IMPLEMENTATION AND INTERPRETATION OF A SCRAP AND FAILURE ORIENTED MULTI-OBJECTIVE OPTIMIZATION CONSIDERING OPERATIONAL WEAR

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ABSTRACT

The tolerancing of products for manufacturing is usually performed at the end of the design process and the responsibility of the designer. Although components are commonly tolerated to ensure functionality, time-based influences, like wear, that occur during operation, are often neglected. This could result in small amounts of scrap after production, but high quantities of failure during operation. To overcome this issue, this paper presents an approach to perform a multi-objective optimization considering tolerances based on a wear simulation. Thereby, mean shifts serve as optimization variables, while the aim of the optimization is to generate an optimal ratio of scrap to failure. In addition, the optimization results are interpreted and further options for the designer are presented. Moreover, the approach is exemplary applied to a use case.

Keywords: Tolerance representation and management, Optimisation, Simulation, Scrap and failure, Operational wear

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1 INTRODUCTION

Today's product development is not limited to the nominal design of components. So, the specification of allowable limits of geometrical deviations also plays a decisive role (Walter et al., 2012). In addition to manufacturing and assembly induced deviations, these can also be influenced by operating conditions (Heling et al., 2017). These time-dependent deviations pose particular challenges to the designer, as they are difficult to identify and to consider in tolerance analysis (Walter and Wartzack, 2013). Contributions like (Bode et al., 2022) deal with the consideration of time-dependent deviations such as wear and show that the tolerancing has a major influence on scrap (after production) as well as on the amount of failure (during operation) due to the deviation depended wear behavior. However, in order to be able to support the designer in tolerancing, such approaches need to contribute to identifying optimal tolerance designs by minimizing scrap as well as failure. Moreover, a proper interpretation of the results is necessary for sufficient further decisions in tolerancing. Therefore, this paper will present a method for tolerance optimization by means of a shift of the dimensions' mean values (mean shift) with respect to scrap and failure considering wear. Subsequently an approach for interpretation of the resulting solutions and further options of action for the designer are outlined.

In the following the state of the art of tolerance management on the basis of time-variant mechanisms and optimization is presented in section 2. Then, the research gap and goal are explained in section 3, followed by the presentation of the new approach in section 4. This approach is exemplary applied on a one-way-clutch in section 5. The paper closes with a conclusion and an outlook in section 6.

2 STATE OF THE ART

This section describes the state of the art regarding time-dependent and operation-oriented tolerancing. Initially, subsection 2.1 presents research work considering wear in tolerancing and service life calculation. Subsequently, subsection 2.2 describes fundamentals of optimization and outlines methods for optimizing tolerances while taking wear effects during operation into account.

2.1 Tolerance management under wear consideration

Though tolerance analysis is subject of various studies and methods, operational influences such as temperature, deformation or wear are often neglected (Zeng et al., 2017). The following papers address this issue by including wear in particular in their calculations. Chou and Chang (2001) use a degradation factor for the consideration of operating influences, whereby a constant linear or quadratic change of the mean and the distribution of parameters is generated. However, the degradation process is only considered with linear or quadratic changes and does not take into account real wear phenomena. To partly overcome this drawback, Liu et al. (2020) present an approach considering quality-loss based on a characteristic wear progress during lifetime. Nevertheless, the influences of manufacturing induced tolerances on the wear behavior are not considered. Zeng et al. show a method modelling the deviations of an assembly over the lifetime of the product (Zeng et al., 2017; Zeng and Rao, 2019). It considers deformations as well as wear. For wear calculation the model of Archard (1953) and Holm (1967), called the Archard wear model, is used. Unlike in (Chou and Chang, 2001) and (Liu et al., 2020) the relevant load for the wear calculation is determined by an Finite-Element-Analysis (FEA) at the beginning of the operation, considering deviations due to manufacturing. Therefore, the wear is linear during operation without consideration of changes in wear behavior due to wear-induced geometrical changes. To overcome this shortcoming, Zhu et al. (2018) present a wear model taking dynamic wear changes into account. The calculation considers dynamic load distribution and time-varying stiffness, leading to a varying wear activity during the operation simulation. However, the approach focuses on reliability analysis and is limited to the application on spur gears. Therefore, Bode et al. (2022) demonstrate a generally applicable approach considering wear in tolerance analysis based on an iterative method for wear calculation. The aim is to model the ratio between scrap (after production) and failure (during operation). Multiple tolerance analyses are performed within this approach, making it possible to compare the amount of scrap at the end of production with the failure at any time step during operation. The failure determination requires further information related to the wear calculation, in addition to the initial distribution of the parameters. Relevant factors for the wear simulation are the operating time,

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the wear-rate, the load on the wear zone and the wear model. Of particular interest for scrap and failure estimation is the comparison of the tolerance analysis before operation and the one after, which is illustrated in Figure 1.

