EXPLORING THE POTENTIAL FOR A FEA-BASED DESIGN OF EXPERIMENTS TO DEVELOP DESIGN TOOLS FOR BULK-METAL JOINING PROCESSES

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ABSTRACT

Over the last 20 years, finite element analysis (FEA) has become a standard analysis tool for metal joining processes. When FEA tools are combined with design of experiments (DOE) methodologies, academic research has shown the potential for virtual DOE to allow for the rapid analysis of manufacturing parameters and their influence on final formed products. However, within the domain of bulk-metal joining, FEA tools are rarely used in industrial applications and limit DOE trails to physical testing which are therefore constrained by financial costs and time.

This research explores the suitability of an FEA-based DOE to predict the complex behaviour during bulk-metal joining processes through a case study on the staking of spherical bearings. For the two DOE outputs of pushout strength and post-stake torque, the FEA-based DOE error did not exceed ±1.2% and ± 1.5 Nm respectively which far surpasses what was previously capable from analytically derived closed-form solutions. The outcomes of this case study demonstration the potential for FEA-based DOE to provide an inexpensive, methodical, and scalable solution for modelling bulk-metal joining process

Keywords: Simulation, Computational design methods, Case study, Optimisation

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1 INTRODUCTION

Bulk-metal forming is a key technology for a broad range of industrial products that combine high material utilisation with low cost and energy requirements at a mass production scale. Groche et al. (2014) and Mori et al. (2013) present a comprehensive review of metal forming operations and the current state of the art. In the development of new products, the trend towards lightweight designs and assemblies is perpetual and requires an ever-increasing need for design optimisation and a deeper understanding of the relationships between the properties and characteristics of the artefact and that of the manufacturing process (Hicks and Matthews, 2010). Robust design (RD), also referred to as Design of Experiments method (DOE), is a systematic and efficient method that aims to study the relationship between multiple input and output variables (Taguchi, Chowdhury and Wu, 2007) instead of relying on the costly use of design margins and overengineering or excessive quality control (Eckert, Isaksson and Earl, 2019). The aim is to choose the optimal value for each input parameter to achieve the desired response despite the potential variation in manufacturing conditions, loads or part tolerances. In general, DOE is a well-researched field, and its fundamental ideas are widely accepted among researchers (Sarema, et al., 2022; Joseph et al., 2019; Oudjene and Ben-Ayed, 2008; Lehman, Santner, and Notz, 2004; Jin, Chen, and Sudjianto, 2003). When paired with commercially available Finite Element Analysis (FEA) software, a virtual DOE can be undertaken that can achieve a higher level of verification and eliminate experimental effort and cost (Kim, 2010; Al-Momani and Rawabdeh, 2008). Despite these opportunities, there remains a gap in most engineering industries when it comes to the application of virtual DOE to evaluate the effect of geometrical, material and load variations (Nerenst et al., 2021; Will, 2015; Coleman, 2012). For the case of designing bulk-metal joining processes, the implementation of FEA has been largely limited to a case-by-case basis and is often left late in the development process. This can lead to large safety factors or overly optimistic designs that are susceptible to failure due to variations in load conditions or manufacturing tolerances. The investigation presented in this paper explores the suitability of an FEA-based DOE to predict the complex behaviour during bulk-metal joining processes with the aim of producing simple and effective design tools. This takes the form of a case study whereby a FEA-based DOE is carried out on the staking of spherical bearings, specifically, the modelling of the joint strength and the change in post-stake torque.

