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PROCEEDINGS

Generative Deep Learning for Hydrodynamic Lubrication Prediction

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ABSTRACT

The prediction of lubrication scenario in sliding bearings plays a pivotal role in evaluating the bearing performance. Aspired by the recent advances in generative deep learning, we propose to implement a deep learning model to achieve fast and accurate prediction of the hydrodynamic lubrication in slider and journal bearings. To realize such purpose, we propose that the pixel distribution in an image and the pressure distribution in lubrication shares similar data structure as they both are organized in a tensor/matrix format. Thus, the classical deep learning method in image generation should be available for generating pressure distributions in lubrication.

To illustrate our proposal, we design and train a deconvolutional neural network to generate lubrication pressure distribution in the hydrodynamic lubrication of a slider bearing. The structure of the deconvolutional neural network is shown in Fig. 1, where the deconvolutional neural network functions to gradually expand the input into the desired pressure distribution in lubrication. In specific, the neural network first adopts a fully-connected layer to expand the input into a latent feature. Then, the neural network reshapes the latent feature into a tensor for the following deconvolutional operations that gradually establish numerous high-level latent features. Finally, the last deconvolutional layer aggregates all latent features into the desired pressure distribution. To guarantee non-linear transformation and smooth training of the deconvolutional neural network, we add a ReLU activation function and batch normalization processing after each deconvolutional layer.

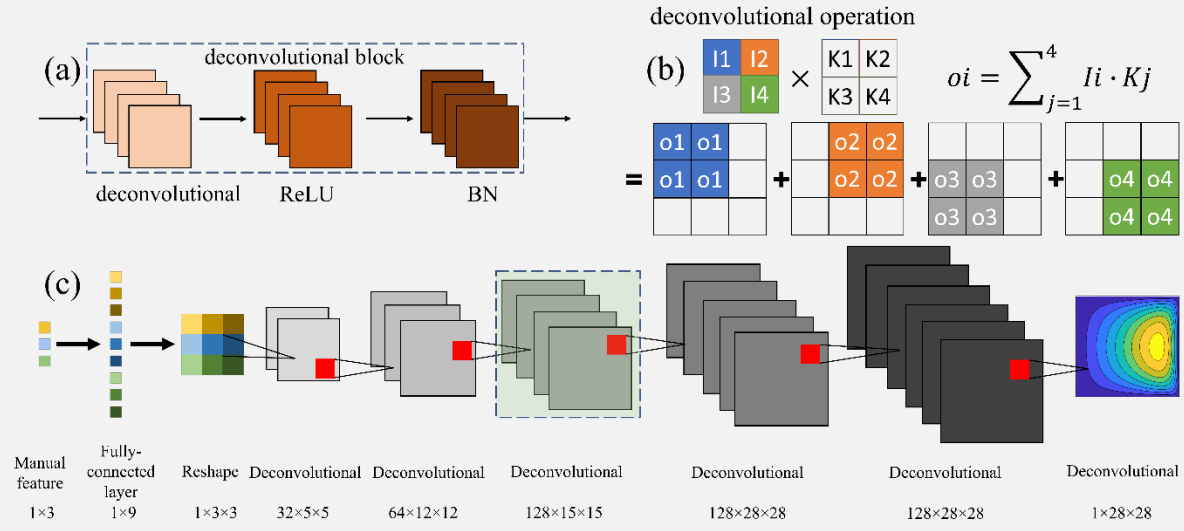


Fig. 1. Illustration of the deconvolutional neural network for hydrodynamic lubrication pressure generation. (a): the deconvolutional block for the 1st to 5th layers; (b): the deconvolutional operation; (c): deconvolutional neural network structure.

After a thorough check of the governing equation of hydrodynamic lubrication, which includes Reynolds equation,

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load balance equation and lubrication film expression, we identify three representative parameters of the hydrodynamic lubrication, i.e., $RP1 = L^2/B^2$,$RP2 = \theta L$, $RP3 = W/(U\eta L^2 B)$, where L and B are slider bearing's dimension, θ is the inclination of the sliding bearing, W is the applied load of the bearing, U is the sliding velocity of the sliding surface, and η is the viscosity of the lubricant. Clearly, these representative parameters arbitrarily determine the entire lubrication scenario. Thus, we designate these representative parameters as the input of the deconvolutional neural network.