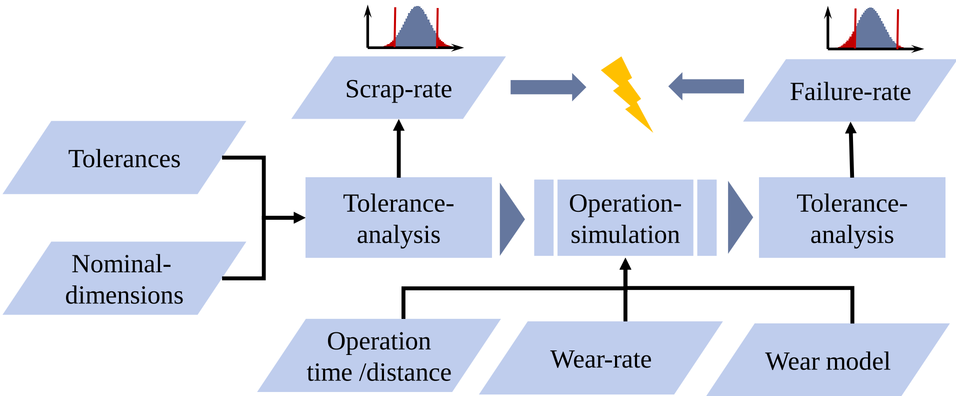

Figure 1. Approach of scrap and failure calculation according to Bode et al. (2022).

2.2 Operation-oriented tolerance optimization

The optimization of tolerances is subject of many publications and complex to implement due to its interdisciplinary nature (Hallmann et al., 2020). In most cases, an optimum should be found between the tightness of tolerances and the level of costs, where costs can refer to both, manufacturing costs and/or costs due to quality loss (Hallmann et al., 2020). Genetic algorithms (GA), belonging to the metaheuristic algorithms, are frequently used because of their problem independent manner (Hallmann et al., 2018). These are based on the generation of several individuals in a population, whereby the subsequent population is created under the influence of the best individuals of the previous generation (Konak et al., 2006). The multi-objective genetic algorithms (MOGA) represents a special form of GA. A solution is searched with several equally valid objective functions. Examples include the simultaneous optimization of decreased manufacturing costs and increased reliability. The result is described by a set of equivalent solutions, which can be represented in the form of a Pareto front. (Konak et al., 2006) The ideal solution of a MOGA would be to reach the minimum of all objectives. This point, which describes the intersection of the minima of both objective functions on the Pareto front, is called the utopia point (Halim et al., 2021). Another way of evaluating the Pareto front is the weighted sum method (Marler and Arora, 2010), where the different objective functions are weighted rather than treated equally.

Some papers deal with tolerance optimization under consideration of operational wear, whereby a cost reduction is usually the main objective or at least one of the objectives. The approaches can be classified according to their optimization variables. While Zhao et al. (2016) only use the tolerance limits as variables, Walter et al. (2015) and Zeng et al. (2022) additionally use mean shifts. Khodaygan (2019) optimizes with asymmetric tolerance zones, which implies tolerance limits and mean shifts. Besides the costs, some authors use additional objectives. Zeng et al. (2022) considers service-life in addition to costs, while Khodaygan (2019) uses quality-loss, manufacturing costs and process capability by means of a multi-objective optimization. All mentioned studies have the disadvantage of linear wear consideration only, with the exception of Walter et al. (2015) using literature data. Varying wear behavior due to wear-induced changing of geometries is not considered in any of them.

3 RESEARCH GAP AND GOAL

The tolerancing of parts, suitable for production and function, is the designer's area of responsibility. This step is usually scheduled at the end of the development prior to production and is often based on a scrap limit, mostly specified by the company. Thereby, the effects of selected tolerance limits on the failure, considering dynamic operational parameters (e.g. wear), are mostly neglected. Likewise operating influences are rarely considered in tolerance optimization, which then in turn are subject to the above-mentioned restrictions of linear or approximated wear consideration. The optimization variables