1.1 Spherical bearing staking

Staking, commonly referred to as upsetting or open die forging, is a cold forming process used in the assembly of plain spherical bearings into a housing. Self-lubricating plain spherical bearings consist of three main components; an inner race that enables the bearing to freely oscillate about three degrees-of-freedom; an outer race that conforms to the inner race and acts as a mating surface for external assemblies; and a composite fabric (liner) bonded to the inside of the outer race that provides lubrication and a low friction interface against the inner race (Figure 1). They are widely used in the aerospace industry due to their high impact resistance, load bearing capacity, and self-lubrication properties (Kim et.al., 2006; Zhang et.al., 2018) and are primarily seen in applications such as fixed and rotary wing pitch control links, dampers, control surfaces, cargo bay doors and undercarriages (Hoo and Green, 1998). In the staking process, the outer race is first prepared by machining circumferential v-grooves into both parallel faces (Figure 1A). These grooves form a thin lip on the outer race that when staked, conforms to the chamfer in a matching housing (Figure 1B). This process produces a lightweight and reliable mechanical joint requiring no additional components in the assembly. The primary concern during staking is the resultant joint strength between the bearing and its corresponding housing. For the first staked bearing of each batch, the machine settings are validated by testing the staked bearing’s joint strength by pushing the bearing out of its housing, in doing so scrapping the part. If the joint strength is not greater than that stated in the part drawing, the staking force is increased in 5kN increments until the minimum joint strength is achieved. This setting is then carried forward for the rest of that batch of bearings. The secondary concern is the change in torque of the bearing during staking. The current understanding is that a bearing's torque would normally decrease (torque-dropout) if the staking load was sufficiently low enough. As the staking load increases, the bearing would return to its original torque and eventually lock-out if the staking load became too large. However, because bearing geometries are unique for each batch it results in large uncertainties in predicting the final torque of the staked bearing.

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This uncertainty results in a number of finished parts requiring expensive and time-consuming reworking to bring the post-stake torque back within tolerance.

