Optimization of crankshaft main bearing lubrication performance considering bearing profiles

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Abstract. It is the aim of this work to reduce friction power loss of main bearings by optimization. To this purpose, elastohydrodynamic (EHD) model is used for EHD calculations for different main bearings. BP neural network is implemented to establish the approximation model for bearings. Then, multi-objective optimization of bearings using genetic algorithm is formulated and conducted. It is found that a more compliant bearing profile can provide hydrodynamic lift during film lubrication while bearing profiles have more significant impact on lubrication performance in comparison to other key parameters. The results of the BP network model using the genetic algorithm agree closely with the calculated value based on EHD-MBD model. The presented approach allows reliably to conduct the optimization of bearings. After optimization, the friction power loss is significantly reduced while the minimum oil film thickness increases and the total pressure drops.

1. Introduction
In the automotive and industrial sector, consumer demand and the increasingly tight environmental legislation motivate the development of more efficient internal combustion engines (ICE). For engine efficiency improvement, friction loss reduction is a key and relatively cost-effective approach, which has been receiving significant attention from tribologists and lubrication engineers alike[1]. Crankshaft main bearings, which are important friction pairs of the engine, transmit power while reducing friction power loss. Recently, the realization of the importance of main bearing lubrication to achieving high-performance output and reducing engine friction power loss has been increasing[2-4]. Considering the strength of the crankshaft, [5]Sun conducted the optimization on main bearings in order to decrease the total friction power loss of the bearings. [6]Zhang used the combination of orthogonal experiments and BP neural network methods to optimize main bearings for reduction of friction power loss. [7]Zhou conducted the optimization on bearings by rationally matching the parameters, such as the shape and location of the oil bore, the surface roughness and the oil type. Although the key bearing parameters considered in the above studies are comprehensive, they do not involve bearing profiles. Profile design has been widely studied in the piston skirt, cam and piston rings, however, there is a lack of work of on bearing profiles. The objective of the current work is therefore to explore the influence of different bearing profiles on bearing performance and reduce friction power loss of main bearings by optimization.

During the design stage of the engine the simulation of friction in the crank mechanism plays a vital role to develop optimum solutions[8-10]. Therefore, a great deal of studies use a multibody dynamics (MBD) model coupled with elastohydrodynamics (EHD) to analyse the lubrication
performance of bearings at present. [11] J. CHOI used multibody dynamics coupled with elastohydrodynamics to analyse bearing lubrication performance, such as pressure distribution and oil film thickness. Moreover, the numerical results were validated and compared with experimental results, which proved the accuracy of the solution. [12] Zhang also conducted the MBD and EHD analysis of lubrication performance of main bearings. The approximation model for bearings is established using Kriging. NSGA is implemented to optimize the multi-objective problem, which is to minimize oil outflow and hydrodynamic friction power loss.

Consequently, the concept of this work is as follows in Fig 1. Section 2 presents the MBD model using AVL Excite Power Unit and the bearing analysis is given. Section 3 describes the concept of bearing optimization as well as the details of the BP neural network and the multi-objective genetic algorithm. In Section 4, results obtained from the optimal solution are discussed and compared to the baseline. Finally, Section 5 concludes this work with a summary.

![Figure 1. The concept of this work](image1)

![Figure 2. MBD model on Excite Power Unit](image2)

### 2. Analysis of bearings

#### 2.1. Simulation model

The bearing analysis is necessary before optimization. In this work, AVL Excite Power Unit is used to build the MBD-based EHD model of the V-type diesel engine as shown in Fig 2. Nonlinear connections in the engine and the elastic deformation of the crankshaft and the engine block are fully considered. The parameters of main bearings are listed in Table 1.

| Parameter/Unit            | Value | Parameter/Unit             | Value |
|----------------------------|-------|----------------------------|-------|
| Width diameter ratio       | 0.306 | Oil supply pressure/MPa    | 0.5   |
| Roughness/μm               | Shell: 0.8/Journal:0.4 | Diameter of oil bore/mm    | 8     |
| Lubrication gap/μm         | 35    | Width of oil groove/mm     | 7     |
| Oil type                   | SAE5W-30 | Height of profiles/μm     | 4     |
| Oil temperature/°C         | 80    | Width of profiles/mm       | 2     |

The most important technology of MBD is the degree of freedom condensation. Due to the large degree of freedom (DOF) of the finite element model for the engine block and the crankshaft, the solved efficiency is very low. AVL Excite Power Unit and Abaqus are used to condense the degree of
freedom of the finite element model. In order to ensure the accuracy of the condensation model and the original finite element model, the first 20 modes information are retained.