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usually include both, cost-neutral mean shifts of the nominal dimensions and changes to the tolerance limits with effect on the manufacturing costs. Especially costs related to the manufacturing process are often difficult to predict, caused by a lack of data on the one hand, but also by the large amount of different types of costs on the other hand (Hallmann et al., 2020). Optimizations carried out using cost-neutral variables do not require exact knowledge of the manufacturing process. Furthermore, instead of a pure consideration of manufactured product quality the actual amount and ratio of unusable parts, before (scrap) and during operation (failure) might be of interest. This can especially be important for designers with expensive products having high repair efforts when failing during operation. A simultaneous optimization of scrap and failure, taking into account deviation-dependent wear, that varies during operation, has not been presented yet. Additionally, when performing such an optimization, the utilization of the solutions by the designer must be clarified.
This results in the two following research questions. How can an optimization targeting scrap as well as failure by considering deviation-dependent wear be realized suitably? And how is it possible to process and present the solutions in such way that the information gained may serve as a basis for further decisions by the designer?
To answer the first question, this paper presents an approach performing a multi-objective optimization based on the wear simulation of Bode et al. (2022), with the objectives scrap and failure, using mean shifts optimization variables. Subsequently, to answer the second question, an approach is presented to process, analyze and enhance the optimization solutions in order to serve as a basis for further tolerance decisions by the designer.

4 IMPLEMENTATION AND INTERPRETATION OF A SCRAP AND FAILURE ORIENTED MULTI-OBJECTIVE OPTIMIZATION CONSIDERING OPERATIONAL WEAR

This section describes the approach resulting from the summarized findings in section 3. It is separated in two parts: The realization of the optimization in subsection 4.1 and the handling of the solution by the designer in subsection 4.2. The optimization generates a Pareto front of optimized relations between scrap and failure. The subsequent analysis provides the designer with principal solutions of the optimization and presents possibilities for the selection of a specific solution as well as potential and options for further improvement. This approach is shown in Figure 2. While the steps 1. to 4. concern the optimization realization, the steps 5. and 6. handle the analysis and further steps by the designer.

4.1 Realization of optimization with wear simulation

The process starts with the identification of the parameters influencing the wear or the Key Characteristic (KC), which is a geometrical parameter, representing the functionality of the product. Of particular relevance are parameters with influence on wear and KC simultaneously. The used term “parameter” refers to linear or angular dimensions of the individual parts or the assembly, since only these are implementable in the used wear simulation. For parameters influencing the wear, especially the ones affecting the normal force on the wear zone have to be determined. For a more detailed description of wear-affecting parameters, see the wear simulation method in (Bode et al., 2022).
Based on this selection, it is possible to define the optimization variables in the second step. In the determination of optimization variables ideally all parameters identified in the first step are implemented as variables in the optimization process. However, a prerequisite for the usability of a parameter is the feasibility of mean shifts on its nominal dimension. For example, this could exclude purchased parts, as it is difficult to influence their manufacturing and thus the mean shift. Additionally, often the set of parameters is too large for all of them to be used as optimization variables. This would lead to overly time consuming calculations. In that case, a sensitivity analysis can identify the most influential parameters. It is useful to limit the optimization range for the chosen variables for two reasons. On the one hand, the optimization time can be reduced. On the other hand, the mean shifts are part of a tolerance optimization different to a parameter optimization in the context of robust design (Heling et al., 2018). Therefore, the limits should be in the order of magnitude of the tolerance range of the parameters to prevent major influences on the overall system.
Prior to starting the optimization, the setting of simulation and optimization parameters is required. Referring to Bode et al. (2022), the wear model and the wear-rate are decisive parameters for wear