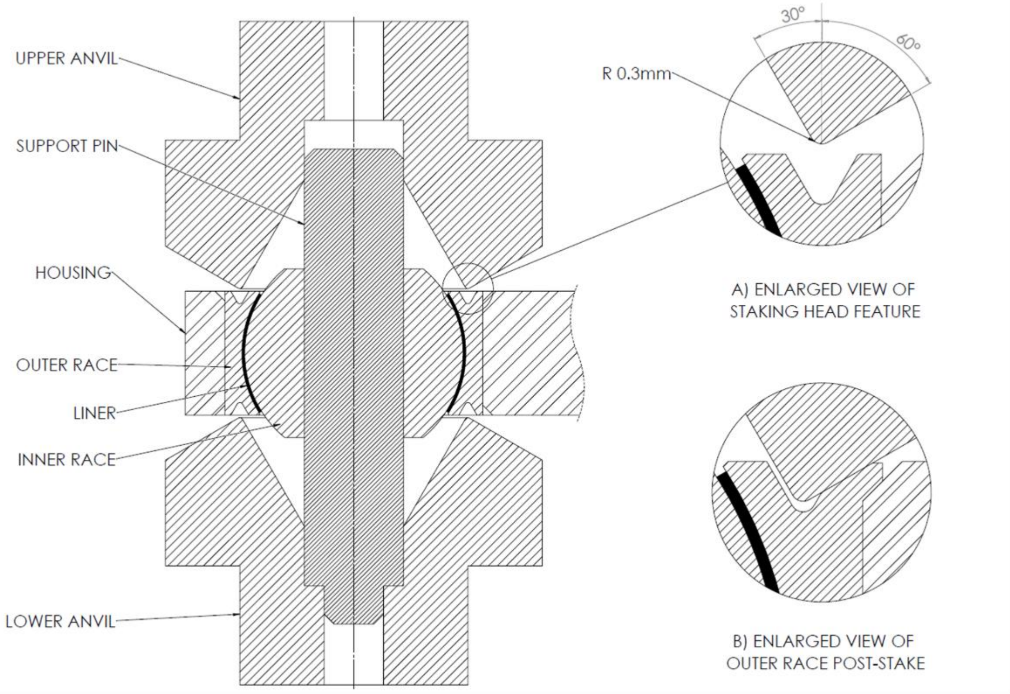

Figure 1. Cross-sectional schematic of the staking process

2 DESIGN OF EXPERIMENTS

Preliminary research identified nine potential design parameters that can influence the pushout strength and post-stake torque: staking force, outer race diameter, interference fit between bearing and housing, staking groove pitch, staking groove depth, housing diameter, Inner race diameter, outer race width, and the housing chamfer depth. A full-factorial Design of Experiments (DOE) would allow for the complete characterisation of the response function but with nine variables to model, this approach would take a prohibitively long time to solve. To reduce the computational workload a screening process was undertaken using a Definitive Screening Design (DSD) to identify the dominant factors and eliminate unnecessary design parameters from the study. DSDs have multiple advantages over traditional screening methods such as fractional factorial designs with their main benefits being the ability to identify non-linear terms and the reduction in confounding between 2nd order terms. A DSD requires an upper, lower and midpoint value for each of parameter to be tested, representing 80%, 20% and 50% respectively. However, many of the geometric features of a bearing scale with respect to the overall bearing size and therefore the absolute dimension for each of these parameters cannot be used for the DSD. For example, the bearing's width typically increases with the bearing's outer diameter. A study of 108 production bearings was carried out to determine the relationship between all of the bearing's dimensions with respect to the outer race diameter which is shown in Table 1. These relationships were used to define the geometries within the computational model with their uncertainties used as the inputs for the DSD model.

Table 1. Geometric characterisation of catalogue bearings and their dimensional variation

Dimension	Geometric Characterisation (mm) ±1 Standard Deviation						
Outer Race Diameter	54.9					±	16.2
Outer Race Width	Outer Race Diameter	x	0.442	+	0.104	±	2.51
Groove Depth	1.32					±	0.04
Groove Pitch	1.61					±	0.05
Groove Root Radius	0.36					±	0.02
Staking Chamfer	1.09					±	0.02
Inner Race Diameter	Outer Race Diameter	x	0.93	-	1.71	±	1.28
Inner Race Width	Outer Race Width	x	1.26	+	0.62	±	2.14
Inner Race Bore	Outer Race Diameter	x	0.66	-	4.91	±	2.88
Housing Width	Outer Race Width			+	0.11	±	0.01
Housing Diameter	Outer Race Diameter	x	1.137	+	11.77	±	4.41
Chamfer Depth	1.03					±	0.04
Interference Fit	0.000					±	0.008

2.1 Computational model

The computational model created to simulate the staking and pushout of the bearings was made using the simulation software ANSYS Workbench (ANSYS, 2021). Due to the symmetric nature of the staking process, a 2D-axisymmetric analysis was used to increase computational efficiency with mesh independency achieved with approximately 38,000 nodes and 13,000 elements. The exact node and element count per simulation varied with respect to the overall bearing size. To accurately capture the plastic deformation experienced during staking, the flow stress for the bearing steel (AMS5643 H1150) and housing (AMS5643 H1025) were modelled using a modified-Hollomon profile and were defined using the following equations:

$$\sigma_{(H1025)} = 1526\dot{\varepsilon}^{-0.0198}\ \bar{\varepsilon}^{\left(0.0528\dot{\varepsilon}^{-0.1398}\right)} \tag{1}$$

$$\sigma_{(H1150)} = 1369\dot{\varepsilon}^{-0.00627}\ \bar{\varepsilon}^{\left(0.0712\dot{\varepsilon}^{-0.0482}\right)} \tag{2}$$

where $\dot{\varepsilon}$ is the true strain-rate and $\bar{\varepsilon}$ is the true strain. The upper and lower staking anvils were modelled as rigid bodies as is typical for bulk-metal forming models (Woodhead et al., 2015; Kalpajian and Schmid, 2008). A coefficient of friction of 0.15 was used for all steel-steel contacts and 0.05 for the self-lubricating liner to inner-race contact. The original intention for the DSD model was for the staking force and bearing geometry to act as inputs and for the pushout strength and post-stake torque to be the outputs. This required the computational model to be split into three sub-steps: staking, post-stake torque measurement, and pushout strength measurement. During the post-stake torque measurement, the staking anvils must not contact the surface of the bearing so that the contact pressure between the inner-race and the self-lubricating liner can be calculated. This posed many challenges with regard to model stability if the staking anvils were to be controlled via a force input. It was decided to control staking anvils via a displacement command (staking depth), converting the staking force from an input parameter into one of the three outputs. The last alteration to the DSD was to reduce the magnitude of the uncertainties for the geometric relationships from Table 1. The DSD, and subsequent DOE, will combine a random combination of each parameter's uncertainty which is not reflective of the actual bearing designs. For example, ball diameter and outer race width scale directly with each other (max-max or min-min) and are never found with one parameter at its smallest value with the other at its largest. This can lead to self-intersecting geometries and ultimately model errors if the parameter variances are too large. For this reason, the variance of the inner race diameter, outer race width and housing diameter were reduced by half. The final DSD table of inputs and run order is detailed in Table 2. Going forward, the maximum and minimum parameter inputs from Table 2 will represent 100% and -100% deviation from the mid-point value.

