three-dimensional models are then validated using analytical and testing functions in simulation programs, such as CAE (Computer Aided Engineering) and CAM (Computer Aided Manufacturing) programs, before being sent to production lines, such as machining centers, lathes, or milling machines, to produce the final product. On the one hand, the use of CAx (Computer Aided Technologies) systems [6] helps to support and simplify design, but on the other hand, such systems can limit designers' creativity [7]. This is due to the fact that modern CAD systems enable designers to create 3D models using parametric feature-based modeling, which was first introduced in the late 1980s. The ability to produce flexible designs defined by design variables and parametric nature was the technique's main advantage. CAD systems were enriched with additional modeling and specific functions over the years, and they were also integrated with CAE and CAM modules, allowing users to work in a single virtual environment. The CAE modules, in particular, enable finite element analysis (FEA/FEA), which solves structural analyses by defining geometry, boundary conditions, and initial conditions [8], while CAM evaluates production geometry created in the CAD environment. Code can be created and used in the CNC machine to create the product once the program and path have been chosen. The modeling procedure, on the other hand, has remained largely unchanged, and thus does not assist designers in creating complex geometry models [9].

The introduction of additive manufacturing (AM) has broken through the technological limitations of subtractive manufacturing, allowing designers to create shapes and geometries that were previously unachievable. Despite a growing knowledge of these possibilities, as previously stated, current CAD systems do not allow engineers and designers to fully utilize them. This is due to the fact that in order to create complex product geometry, designers and users must adapt features intended for traditional manufacturing methods. In fact, CAD systems use the same terminology as manufacturing and design systems to describe these functions. These functions are then applied to traditional manufacturing processes that have been developed to make the most of them. As a result, it is clear that using CAD functions for AM-oriented design is a time-consuming and labor-intensive process, the result of which is highly dependent on the users' individual skills and experience [10]. In this sense, it is fairly obvious that topological optimization and generative design programs could be an effective and useful tool not only for the analysis and optimization of geometric shapes, but also for assisting users in defining the shape of 3D models during the conceptual and modeling phases.

Unlike the traditional design process, which relies on CAD systems to generate precise geometry that adheres to the user's specifications, the introduction of TO and GD allows designers to concentrate on the function of the designed product rather than its appearance, with optimization programs generating design alternatives. The first stage is the same for both methods, and it requires the use of a CAD system, but only to define the functional surfaces. Furthermore, both methods share the final stage, which involves the use of CAM systems to ensure precision manufacturing. Unlike the CAM systems stated above, these AM-specific tools are designed to improve printing capabilities, optimize component orientation, number and type of supports, and, more recently, estimate part deformation due to the strong stress gradient formed during printing [11].

3. Topology

Topological optimization is a method for optimizing material distribution in a given space while taking load and boundary conditions into account. It's typically utilized during the early design phase to examine and evaluate a variety of design possibilities based on given characteristics like weight reduction, stiffness increase, stress reduction, strain reduction, and so on. [5]. Topology optimization applications are designed to make it easier for users to execute iterative design processes and multiple numerous variant analyses. They also encourage creativity, with the latter presenting answers that are typically overlooked. Along with shape and dimensional optimization, topology optimization is one of the three main categories of structural optimization. Shape optimization takes into account provided contour characteristics defined by node locations, while design requirements and objectives (e.g., stress reduction or fatigue life extension) must be assigned (Fig. 1). Dimensional optimization involves changing the values of design parameters linked to the cross-sectional areas of elements to find the best solution in terms of mass, stress, strain, and other factors. The latter is typically used to solve problems regarding beam structures, support bars.

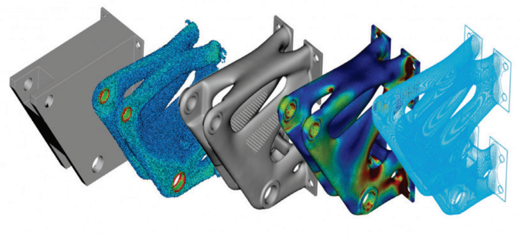


Figure 1: Example of topology optimization [12].