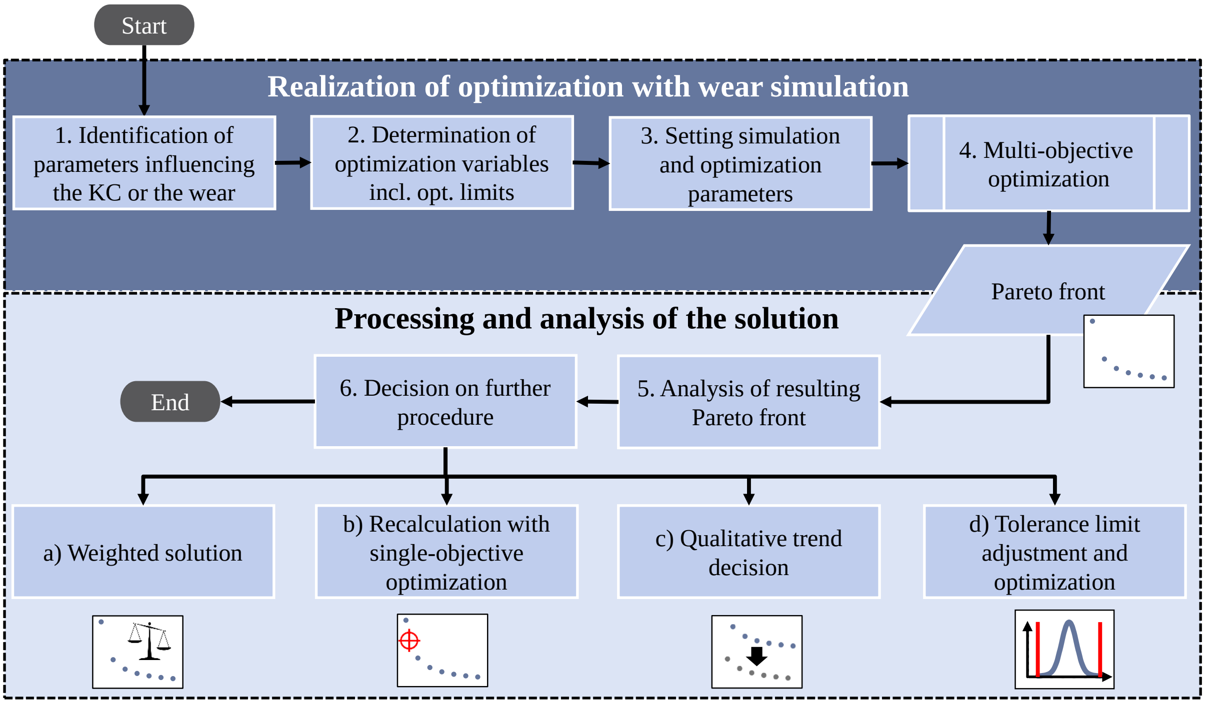

Figure 2. Step-by-step flow-chart of the presented approach.

simulation. When it comes to wear model, the approach according to Archard and Holm (Archard, 1953; Holm, 1967) has proven to be practical (Bode et al., 2022). The wear-rate depends on the application and lubrication. The optimization parameters of the MOGA may vary with the choice of the specific algorithm and therefore are not discussed in detail. However, the aim is to minimize the two objectives scrap and failure. For the specific implementation, see section 5.

Before performing the optimization, an addition to the sampling of the individuals is specified. The presented algorithm generates the deviation of a dimension by adding the scattering within the tolerance limits on the nominal measure (mean value) of the parameter. While the mean value is subject to optimization (mean shift), the scattering remains identical regardless of this mean shift. Since the wear simulation is based on sampling, the scatter would be recalculated for each sample. To avoid the influence of the repeated scattering, a Monte-Carlo Sampling (MCS) of the distribution is done once at the beginning for each optimization variable and then applied to all samples. The mutli-objective optimization results in a Pareto front. Figure 3 shows an example how such a front may progress.

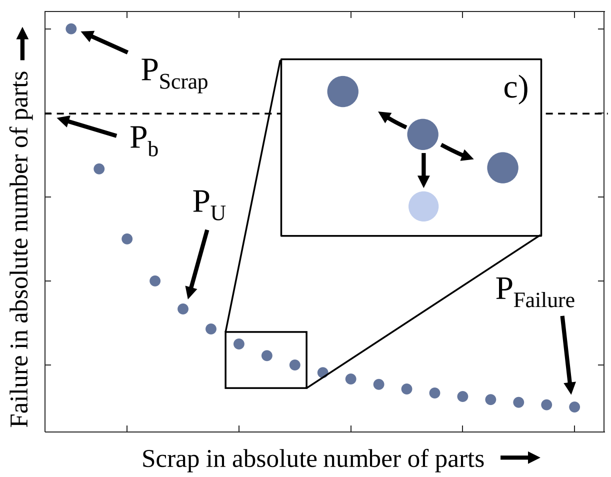

Figure 3. Exemplary progress of a Pareto front with different analysis points (P) and further options of action.

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4.2 Processing and analysis of the solution

This is where the second part of the approach starts, which concerns the handling of the solutions. Prior to making decisions on how to proceed, an analysis of the Pareto front is necessary. Therefore, the three points are calculated, defining the solution range: The point P_U, which is closest to the utopia point, and the minimum solutions of the two objective functions P_{Scrap}, $P_{Failure}$. All three points are marked in Figure 3 and frame the possible solutions for the objectives by providing an outline of the relation between the amount of scrap to the amount of failure. They allow the designer to have an initial estimation whether the solution space is within an acceptable range. For a more dedicated analysis, additional points may be determined. For example, it is possible to identify the point closest to the 3σ limit in terms of the amount of scrap (scrap < 0.27 % of all samples).