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Table 2. DSD design table. A list of input parameters and respective run order. +, - and 0 represent the upper (100%), lower (-100%) and midpoint (0%) parameter values, respectively.

Factor	Inner Race Diameter	Groove Depth	Groove Pitch	Outer Race Diameter	Outer Race Width	Chamfer Depth	Housing Diameter	Inter-ference	Staking Depth
Model Limits (mm)	0.6408	1.360	1.659	71.12	1.254	1.062	2.208	0.008	0.51
	0	1.315	1.608	54.93	0	1.027	0	0	0.43
	-0.6408	1.271	1.557	38.73	-1.254	0.992	-2.208	-0.008	0.35
Run Order									
1	0	+	+	+	+	+	+	+	+
2	0	-	-	-	-	-	-	-	-
3	+	0	-	-	+	-	+	+	-
4	-	0	+	+	-	+	-	-	+
5	+	-	0	-	+	+	-	+	+
6	-	+	0	+	-	-	+	-	-
7	+	-	-	0	-	+	+	-	+
8	-	+	+	0	+	-	-	+	-
9	+	+	+	-	0	-	-	-	+
10	-	-	-	+	0	+	+	+	-
11	+	-	+	+	-	0	-	+	-
12	-	+	-	-	+	0	+	-	+
13	+	+	-	+	-	-	0	+	+
14	-	-	+	-	+	+	0	-	-
15	+	+	+	-	-	+	+	0	-
16	-	-	-	+	+	-	-	0	+
17	+	-	+	+	+	-	+	-	0
18	-	+	-	-	-	+	-	+	0
19	+	-	+	+	+	-	+	-	-
20	-	+	-	-	-	+	-	+	+
21	0	0	0	0	0	0	0	0	0

2.2 Parameter screening

The primary output from the DSD was three regression models that predict the staking force, pushout strength and post-stake torque. Each regression model contained all nine parameters with their linear, square, and two-way interactions with an R-squared value of 0.9997, 0.9944, and 0.9838, respectively. Using a Pareto chart, it was possible to identify which parameter was contributing the least towards each regression model's accuracy. By removing this parameter and recalculating the regression model, it was possible to calculate the effective contribution of that parameter. This was repeated for all parameters with the results against each of the three outputs shown in Figure 2. A decision was made to eliminate the parameters groove depth, inner race diameter and outer race width from the final DOE model. This was done because their contribution to the three outputs was minimal and to reduce the total number of runs in the final DOE (Figure 2).