These methods, unlike topology optimization, do not allow the addition or removal of new elements or voids in the base structure, only the modification of parameter values [13]. Furthermore, shape and dimension optimization approaches necessitate the creation of an initial parametric model, whereas topology optimization just necessitates the creation of a defined initial volume. Many topology optimization methods are based on various algorithms, which can be either deterministic or stochastic. Due to the element of unpredictability, stochastic algorithms are more suitable for searching many solutions, making them more ideal for the conceptual phase [14]. For given design parameters, objective functions are commonly defined as minimization or maximization functions in algorithms. In the case of single objective optimization, every optimization method must have at least one explicit criterion describing the design process. Usually, the problem is defined by a combination of criteria. The criteria may be contradictory, resulting in a variety of solutions that satisfy the provided criteria in different ways, rather than a single best solution to the problem. Multi-objective optimization (MOO) is a technique for finding solutions when numerous criteria must be met. This technique is appropriate for application in design instances when there are often conflicting criteria. Reduce cost while increasing the factor of safety is a common example of conflicting criteria, which is usually accomplished by material selection, stiffness, and other features. The MOO's purpose is to seek for solutions that have the best trade-offs between all relevant criteria while concurrently including all criteria. These methods will, of course, enhance one or a few elements while deteriorating others. This isn't to say that the methods are useless [15].

3.1. Generative design

In the 1980s, generative design research began, but most of what was published at the time was entirely theoretical, with no examples of implementation. With the advancement of computers and technology, researchers started to look for ways to improve and enable generative design by utilizing these new tools. Initial interest was made in the subject of architecture [17], but shortly after, researchers began to look into possible opportunities and applications in other fields that could benefit from the combination of computing and evolutionary theory similarities. Vajna et al. [18] established autogenetic design theory in the field of design, where they looked at how the design process as part of the product development process and the natural process of evolution are similar. "In evolutionary terminology, the product development process may be defined as the ongoing optimization of a fundamental solution subject to initial conditions, boundary conditions, and restrictions," they wrote. These elements have an impact on the evolution of design as well as creating space for it. They can be expressed as orders, client requirements, spontaneous thoughts, recommendations, and so on, and they can be updated in a way that is similar to natural environmental changes. There is still no commonly acknowledged definition of generative design due to the wide range of applications. "Generative design systems are focused at generating new design processes that yield spatially innovative, yet efficient and buildable designs by using existing computational and manufacturing capabilities," Shea et al. [17] stated. 'Generative design is a design-driven, parametrically limited exploration approach that operates on parametric-based CAD systems structured to promote design as an emergent process,' according to Krish [19]. However, there are currently design applications that aren't limited by parametric models that go beyond the use of regular CAD programs [20, 21].

Multiple designs are developed using a method called generative design, which involves some automation and autonomy in the process. The design process uses nature's evolutionary approach, starting with one or more different designs and evolve over time into more appropriate forms for specific situations. Designs that do not fulfill the design criteria or do not fit the conditions are eliminated, and the search (evolution) process continues in different directions. Users could also be included in the process that allows them to intervene throughout the generation process. Users are involved in the process primarily to establish constraints and design parameters before generation starts, but customers could also be included to allow them to participate on the generation process. Despite the fact that generative design can only be done with a pen and paper and a set of rules, the concept is commonly used to refer to computationally assisted design. The created results can be in a variety of formats, including photos, models, sounds, and animations, and so this technology can be applied to a variety of fields, including architecture, design, art, music, fashion, and others. The use of algorithms as a basis for design creation is usually associated with generative design. In several commercial CAD tools for design, generative design programs have recently been introduced as stand-alone modules. Initially, generative design tools were based on topology optimization methods, notably the Log-structured merge (LSM) approach [16]. Since they operate with dynamic boundaries rather than local density variables, they can be network-independent [22], which means they have different design setup criteria than topology optimization. LSMs is known for its adaptability and ability to deal with complex topological changes (Figure 2).

Figure 2: Example of generative design optimization [23].

3.2. Topology optimization-based generative design

Design geometries (shape or size) are not used as design parameters in topology optimization. Essentially, it discretizes the entire design space and assigns the material density of each part within it. The density of the materials in the grid is then used to create a design space. This method can represent a variety of topologies and is used to discover the best design for a specific goal (typically compliance minimization) [24-26]. Topology optimization is a method for getting beyond the restrictions of parametric generative design, such as when geometrical parameterizations aren't enough to cover a wide design space.