The final step, decision on further procedure, identifies possible alternatives for taking action. Four options have proven to be useful and are listed in Figure 2 from a) to d). If the designer is reasonably satisfied with the solutions of the optimization, there is the possibility of selecting a weighted solution, as pointed out in option a) in Figure 2. The weighting describes the ratio between the amount of scrap and the amount of failure. For example, a weighting of 1:1 would correspond to the point P_U. Thus, the corresponding mean shifts resulting in point P_U would be most suitable. However, it may happen that there is no suitable Pareto point for a specific amount of failure or scrap selected by the designer. This may occur because of the amount of individuals the optimizer creates per generation. Due to the limitation of individuals, only a selection of optimal Pareto points can be presented, although there may be many more. The designer has the possibility to perform a recalculation with the help of a single-objective optimization. It is assumed that the designer requires a solution near P_b in Figure 3. However, no suitable Pareto point exists in this area due to the finite number of individuals. To overcome this drawback, option b) describes a single objective optimization by defining the amount of failure by a constraint and using the scrap as objective only. Thus a point with the optimal scrap for a given failure in the area of P_b will be searched.

To obtain a basis for future decisions - option c) - the qualitative trend decision, enables the designer to qualitatively investigate adjustment options to the current solutions. The advantage of this option is the fast determination of the correlations between mean shifts and scrap/failure quantities in order to analyze future decisions for their impact on these. Two alternatives need to be classified: The displacement in the direction of the Pareto front and the displacement in the direction of the failure objective (see Figure 3). For the displacement in the direction of the Pareto front, the optimization variables of the starting point and the neighboring point are compared. The trend of the variables towards the nearest point becomes visible. This trend may serve as a support for future decisions as it helps to anticipate the behavior of the objectives due to variable changes. This option should be handled with care, as non-linear relationships can lead to non-intuitive shifts and the point may drift from the Pareto front and therefore is no optimal solution. A recalculation using the wear simulation is recommended. To shift the points in the direction of the failure, an adjustment of the wear-related parameters is necessary. This may be useful, if the failure on the global Pareto front appears to be too high in relation to the scrap. Possible points of action include a change in the wear-rate due to a modification of the lubrication or a load reduction on the wear zone, considering these are no tolerance management options, but interventions in operational behavior. Since the resulting points are not located on the original Pareto front, they might not be optimal solutions. Therefore, the described approaches in c) only serve as qualitative assistance for decision making. For optimal solutions, a re-optimization is inevitable.

Since the current approach only uses cost-neutral mean shifts as variables, the last option, the tolerance limit adjustment and optimization, includes the tolerance limits as optimization variables. It needs to be noted that changes in the tolerance limits could result in changing manufacturing costs. However, the cost-restriction by penalty functions is possible (Hallmann et al., 2020). The benefit of this option is the acquisition of further optimal solutions, although it requires a considerable amount of time.

5 APPLICATION

In the following, the approach described above will be applied to a one-way-clutch. This section is seperated in the realization of the optimization described in subsection 5.1 and the processing and analysis of the resulting solutions in subsection 5.2. The use case is described by Fortini (1967) and Chase

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et al. (1995). Its function is to allow rotation in one direction and block it in the other one. To fulfill this requirement the angle Θ, shown in Figure 4 on the left must not exceed 7.6° or undercut 6.4°.

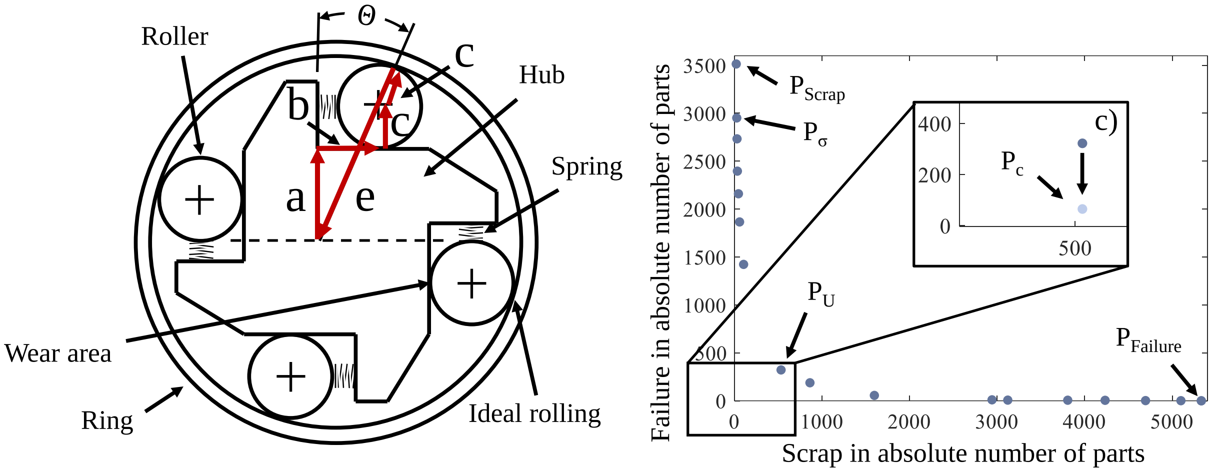

Figure 4. Left: Outline of a one-way-clutch with relevant dimensions as vectors according to Fortini (1967).; Right: Resulting Pareto front with different points.