To able to describe the influence of the surface roughness on the bearing lubrication performance, the average flow model proposed by [13] Patir and Cheng is applied to describe to the lubricant and the Greenwood and Tripp[14] model is used to describe the metal–metal contact in this work. In a body shell fixed coordinate system such an average Reynolds equation as developed by Patir and Cheng can be defined as Eq.(1):

$$\frac{\partial}{\partial \theta} \left( \gamma \varphi_\theta \frac{h^3}{12\eta} \frac{\partial p}{\partial \theta} \right) + \frac{\partial}{\partial x} \left( \gamma \varphi_x \frac{h^3}{12\eta} \frac{\partial p}{\partial x} \right) = \left( \frac{v_1 - v_2}{2} \right) \frac{\partial}{\partial \theta} (\gamma h + \gamma \varphi_s) + \frac{\partial (\gamma h)}{\partial t}$$ (1)

$$\eta(p, T) = 1.5 \times 10^{-4} e^{\left( \frac{72.01}{T+71.123} \right) 1.5 \times 10^{10} p}$$ (2)

Where \( \theta, x \) denote the circumferential and the axial direction, respectively. \( p \) is the hydrodynamic pressure and \( h \) the oil film thickness which is dependent on \( \theta \) and \( x \). \( \gamma \) is the oil fill ratio and \( \sigma \) is the integrated surface roughness. The influence of surface roughness is considered by the pressure flow factors \( \varphi_\theta, \varphi_x \) and the shear flow factor \( \varphi_s \). Further, \( v_1, v_2 \) denote the sliding speeds of the facing surfaces. The oil viscosity \( \eta \) is considered temperature and pressure dependent in this work, see Eq.(2), according to Vogel and Barus were derived from experimental data.

2.2. Lubrication performance of bearings

2.2.1. Difference main bearings. Two important properties related to reliability in lubricated bearings are the minimum oil film thickness (MOFT) and the total friction power loss (TFPL) that are depicted in Fig 3 for all the main bearings. Four bearings are marked as MB1~MB4 from the free end to flywheel, respectively.

As is shown in Fig.3, the TFPLs are for all main bearings very large and reach to a maximum of 2.1kW, which indicates that wear occurs in the bearings with significant friction power loss due to asperity contact. Further it is interesting to note that the MOFT changes insignificantly from about 0.5 to 0.76\( \mu \)m between the different bearings, but is below 0.9\( \mu \)m (the integrated surface roughness), which is the boundary lubrication threshold. The bearings, which are partly characterized to be in the boundary lubrication regimes, will result in many engine durability and reliability issues, such as excessive wear, component seizure and catastrophic failure. Therefore, bearing design needs to be optimized to protect the engine and reduce friction power loss. Further, the performance of different main bearings is close to each other. In this regard, only one bearing needs to be selected to investigate for improvement of optimization efficiency. MB1 is selected for analysis and optimization in this work.
2.2.2. Difference bearing profiles. As is shown in Fig 4, symmetrical bearing profiles mainly include liner profiles and quadratic profiles in practice. Table 2 shows the parameters of difference bearing profiles in this work.

| Type                  | Height of profiles/μm | Width of profiles/mm |
|-----------------------|------------------------|----------------------|
| Case1/No profiles     | /                      | /                    |
| Case2/Quadratic profiles | 4                      | 2                   |
| Case3/Quadratic profiles | 6                      | 13                  |
| Case4/Liner profiles  | 6                      | 13                  |

It is interesting to note that the TFPL of Case 3 decreases as a whole and the MOFT of Case 3 increases in comparison to the Case 1, however, the opposite results were obtained for the Case 2, where the TFPL of Case 2 increases sharply and the MOFT of Case 2 decreases in comparison to the Case 1, see Fig 5 and Fig 6, which demonstrates that different bearing profiles have different impact on performance of bearings and a more compliant profile can provide hydrodynamic lift during film lubrication. Thus, bearing profiles are expected to be considered to conduct the optimization of bearings. Further it is instructive to note that the bearing performance does not vary significantly between quadratic profiles (Case 3) and liner profiles (Case 4). Therefore, the height of quadratic profiles and the width of quadratic profiles are chosen as key parameters in this work.