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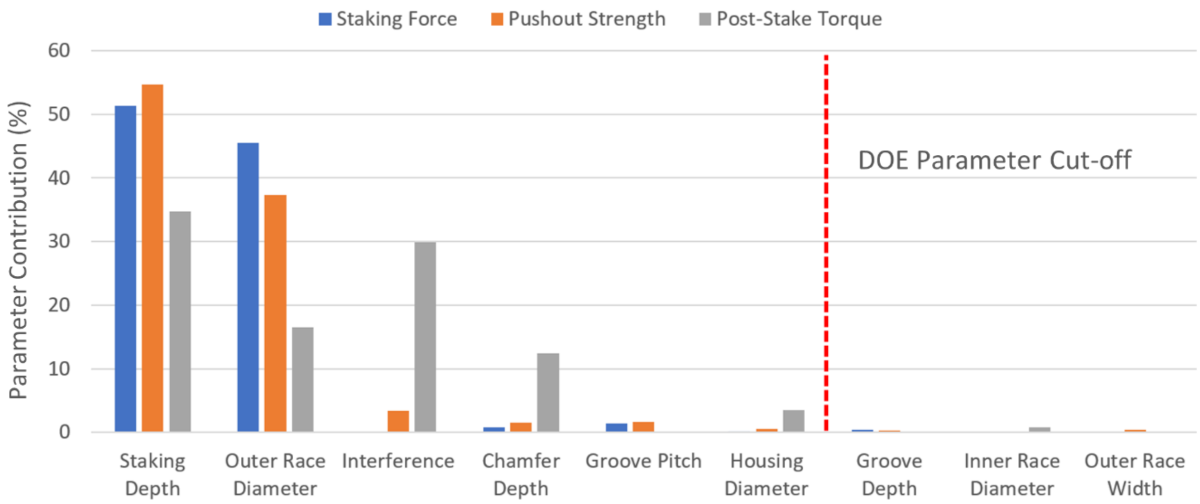

Figure 2. Relative contribution for each DSD parameter

The secondary output from the DSD was an indication of the linearity of each input parameter through main effect plots as demonstrated in Figure 3. When displayed in this format it is possible to determine if a parameter has a linear or non-linear effect on the model's output. Only two levels are required for a parameter in the DOE if the mean effects plot returns a linear response. If the response is quadratic, then a minimum of three levels is required. This is due to the DSD being a reduced three-level model and therefore has no information about higher-order interactions. When comparing the mean effects plots across all three DSD outputs, it was found that the outer race diameter and housing diameter always produced a linear response whilst all other parameters produced a quadratic response in at least one of the outputs. Therefore, the initial DOE model was a mixed-level design requiring $2^2 \times 3^4 = 324$ simulations.

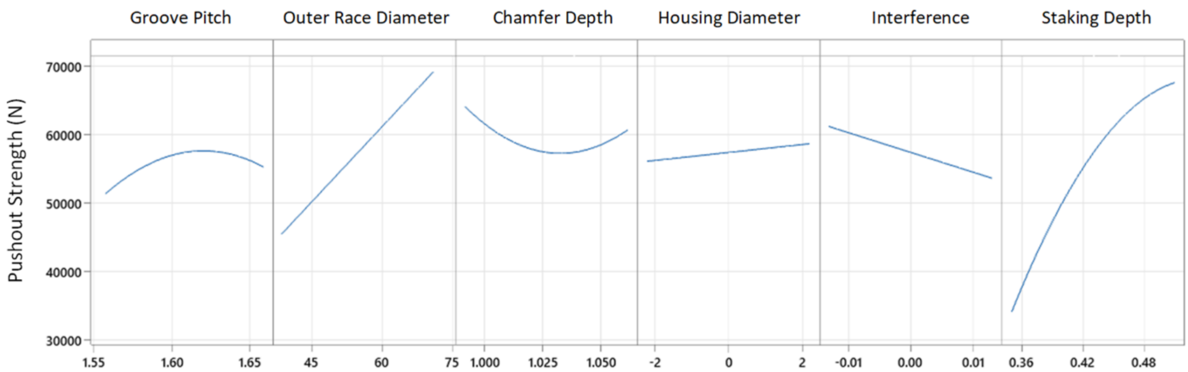

Figure 3. The main effects plot for pushout strength; showing a non-linear response for groove pitch, chamfer depth and staking depth. All dimensions in mm

After the 324 simulations were complete, it was necessary to validate if the mixed-level design's quadratic parameters were of sufficient resolution. To achieve this, three regression models were tested against a new batch of simulations produced by randomising the values for the input parameters. By comparing the residual error of each regression model against each parameter, it was possible to identify patterns in the residuals indicating a lack of resolution in any given parameter. The staking depth parameter was increased to five levels (Table 3) resulting in an additional 216 simulations to be completed with a final mixed-level DOE of $2^2 \times 3^3 \times 5^1 = 540$ simulations.