To prepare the relevant dataset for the training and evaluation of the neural network, we utilize finite element method to generate approximately 40,000 different hydrodynamic lubrication scenarios with regard to various working conditions, where 70% of the data are divided into training dataset and the remaining as test dataset. The training dataset thus works to guide the neural network training with the target of minimizing the mean square error between neural network output and the reference output in the dataset:

$$\mathrm{MSE} = \frac{1}{N_k}\sum_{k=1}^{N_K}\sum_{i=1}^{28}\sum_{j=1}^{28}\left(o_{i,j,k} - d_{i,j,k}\right)^2 \tag{1}$$

where N_k is number of samples of the current training batch, $o_{i,j,k}$ is the pressure of the node (i, j) generated by neural network and $d_{i,j,k}$ is the pressure provided by the training dataset. After neural network training, we utilize the test dataset to evaluate the neural network's performance. Fig. 2 compares the hydrodynamic lubrication pressure distribution obtained from the neural network and reference data. Clearly, the neural network succeeds at predicting the lubrication pressure distribution accurately.

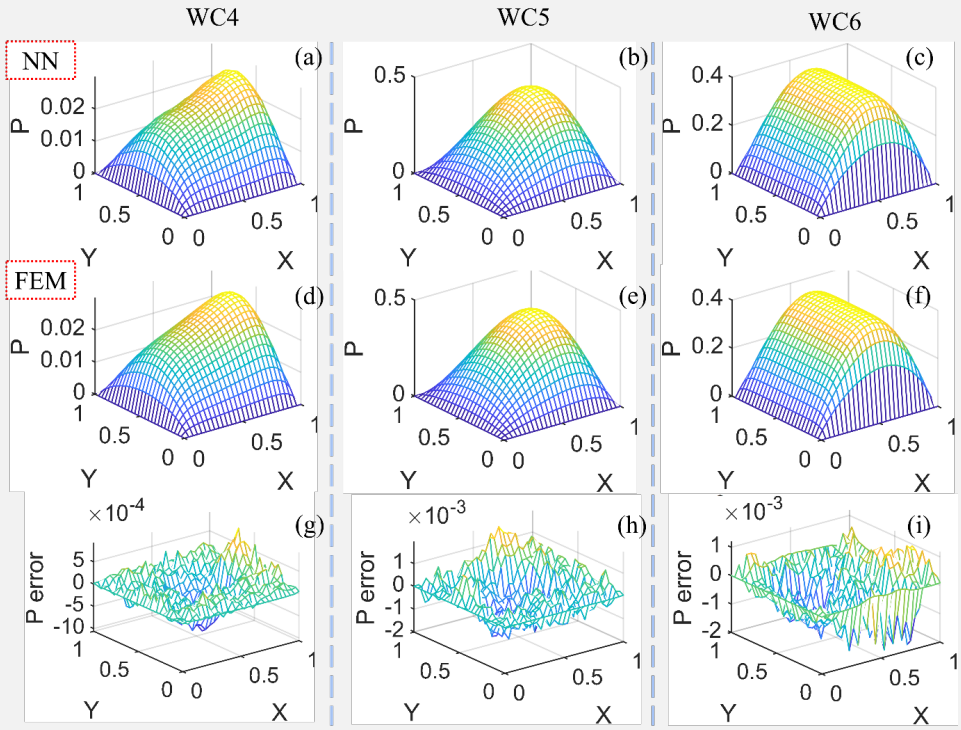


Fig. 2. Comparison of the hydrodynamic lubrication pressure between neural network generation (a-c) and FEM calculation (d-f) on the test dataset. (g-i): error between neural network prediction and FEM results.

(WC4: $L^2/B^2 = 19.1448, \theta L = 1.3229 \times 10^{-6}, W/(U\eta L^2 B) = 2.1792 \times 10^8$;

WC5: $L^2/B^2 = 0.8886, \theta L = 9.2832 \times 10^{-7}, W/(U\eta L^2 B) = 2.217 \times 10^{10}$;

WC6: $L^2/B^2 = 0.0203, \theta L = 1.4034 \times 10^{-5}, W/(U\eta L^2 B) = 1.6713 \times 10^7$).