2.3. Design variables
Main bearings have many parameters and seven key parameters are selected according to the previous studies and considering bearing profiles as is shown in Table 3. If all of the 7 parameters are used as design variables, computational resources will be wasted and some parameters only have little impact on the lubrication performance. Due to the objective of this work is to reduce the friction power loss of main bearings, the TFPL of MB1 serves as the screening indices. Orthogonal experiments and the analysis of variance are used to screen the significant parameters of bearings. Orthogonal array can provide an effective experimental performance with a minimum number of experimental trials. In total, 12 simulation experiments are obtained. The sum of squares (Eq.3) of the key parameters, listed in Table 3, can represent their importance to objective. By ranking the sum of squares, the top three significant parameters, the height of profiles, the width of profiles and oil supply pressure, are chosen as the design variables.
\[ SS_T = \frac{1}{t} (K_1^2 + K_2^2) - \frac{(\sum_{i=1}^{N} y_i)^2}{N} \]  

(3)

Where, \( SS_T \) is the sum of squares, \( N \) is the number of the experiment, \( t \) is the number of the level, \( y \) is the TFPL, and \( K \) is the sum of \( y \) of the corresponding level.

Table 3. The sum of squares of all the key parameters

| Parameter/Unit                  | Low level | High level | \( SS_T \) |
|---------------------------------|-----------|------------|-------------|
| Diameter of oil bore/mm        | 4         | 12         | 0.3         |
| Width of oil groove/mm         | 4         | 10         | 0.8         |
| Lubrication gap/μm              | 25        | 45         | 0.1         |
| Oil supply pressure/MPa        | 0.3       | 0.8        | 1.1         |
| Oil supply temperature/°        | 80        | 120        | 0.8         |
| Width of profiles/mm           | 1         | 9          | 49.1        |
| Height of profiles/μm           | 1         | 6          | 3.0         |

3. Optimization of Bearings

3.1. Design of experiment (DOE)

In order to obtain enough information for establishing the approximation model of bearings, the optimal Latin hypercube sampling (LHS) is used to conduct the design of simulation experiments. The baseline values and the corresponding spans of the three design variables are depicted in Table 4. Totally, 25 simulation experiments are obtained.

Table 4. Baseline value and span of design variables

| Parameter/Unit                  | Baseline | Span       |
|---------------------------------|----------|------------|
| Oil supply pressure/MPa         | 0.5      | [0.3,0.8]  |
| Width of profiles/mm            | 2        | [1,13]     |
| Height of profiles/μm           | 4        | [1,6]      |

3.2. BP neural network modeling

The S-type function (4) is used to establish the model, and its ideal output can only be close to or equal to 1. Thus, the TFPL and MOFT need to be normalized according to Eq. (5), which will improve the predictive ability of the BP neural network model.

\[ y = \frac{2}{1 + e^{-2x}} - 1 \]  

(4)

\[ Y_i = 0.1 + 0.8 \times \frac{T_i - T_{min}}{T_{max} - T_{min}} \]  

(5)

Where, \( Y \) is the normalized value, \( T \) is the original value. Among all of the experiments, 80% of experiments is used to train, 10% for validation and 10% for test. The regression (6) and the mean square error (7) are used to ensure the accuracy of the model.

\[ R = \frac{\sum_{i=1}^{N} (T_i - \bar{T})(Y_i - \bar{Y})}{\left(\sum_{i=1}^{N} (T_i - \bar{T})^2\right)^{\frac{1}{2}} \left(\sum_{i=1}^{N} (Y_i - \bar{Y})^2\right)^{\frac{1}{2}}} \]  

(6)
\[
MSE = \frac{1}{N} \sum_{i} (T_i - Y_i)^2
\]  
(7)

Where, \(N\) is the number of experiments, \(T\) is the predictive value of the BP neural network model, \(Y\) is the calculated value of the MBD model. Fig 7 shows that after 31 epochs, all the mean square error is less than 0.5% and Fig 8 shows the regression is 0.9989, which demonstrates the BP neural network model is accurate enough in this work.