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Table 3. Final DOE parameter inputs

Parameter	Level	Value (mm)				
Staking Depth	5	0.35	0.39	0.43	0.47	0.51
Outer Race Diameter	2	38.730				71.127
Interference	3	-0.00762		0		0.00762
Chamfer Depth	3	0.992		1.027		1.062
Groove Pitch	3	1.557		1.608		1.659
Housing Diameter	2	-2.207				2.207

3 RESULTS

With the competition of 540 simulations, three regression models were produced to predict the staking force, pushout load, and post-stake torque with R-squared values of 0.9999, 0.9989, and 0.9948, respectively. However, this is only an indication of the regression model's ability to predict the DOE simulations and does not represent the real-world performance of the models where each parameter would vary continuously between their respective limits. To derive a meaningful uncertainty to describe the model's performance, a new batch of simulations were run with randomised values for each of the input parameters. Whereas the upper and lower limits used for the DOE model were reduced to avoid geometric errors from extreme combinations of parameters, for the randomised dataset these limits were increased to match the entire range of possible bearing geometries (100% and -100% represent the original DOE model upper and lower input limits with some parameters now extending to ±300%). Any failed simulations due to impossible bearing geometries were removed from the randomised dataset. In total, 430 randomised tests were simulated and when combined with the DOE simulations the total runtime was 280 hours (AMD CPU Ryzen 9 3950x @4.2GHz). From this dataset, it was possible to calculate the model's error as a function of each parameter's deviation from its mid-point. Whilst beneficial for understanding the behaviour of each parameter, it does not help with developing an overall understanding of the model's error. To achieve this, each simulation was ranked by its maximum absolute parameter deviation, grouped, and their errors averaged together (Figure 4). With the model's statistical analysis complete, a staking design tool was created that calculates the pushout strength and post-stake torque as a function of the staking force as shown in Figure 5.

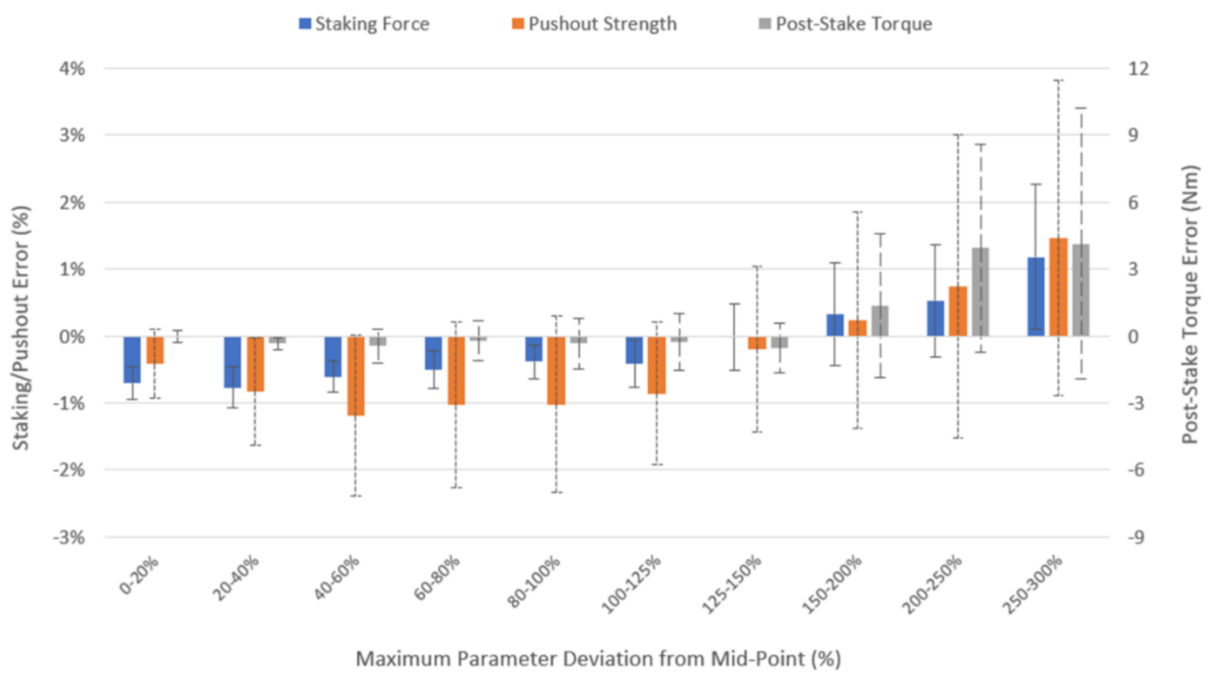

Figure 4. DOE model error with 95% confidence intervals.