Therefore, Θ is the KC of this application and depends on the hub height a, the roller radius c and the ring radius e, shown in Figure 4 on the left. This results in equation 1:

$$\Theta = \cos^{-1}\left(\frac{a+c}{e-c}\right). \tag{1}$$

5.1 Realization of optimization considering wear simulation

The first step in the method presented in section 4 is the identification of parameters influencing the KC or the wear. Referring to equation 1, a, c and e are the main KC-influencing factors. To determine the parameters influencing the force on the wear area, the location of this area has to be identified first. For simplification, it is assumed that wear occurs between hub and roller only, with ideal sliding between roller and ring (see Figure 4 on the left). The force on the wear area originates from the spring, whereby it is shown in (Bode et al., 2022) that the main influencing factors are likewise a, c and e. Thus, these three parameters are ideal optimization variables, which are to be defined in the second step. The optimization limits are set to 1 mm and frame the original nominal dimensions defined in (Chase et al., 1995). Table 1 shows the applied rigid tolerance limits of the optimization variables a, c and e obtained from (Chase et al., 1995) together with the distribution type and the optimization limits.

Table 1. Tolerance and optimization information of the dimensions.

Dimension	Tolerance in mm	Distribution	Tolerance range	Optimization limits in mm
a	±0.0125	normal	$\pm 3\sigma$	27.0 - 28.0
c	±0.01	normal	$\pm 3\sigma$	11.0 - 12.0
e	±0.044	normal	$\pm 3\sigma$	50.0 - 51.0

The simulation parameters to be defined in step three (see Figure 2) are adopted by (Bode et al., 2022). Thus, the maximum number of revolutions is 150e+6 and the wear-rate is 9.76e−11 $\frac{\text{mm}^3}{\text{Nmm}}$. The Archard wear model according to Archard (1953) and Holm (1967) has proven to be practicable as wear calculation method. Due to the high number of simulations that must be performed for such an optimization, the number of samples per individual of a generation is set to 10,000. Unlike to (Bode et al., 2022) the wear calculation is performed every 10,000 revolutions, which corresponds to 15,000 wear calculations of the specified amount of rotations. The optimization is performed with MATLAB®(R2021b). The maximum amount of generations is set to 200 and the function tolerance to 0.0001. For every other setting, the default settings of the function *gamultiobj* are applied. Additionally the $\cos^{-1}(x)$ used in

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equation 1 is only defined for $x \in [-1,1]$. From $a,c,e \geq 0$ and $e > c$ follows $\left(\frac{a+c}{e-c}\right) \in [0,1]$. In other words, the following linear constraint applies:

$$a + 2c - e \leq 0 \tag{2}$$

Subsequently the optimization is performed, which ends after 176 generations in this case due to no more significant changes between iterations. The result is a Pareto front shown in Figure 4 on the right and analyzed in the following section.

5.2 Processing and analysis of the solution

As described in section 4, the points P_U, P_{Scrap} and $P_{Failure}$, which frame the solution space and serve as orientation, are identified first. The amount of scrap and failure for these points is given in Table 2 together with the corresponding mean values of the optimization parameters. Additionally they are marked in Figure 4 on the right.

Table 2. Scrap, failure and mean values of a, c, e for different points.

Point	Scrap	Failure	a in mm	c in mm	e in mm
P_U	531	322	27.722	11.462	50.919
P_{Scrap}	19	3514	27.725	11.448	50.917
$P_{Failure}$	5332	0	27.713	11.484	50.925
$P_{3\sigma}$	25	2951	27.716	11.453	50.916
$P_{Initial}$	22	3507	27.645	11.430	50.800
P_c	531	56	27.722	11.462	50.919

Two findings can be derived from the table: The differences between the optimized mean values are relatively small, which indicates a high sensitivity of scrap and failures to the variables. In addition, it is apparent that failure during operation is avoidable at very high scrap counts, whereas even at high levels of failure, scrap cannot be prevented entirely, although the effect of the sample size should not be omitted.

The last step of the proposed approach in Figure 3 describes four options for further action, which are exemplary applied for this use case. The selection of a solution from the Pareto front with a certain weighting between scrap and failures, proposed in a) is possible. Potential selections include, for example point P_U with a 1:1 weighting. Besides, the 3σ limit for scrap can be interesting for the designer. The corresponding data for such point $P_{3\sigma}$ with scrap $\leq (3\sigma = 27$ parts) is presented in Table 2 and marked in Figure 4 right. This point is especially interesting in comparison with the scrap and failure results of the initial variable values according to Chase et al. (1995) (see $P_{Initial}$ in Table 2). It becomes evident that the mean shift led to a minimal increase in the amount of scrap but a significant decrease in the amount of failure.