Topology optimization and generative design are in a split in terms of design objective because the aforementioned is a design optimization method that focuses on a one specific best design, while the latter is a design exploration method that automatically generates a wide range of designs that satisfy user-defined design conditions [27].

Multiple local optima may exist for a same topology optimization problem (under the same force and boundary conditions). For example, depending on the starting design, the penalization factor, the type and parameters of the filtering mechanism, and the ending criteria, several optimal topology designs can be obtained (number of iterations). One can get a variety of results by changing these variables. The second method is to solve a multi-objective (disciplinary) optimization problem to discover a Pareto set. A Pareto set can be found, for example, by reducing compliance for two or more load situations [28]. Finally, designers might broaden the topology optimization problem's definition. According to Matejka et al. [29], generative design (topology optimization-based) alters problem defining variables, whereas parametric design varies geometry parameters directly. By altering force and boundary conditions, volume fraction, voxel size, materials, and manufacturing limitations, designers can establish numerous design problems. It is feasible to get as many designs as there are design problems in this method.

4. Application of modifications for structural optimization of spur gear wheel body

In practice, we often encounter geared gearboxes of larger dimensions. Here, particularly, the design optimization of the shape of the larger gear bodies plays an important role. There is an economic aspect, which concerns material savings, but mainly the design direction to design the lightest possible structure while maintaining maximum strength and reliability of the transmission.

4.1. Defining the geometric parameters of the spur gear

For a practical demonstration of the body shape optimization procedure, the following basic gearing parameters were designed: number of teeth z = 71, normalized modulus value m = 2.5 mm, pressure angle α = 20°, addendum coefficient: $h_a^* = 1$, clearance: $c_a^* = 0.25$ and gearing width coefficient Ψ=20. These parameters were based on the practical requirement to design a gear body shape that would keep the weight of the gear as low as possible while maintaining the strength of the gearing.

Other requirements were that the connection hole on the body should have a diameter of d_h = 55mm. The width of the gear hub had to be greater than the width of the gearing with a value of L = 60mm. Figure 3 shows the shape of the gear at maximum weight, i.e. the full shape of the gear body, which became the basis for comparison with the proposed design changes to the gear body. The deformation of the gearing, and therefore the strength of the gearing on such gear wheel, is greatest.

According to norm STN 01 4686, the minimum thickness of the web is defined to be at least 0.3 times the width of the gearing, i.e. in this case f = min 0.3b = min 0.3·50 = min 15mm. At the same time, the minimum value of the rim is defined to be at least 3.5 times the value of the modulus, i.e.

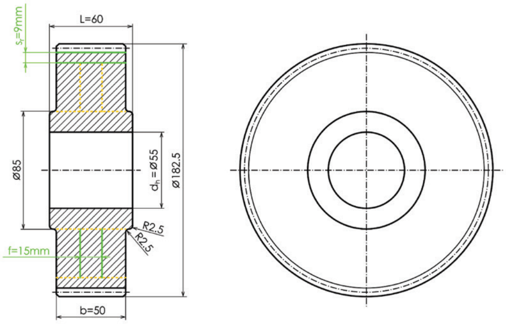


Figure 3: Full gear wheel shape with minimum of given parameters (MODEL 1).

s_R = min 3.5m = min 3.5·2.5 = 8.75mm, so the rim thickness value s_R = 9mm has been chosen. Body modifications i.e. optimization, was carried out in a way where the aim was to achieve the possible lowest weight for gear wheel while maintaining an adequate deformation values

The following gear wheel models were designed with the following body modifications - Figure 4. These modifications were based on the defined minimum thickness of the rim while maintaining the full width of the gear web (no modification of the web thickness).