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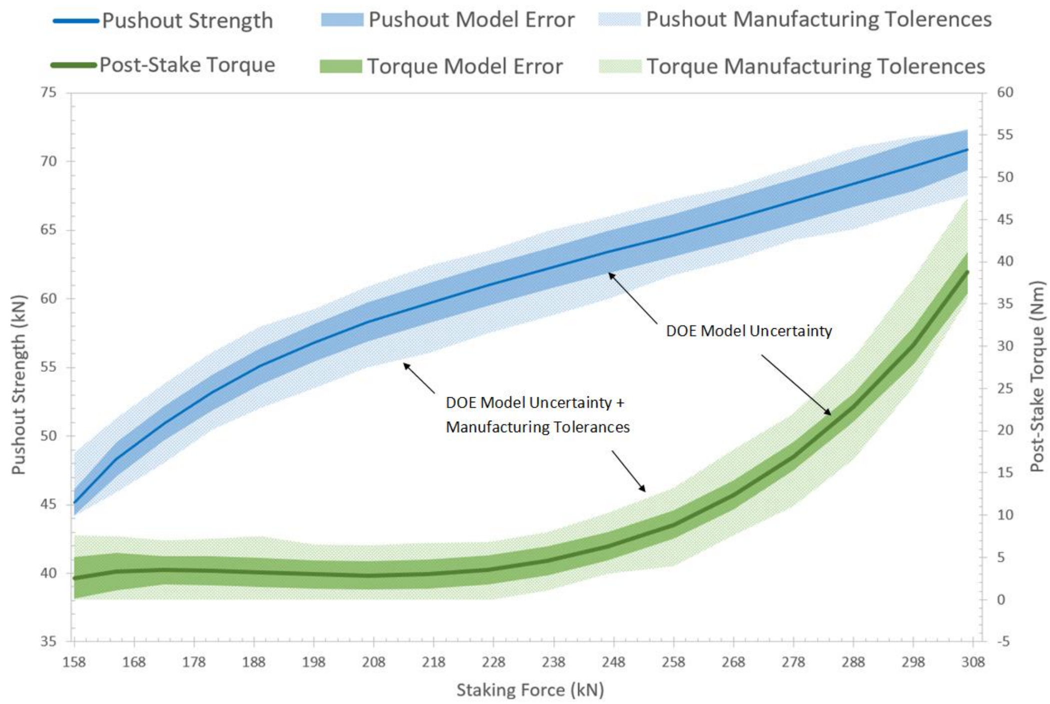

Figure 5. Example of the staking design tool output. The Inner and outer shaded bands represent a 95% confidence interval for the model's inherent uncertainty and the combination of the model's uncertainty and manufacturing tolerances, respectively.

The closed-form solutions that make up the staking design tool were further scrutinised to understand how manufacturing tolerances could influence the model. Through the use of Monte Carlo simulations, the manufacturing tolerances for the bearing's interference fit and chamfer depth were found to produce the greatest response (Figure 6). This probabilistic analysis provides greater insight into the staking tool's behaviour than just relying on the overall output from Figure 5.