3.3. Multi-objective optimization of bearings

Multi-objective genetic algorithm is implemented to optimize the bearing. There are two optimization objectives and three constraints (8) in this work.

Objectives: \(\begin{align*}
\min f_1 \\
\frac{f_2}{\sigma} > 1
\end{align*}\)  
Constraints: \(\begin{align*}
1 < h < 6 \\
1 < w < 13 \\
0.3 < p < 0.8
\end{align*}\)  
(8)

Where, \(f_1\) is the TFPL of MB1, \(f_2\) is the MOFT of MB1, \(\sigma\) is the integrated surface roughness, \(h\) is the height of profiles, \(w\) is the width of profiles, \(p\) is the oil supply pressure.

Before the optimization, some required parameters are as follows: the size of population is 200; the maximum number of generations is 300; the tolerance of fitness function is \(1 \times 10^{-4}\); the probability of crossover and mutation is 0.8 and 0.01 respectively. After 266 generations, one solution is selected from the Pareto solutions based on design requirements in Fig 9. The optimum values of three design variables are as follows: the width of profiles is 5.3μm; the height of profiles is 10.1mm; the oil supply pressure is 0.39MPa.

The results from BP network model are for the optimized bearing compared to the results obtained from EHD-MBD model, see Fig 10. As can be seen from the results, the total friction power losses calculated by both methods are very close with a difference of 6.4%, while the results are again very close with 1.036μm and 0.94μm predicted by BP network model and EHD-MBD model, respectively, in terms of the minimum oil film thickness. Consequently, it is found that the results of the BP network model using the genetic algorithm agree very closely with the calculated values and the presented approach allows reliably to conduct the optimization of bearings.
4. Results and Discussion

During about 20° ATDC of No.1 and No.2 cylinder, for the baseline MOFT drops significantly below the boundary lubrication threshold, see Fig 11 and Fig 12, the increase in TFPL due to severe amount of asperity contact is very sharp. As expected, the increase in MOFT for the optimized MB1 is almost sufficient to avoid lots of asperity contact and the bearing is characterized to be in the mixed/full-film lubrication regimes so the TFPL reduces significantly, which cuts fuel consumption and emissions of the engine.

Further, it appears from the results that the presented total pressures occur only at the outermost bearing shell edges and drop sharply within a few millimetres at the point of maximum load as is shown in Fig 13. The concentration of asperity contact in these areas is a consequence of the elastic deformation of the shell and journal under load and, therefore, these areas are particularly subject to wear, which make it difficult to be mixed/full-film lubrication. Fig 14 shows that the wear state of MB1 is obviously improved and the total pressure is decreased to about 120MPa by optimization.

Consequently, it is found that the TFPL of MB1 is reduced from 1.607kW to 1.186kW, dropped by 26.2%. The MOFT is increased from 0.5µm to 0.94µm, which is an augment by 67.9%. The total pressure is declined from 183.1MPa to 121.2MPa, which corresponds to almost a 30% reduction. The lubrication performance of the MB1 is remarkably improved from all aspects after optimization, see Table 5.
5. Conclusion
In this work, the optimization of lubrication performance for crankshaft main bearings is investigated. The approximation model is established using LHS and BP neural network. Genetic algorithm are implemented to conduct the optimization. The friction power loss of the bearing has been reduced finally.

Multi-body dynamics model of the V-type diesel engine is developed using AVL Excite Power Unit on which the lubrication performance of different main bearings and different bearing profiles is analyzed. Moreover, friction power loss and the minimum oil film thickness serve as lubrication performance indices. Results show that the performance of different main bearings is close to each other and a more compliant bearing profile can provide hydrodynamic lift during film lubrication while bearing profiles have more significant impact on lubrication performance in comparison to other key parameters. So, bearing profiles are expected to be considered to conduct optimization of bearings.

After optimization, the total friction power loss is reduced from 1.607kW to 1.186kW, which is still a reduction by almost 26%; the minimum oil film thickness increases from 0.5μm to 0.94μm, which is sufficient to avoid severe amount of asperity contact; the total pressure could be reduced from 183.2MPa to 121.1MPa, which corresponds to almost a 30% reduction. This result demonstrates the efficiency in reducing friction by choosing reasonable oil supply pressure and a more compliant bearing profiles.

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