Although the Pareto front exhibits omissions in some areas, in this example a single-objective optimization as provided in option b) is refrained. Due to the very small differences between the mean values of the Pareto points, very small and hardly manufacturable changes in the mean values are to be expected in the solution of such an optimization. For the same reason, the displacement in direction of the Pareto front, as suggested in option c) is not recommended. However a displacement in the direction of failure by adapting the wear parameters may be beneficial. For example, adjusting the sliding characteristics by changing the lubrication can result in an improvement of the failure quantity. For this use case, the wear-rate is reduced from $9.76e{-}11\ \frac{mm^3}{Nmm}$ to $8.4e{-}11\ \frac{mm^3}{Nmm}$ and recalculated for P_U. The values for the wear-rate usually have to be experimentally determined and are therefore just based on assumptions in this case. The higher value is adopted from (Bode et al., 2022), while the lower one is chosen to show a difference on the amount of failure. The result is displayed in Figure 4 right. The corresponding data are described in Table 2 (see P_c). A decrease in failure is clearly visible, although it is important to note that, for one thing, this is an intervention in the wear behavior and, for another, no longer an optimum. However, an estimation of the behavior of failure due to different lubrication by the designer is certainly possible. Alternatively, a different spring could have been installed in this case, thus changing the load on the wear area. Option d) describes the extension of the optimization variables by the tolerance limits

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of the parameters presented above. The implementation is possible for the use case, but would exceed the scope of this paper by re-optimizing and repeated evaluation of the resulting Pareto front and is therefore omitted.

5.3 Discussion

The exemplary application of the approach initially shows the feasibility of an operation-oriented tolerance optimization using mean shifts and taking tolerance-induced wear behavior into account. Subsequently, relevant points on the resulting Pareto front could be identified and especially a comparison of P_{σ} and $P_{Initial}$ showed a significant improvement with respect to the initial values. In a further step, selected options for action were successfully applied iteratively. In the future, these may contribute to a better understanding of the relationship between mean shifts, scrap and failure by the designer. However, due to the small shifts of the variables between the Pareto points, not all options for action could be applied and the realization of these mean shifts in production is questionable. In addition, the wear simulation is based on information such as the wear-rate, which can usually only be determined on the basis of experiments.

6 CONCLUSION AND OUTLOOK

The proposed approach enables a multi-objective optimization by dimensional mean shifts with focus on scrap and failure. Moreover, the approach allows the designer to analyze the resulting Pareto front in order to identify suitable solutions to use it as a basis for further options of action presented in the last step of the method. It was exemplary demonstrated on a one-way-clutch. This new approach enables the designer to deal with the trade-off between scrap and failure, taking into account operational tolerance-influenced wear.

In future research, this approach could be integrated into a process-oriented method, where production parameters are directly assigned instead of tolerances and mean shifts. This will enable a more feasible implementation.

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REFERENCES

Archard, J.F. (1953), "Contact and rubbing of flat surfaces", *Journal of Applied Physics*, Vol. 24 No. 8, pp. 981–988, http://doi.org/10.1063/1.1721448.

Bode, C., Schleich, B. and Wartzack, S. (2022), "Consideration of operational wear in tolerance analysis for process-oriented tolerancing", *Procedia CIRP*, Vol. 114, pp. 177–182, http://doi.org/10.1016/j.procir.2022.10.024.

Chase, K.W., Gao, J. and Magleby, S. (1995), "General 2-d tolerance analysis of mechanical assemblies with small kinematic adjustments", *Journal of Design and Manufacturing*, Vol. 5, pp. 263–274.

Chou, C.Y. and Chang, C.L. (2001), "Minimum-loss assembly tolerance allocation by considering product degradation and time value of money", *The International Journal of Advanced Manufacturing Technology*, Vol. 17 No. 2, pp. 139–146, http://doi.org/10.1007/s001700170202.

Fortini, E. (1967), *Dimensioning for interchangeable manufacture*, Industrial Press, New York.

Halim, A.H., Ismail, I. and Das, S. (2021), "Performance assessment of the metaheuristic optimization algorithms: an exhaustive review", *Artificial Intelligence Review*, Vol. 54 No. 3, pp. 2323–2409, http://doi.org/10.1007/s10462-020-09906-6.

Hallmann, M., Schleich, B., Heling, B., Aschenbrenner, A. and Wartzack, S. (2018), "Comparison of different methods for scrap rate estimation in sampling-based tolerance-cost-optimization", *Procedia CIRP*, Vol. 75, pp. 51–56, http://doi.org/10.1016/j.procir.2018.01.005.