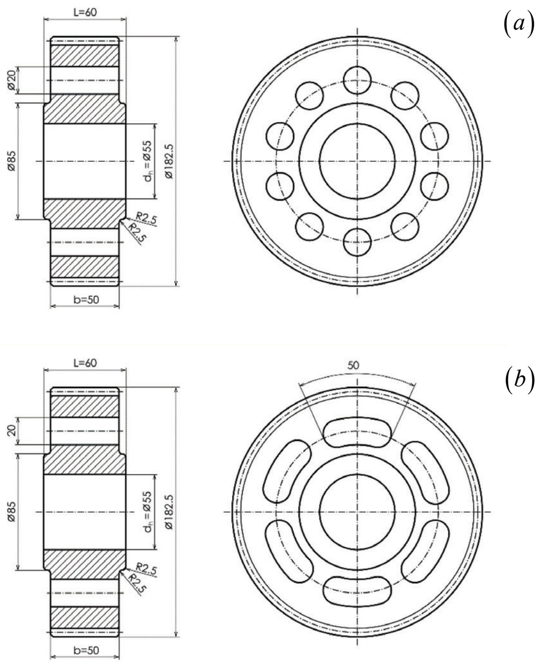


Figure 4: Optimization of the gear body by holes and grooves. a) MODEL2. b) – MODEL 3.

Figure 5 shows the proposed changes to the gear body with the modification - reducing the thickness of the web to the minimum possible value of f = 15 mm.

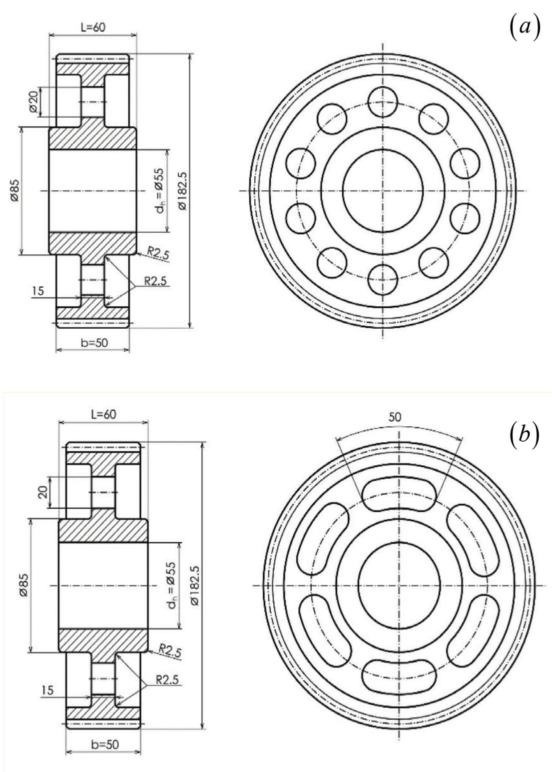


Figure 5: Optimization of the gear body by holes and grooves with reduced web thickness a) MODEL 4. b) – MODEL 5.

4.2. Gearing deformation

Plastic deformation occurs when a component is loaded with a force exceeding the yield strength, which causes permanent deformation of the shape even after the stress is relieved. Plastic deformation is very detrimental to gears because the position of the gearing changes during meshing, which affects the stress shared between the gearing. Tooth stiffness is a parameter which we understand as the force applied per width unit at which a deformation of 1 μm is produced. The meshing stiffness is a very important factor on which the sizes of the gearing modifications depend. If the variation of the stiffness during the meshing is minimal, the generation of noise and vibration is reduced. It is determined by calculation or experiment. The theoretical determination of the stiffness is quite difficult because of the complexity of the tooth shape.

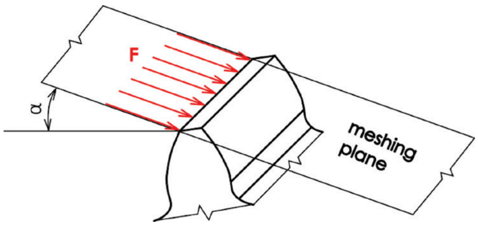


Figure 6: Expression of the width load by a single force.

In this case, the deformation was investigated when the force was applied to the gear head (Figure 6). If the meshing coefficient is a number greater than 1, the resultant force acting on the tooth flank Ftb varies during meshing, depending on the number of gear pairs meshed together. To investigate the issue of the effect of body shape on deformation, a more unfavorable loading method was considered, namely when only one pair of teeth is meshing.