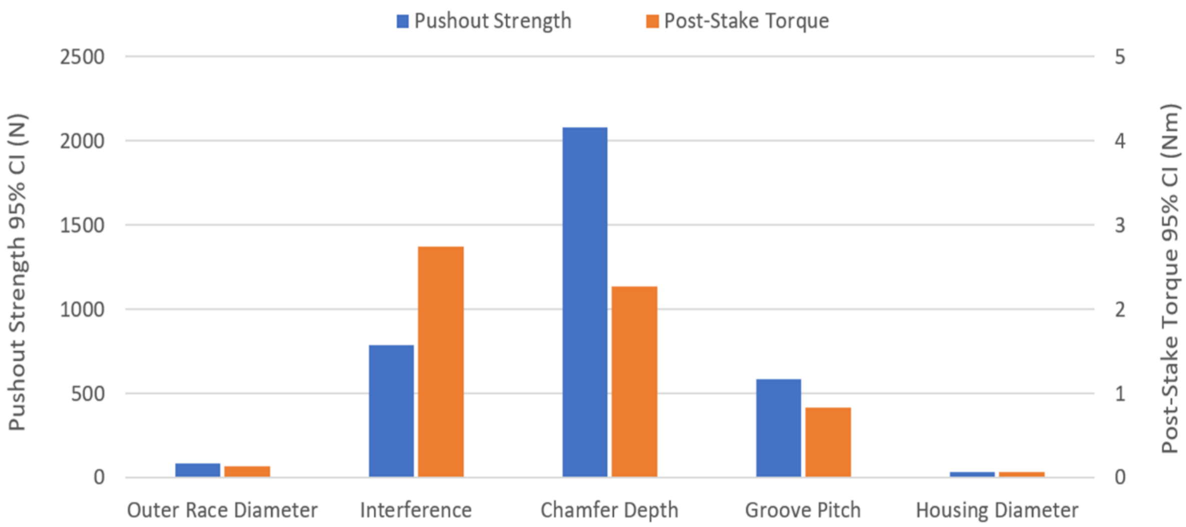

Figure 6. Impact of manufacturing tolerances

4 DISCUSSION

The FEA-based DOE approach presented in this paper has proved to be successful for the product development of the staking of bearings. With process uncertainties for the staking force and pushout strength not exceeding ±1.2% and post-stake torque ± 1.5 Nm (within the DOE parameter limits), far exceeding what was previously capable from analytically derived closed-form solutions. These uncertainties increase by approximately a factor of three as parameters reach ±300% to accommodate all possible parameter inputs. Whilst not unexpected and still within acceptable limits, this increase

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was a result of the desire to create a single DOE to model the entire bearing design space. It is strongly suggested that for similar instances multiple DOE models should be created that focus on narrower regions of the design space. This has two primary benefits. The first is a reduction in each DOE model's uncertainty due to the reduced range of each of the parameter inputs. Secondly, if no geometric errors are encountered during the DOE screening stage, then depending on the required depth of post-analysis the randomised validation simulations may not be required saving considerable simulation time. Ultimately, this decision will depend on the individual requirements of each industry project and the sensitivity of the process's input parameters. Although this case study demonstrates the suitability of FEA-based DOE for metal joining processes, a key difference between industry projects and this case study was a lack of time constraints. The presented work was relatively unbounded in time, allowing for more parameters at higher levels to be studied for greater model accuracy at the cost of longer simulation times and post-analysis. However, DOE are by their nature scalable and as such can still provide meaningful results in shorter timeframes at the cost of the model's error. Additional input parameters could be requested at a later stage with the required extra runs simply being appended to the already solved dataset.

5 CONCLUSION

The purpose of this investigation was to prove the suitability of a FEA-based DOE approach to create closed-form solutions to complex bulk-metal joining processes. For the staking of bearings, the approach presented in this paper allowed the designer to produce representative results and it would be expected that this performance can be replicated in a variety of bulk-metal joining operations. When contrasted against either physical trials or an ad hoc style of FE design exploration, it was shown that a FEA-based DOE can provide an inexpensive, methodical, and scalable approach for developing a comprehensive understanding of the desired bulk-metal joining processes.

6 FUTURE WORK

The knowledge created from a FEA-based DOE is extensive but from the viewpoint of a designer, this knowledge can be hard to utilise to its full potential as a once previously complex metal joining process is now replaced with an equally complex series of regression equations. Further work is required to develop a standardised process for extracting the most relevant behaviour of the model and presenting it in a form that can be understood by an end user.

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