Hallmann, M., Schleich, B. and Wartzack, S. (2020), "From tolerance allocation to tolerance-cost optimization: a comprehensive literature review", *The International Journal of Advanced Manufacturing Technology*, Vol. 107 No. 11-12, pp. 4859–4912, http://doi.org/10.1007/s00170-020-05254-5.

Heling, B., Hallmann, M. and Wartzack, S. (2017), "Hybrid tolerance representation of systems in motion", *Procedia CIRP*, Vol. 60, pp. 50–55, http://doi.org/10.1016/j.procir.2017.02.048.

Heling, B., Schleich, B. and Wartzack, S. (2018), "Robust-design-optimization of mechanisms based on kinematic requirements considering uncertainties", *Procedia CIRP*, Vol. 75, pp. 27–32, http://doi.org/10.1016/j.procir.2018.04.048.

Holm, R. (1967), *Electric Contacts: Theory and Application*, Springer, Berlin and Heidelberg, fourth completely rewritten edition edition, http://doi.org/10.1007/978-3-662-06688-1.

Khodaygan, S. (2019), "A multiple objective framework for optimal asymmetric tolerance synthesis of mechanical assemblies with degrading components", *The International Journal of Advanced Manufacturing Technology*, Vol. 100 No. 9-12, pp. 2177–2205, http://doi.org/10.1007/s00170-018-2658-6.

Konak, A., Coit, D.W. and Smith, A.E. (2006), "Multi-objective optimization using genetic algorithms: A tutorial", *Reliability Engineering & System Safety*, Vol. 91 No. 9, pp. 992–1007, http://doi.org/10.1016/j.ress.2005.11.018.

Liu, X., Mao, K., Wang, X., Wang, X. and Wang, Y. (2020), "A modified quality loss model of service life prediction for products via wear regularity", *Reliability Engineering & System Safety*, Vol. 204, p. 107187, http://doi.org/10.1016/j.ress.2020.107187.

Marler, R.T. and Arora, J.S. (2010), "The weighted sum method for multi-objective optimization: new insights", *Structural and Multidisciplinary Optimization*, Vol. 41 No. 6, pp. 853–862, http://doi.org/10.1007/s00158-009-0460-7.

Walter, M., Spruegel, S. and Wartzack, S. (2012), "Tolerance analysis of mechanism taking into account the interactions between deviations using meta-models", in: *Proceedings of NordDesign 2012, the 9th NordDesign conference*, DS / Design Society.

Walter, M., Spruegel, T. and Wartzack, S. (2015), "Least cost tolerance allocation for systems with time-variant deviations", *Procedia CIRP*, Vol. 27, pp. 1–9, http://doi.org/10.1016/j.procir.2015.04.035.

Walter, M. and Wartzack, S. (2013), "Statistical tolerance-cost-optimization of systems in motion taking into account different kinds of deviations", in: M. Abramovici and R. Stark (Editors), *Smart Product Engineering*, Lecture Notes in Production Engineering, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 705–714, http://doi.org/10.1007/978-3-642-30817-8{_}69.

Zeng, W. and Rao, Y. (2019), "Modeling of assembly deviation with considering the actual working conditions", *International Journal of Precision Engineering and Manufacturing*, Vol. 20 No. 5, pp. 791–803, http://doi.org/10.1007/s12541-019-00014-2.

Zeng, W., Rao, Y., Long, C. and Wang, P. (2017), "Prediction of service life for assembly with time-variant deviation", *IOP Conference Series: Materials Science and Engineering*, Vol. 212, http://doi.org/10.1088/1757-899X/212/1/012021.

Zeng, W., Yi, J., Lin, R. and Lu, W. (2022), "Statistical tolerance–cost–service life optimization of blade bearing of controllable pitch propeller considering the marine environment conditions through meta-heuristic algorithm", *Journal of Computational Design and Engineering*, Vol. 9 No. 2, pp. 689–705, http://doi.org/10.1093/jcde/qwac023.

Zhao, Y.M., Liu, D.S. and Wen, Z.J. (2016), "Optimal tolerance design of product based on service quality loss", *The International Journal of Advanced Manufacturing Technology*, Vol. 82 No. 9-12, pp. 1715–1724, http://doi.org/10.1007/s00170-015-7480-9.

Zhu, L., Zhang, Y., Zhang, R. and Zhang, P. (2018), "Time-dependent reliability of spur gear system based on gradually wear process", *Eksploatacja i Niezawodnosc - Maintenance and Reliability*, Vol. 20 No. 2, pp. 207–218, http://doi.org/10.17531/ein.2018.2.05.