To determine the deformation in the gearing, it is necessary to know the force ratios in the gearing. These were determined based on the power, angular velocity and dimensions of the gear wheel, where F = 5000 N. The analysis was done in Cosmos software. Mesh was different for gear body and gearing, where finer mesh was applied in the tooth area for more accurate deformation results. Such analyses were carried out by other papers. [30-32] Deformation results seen in fig. 7,8,9 are in a force direction.

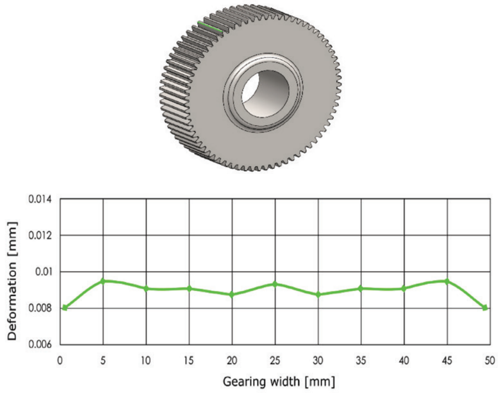


Figure 7: Deformation of the gearing along the width of the wheel of model No.1.

The deformation problem was solved using the finite element method. Figure 7 shows the deformation along the width of the gearing. The deformation along the tooth width is not constant. Since it is a full body gear wheel, its value is minimum with respect to other models.

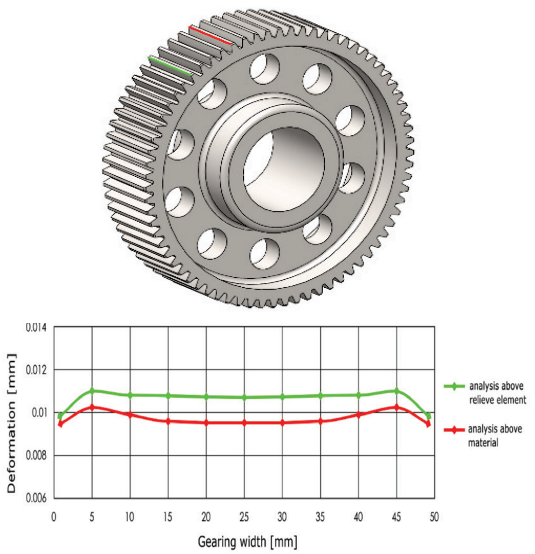


Figure 8: Deformation of the gearing along the width of the wheel of model No.4.

The gearing deformation on model 2 (Fig. 8) takes on different values depending on whether the tooth is located above or outside the relief hole. The deformation of the tooth above the hole is greater.

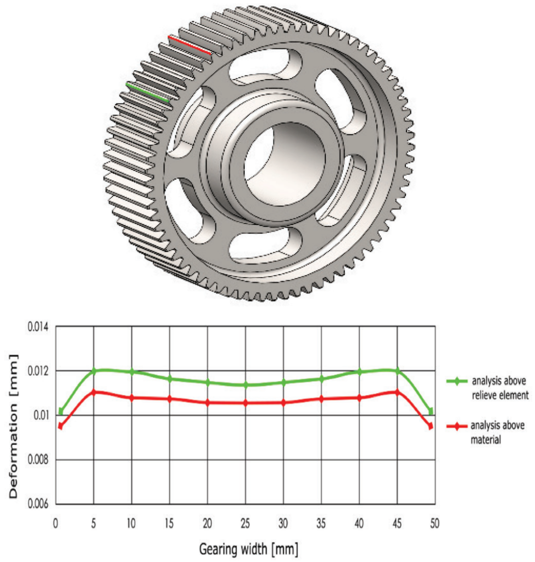


Figure 9: Deformation of the gearing along the width of the wheel of model No.5.

Figure 9 shows the deformation along the width of the gearing as solved in model 3. The tooth studied in the middle above the relief groove has the largest deformation.

The comparison of the deformation value on the gearing of each model is shown in Table 1. The deformation values measured in the middle of the gear width were processed into this table as well.

