Efficient Machine Learning Optimization of Gear Micro Geometry and Comparison with Manually Designed Gears

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KEY WORDS:Standardised, Vibration, noise, and ride comfort, gear noise, optimization technique. Free, Micro geometry, machine learning (B3)

Optimization of gear micro geometry guided by machine-learnt surrogate models is compared to a past engineer-led optimization and proven to be a highly efficient technique. Initially, gear micro geometry is optimized for a single torque to allow direct comparison with the original manual optimization, however, consideration of multiple operating conditions and robustness are explored in the full manuscript. Three gears are optimized (idler, and two input gears) with each having distinct micro geometries. The idler gear meshes with the two input gears labelled left (L) and right (R) with the optimization targeting improved noise, vibration, and harshness (NVH) and durability across both meshes under 90Nm of torque.

Whilst the primary goal of the optimization the reduction of the first harmonic of transmission error (TE) evaluated by loaded tooth contact analysis (LTCA) at each mesh, it is important that the first harmonic not be optimized at the expense of higher harmonics. For this reason, the weighted harmonic sum of transmission error (WHSTE) will be minimised across both meshes:

$$\mathrm{WHSTE}_m = \sum_{n=1}^{10} n\,\delta_m^{(n)}, \tag{1}$$

where $\delta_m^{(n)}$ is the n^{th} TE harmonic for gear mesh m which can take one of two values L (left) or R (right). The optimization technique will minimise the root sum of squares of the WHSTE across both meshes: Target = $\sqrt{\mathrm{WHSTE}_L^2 + \mathrm{WHSTE}_R^2}$. To ensure that stress is well-distributed over each mesh, we use edge load factors:

$$\mathrm{LF}_{m,e} = \frac{\max(\boldsymbol{\sigma}_{m,e}) - \min(\boldsymbol{\sigma}_{m,!e})}{\max(\boldsymbol{\sigma}_{m,!e}) - \min(\boldsymbol{\sigma}_{m,!e})}, \tag{2}$$

where $\boldsymbol{\sigma}_{m,e}$ is the stress on mesh m along edge e (top, bottom, left, or right) and $\boldsymbol{\sigma}_{m,!e}$ is the stress everywhere other than that edge. To ensure the optimization technique returns durable micro geometries, we constrain left and right edge load factors to be below 75% and top and bottom edge load factors to be under 50%.

The optimization begins by training a machine-learnt surrogate model on a set of initial samples. After the initial surrogate model has been fit to the data, this surrogate model is used to select a new micro geometry for analysis that is likely to meet the constraints, achieve a better target, or explore unseen regions of the problem space. This efficient and global optimization technique can find high performing micro geometries in a short amount of time. Requiring 200 LTCA analyses (see right panel of Fig. 1), the optimisation took between 15 and 20 minutes on a desktop with an Intel Core i9-14900K with 128GB of RAM.

The optimization technique improves the transmission error beyond that of the manually optimized baseline within 50 iterations. The quality of this micro geometry is demonstrated through its improved TE over the manually optimized baseline and any micro geometriy identified in a computationally expensive 100,000 sample Monte Carlo study over the optimization space (see left panel of Fig. 1). The optimized micro geometry parameters are then rounded to the nearest micron. The manually and ML optimized micro geometries are qualitatively similar, however, the optimizer achieves slightly improved centralization of stress on the left input to idler mesh through its satisfaction of edge load factor constraints (see Fig. 2). Further optimizations such as considering identical input gears (to save on manufacturing costs), manufacturing robustness, and torque robustness are considered in the main text.

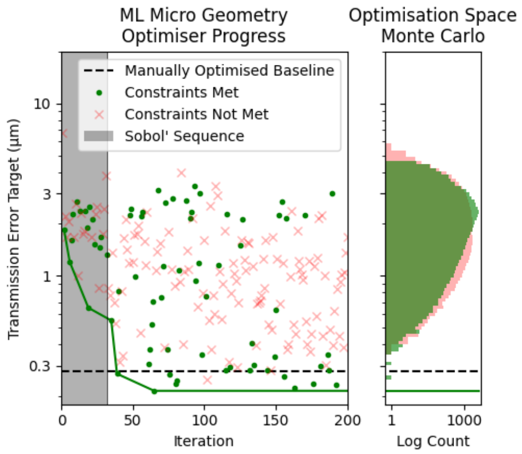

Figure 1 Micro geometry optimizer (left) compared to a 100,000 sample Monte Carlo experiment over the optimization space (right). In both plots, the transmission error target is defined in the main text as the root-mean-square of the weighted sum of transmission error across both gear meshes.

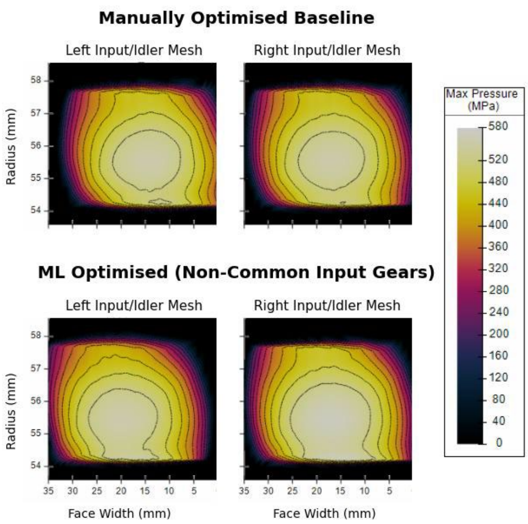

Figure 2 Contact patches for both gear meshes before and after optimization.