4.3. Analysis of the effect of body shape optimization on gear wheel weight

Gear wheel weight losses are presented in percentual form compared to the heaviest body type, which was the solid body type with a value of 8.929kg. For the first two modifications of wheel body the weight loss was 13.72% for full body with relieve holes, and 23.96% for full body with relieve grooves through whole material. These modifications resulted in the least significant changes made, where the best result for weight loss was only almost 25%.

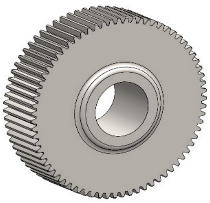
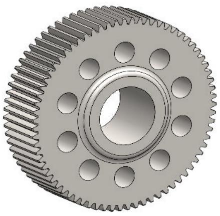
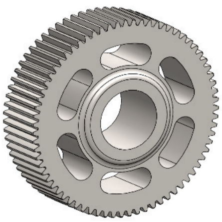
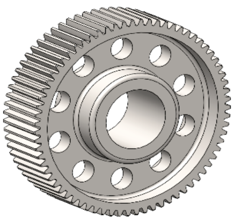
In the next step it was conducted that there needed to be a supplementary weight loss procedure in a form of circular grooves in a wheel body, where the web connecting gearing and hub will be left in a symmetric manner. Also, the relieve segments was kept. These two gear wheel bodies resulted in the best results weight loss wise. 47.15% weight loss was achieved for the body with relieve holes and for the body with relieve grooves the value was 50.22%. Results are much more satisfactory compared to the first two modifications. There can be also stated that weight losses were similar which makes it not possible to choose best optimum only from weight loss perspective. Therefore, another evaluation needs to be between the deformation values.

4.4. Analysis of the effect of body shape optimization on gear wheel deformation

The best deformation values comparison is the best to the value of solid body without any relieves, given the fact that this variant had the least deformed gearing. For the values analyzed above the material the variants with relieve holes performed the best, almost the same as solid body variant. The worst results were on variant 3 a 5, from which the variant 5 had the highest deformation value.

Comparing the results above relieve elements shoved that best variant was no.2 and the worst one was no5. The other two variants had the results almost identical located in a middle of a variant 2 and 5 range.

Table 1: Gear body optimization results.

Image of the model with label	*Total weight [kg]*	*Weight loss [%]*	*Deformation of the gearing in the middle of the width [mm]*	
			Above the hole	*Above the material*
Model 1 	8.929	-	-	0.00935
Model 2 	7.704	13.72	0.00986	0.00947
Model 3 	6.790	23.96	0.01085	0.01002
Model 4 	4.719	47.15	0.01079	0.00962
Model 5 	4.445	50.22	0.01157	0.01068

5. Conclusions

From the proposed models/variants, the best weight reduction was for variants 4 and 5. But variant 5 had the worst results of deformation among all of the proposed models. Variant 4 resulted in close weight reduction to the best variant out there and also good or mediocre results for gearing deformation. Although, models 2 and 3 had quite low deformation results (compared to the lowest value), the weight reduction was unsatisfactory. With these factors in mind the best performing optimization would be achieved with model 4, given the weight loss percentage and deformation values. Further optimization variants and evaluations accommodating software generation of body shapes will be done in following research, which will have a basis in this manuscript.

Topology optimization typically uses network-dependent optimization methods such as Solid Isotropic Material with Penalization method, which has been widely studied and modified to a level that provides useful optimal results, but the initial geometry required for the study limits the final shape of the generated designs. To solve this problem from the user's perspective, it is possible to set up the initial model as a very large design space, but this process can require considerable effort if there are multiple components with complex geometries around the target design part. Another disadvantage of this program is that it will only create one design per study.

On the other hand, generative design programs based on the level set method for optimization do not require a fully defined design space, which leaves more possibilities for design variation algorithms. However, setting up a study geometry for generative design would require users to adopt a different mindset and approach to design. Generative design programs are relatively new, and their algorithms still require further modifications to achieve quality results.

Currently, none of the programs take into account the cost of material and manufacturing process, which is one of the main concerns of designers, so its implementation should be considered in future versions of the programs. However, further research is needed to see how the implementation of these programs in the early stages would affect the work process of the current designer.

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