In Fig. 2, the consistent results between the neural network prediction and FEM calculation confirms that the deconvolutional neural network is a novel approach for hydrodynamic lubrication design. Beside applying the neural network for conventional lubrication prediction, we further found that the network is also applicable to hydrodynamic lubrication with cavitation. Detailed information could be referred to our recent work [1].

To unveil the hidden mechanism of how the deconvolutional neural network obtains the desired lubrication pressure distribution from the input parameters, we extract and visualize the latent representation the deconvolutional kernels constructs. Fig. 3 plots some representative latent features the last deconvolutional layer learned after training. Fig. 3 indicates that, while different deconvolutional kernels could establish different latent features, none of any single deconvolutional kernel obtains continuous latent features. The constructed features resemble a checkerboard that meaningful latent features are isolated by zero-value features. Thus, series of deconvolutional kernels (128 kernels in the 5th layer in Fig. 1) are required to achieve lubrication prediction at different scales. The different kernels thus learn to construct the latent lubrication pressure features from the correspondent scales and locations.

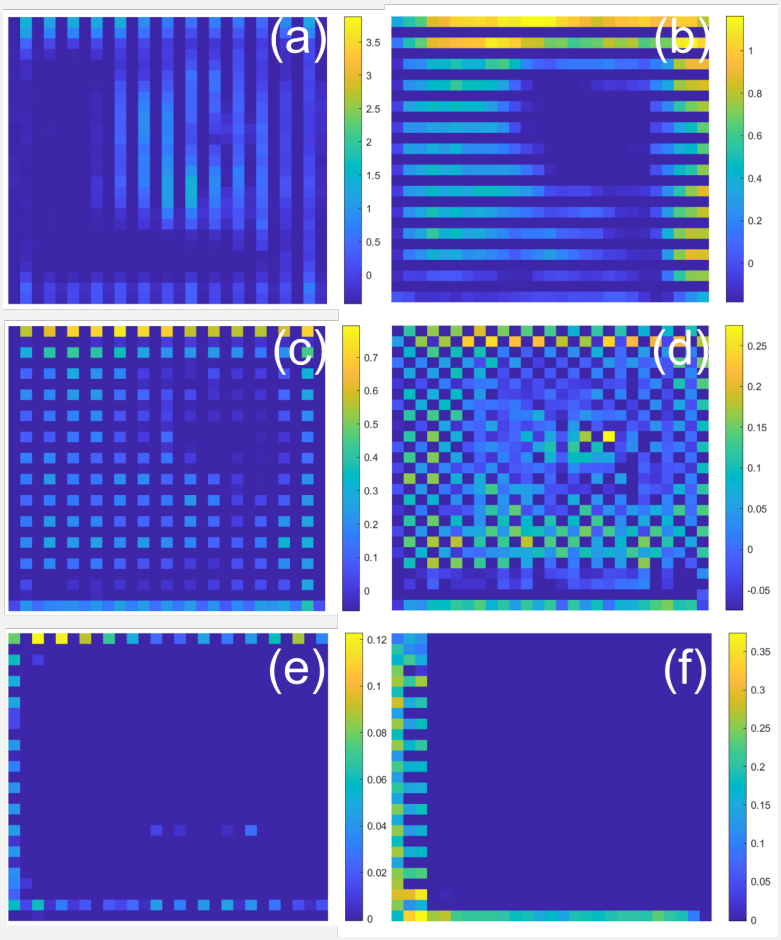


Fig. 3. Some latent features generated in the 5th layer under the working condition of $L^2/B^2 = 0.7017$, $\theta L = 1.2471 \times 10^{-5}$, $W/(U\eta L^2 B) = 3.6421 \times 10^8$. (a-b): Latent feature generated along and across the entrainment direction. (c-d): latent features inside the domain resembling a checkerboard; (e-f): latent features generated at the boundaries.

In conclusion, we construct and train a deconvolutional neural network for the fast and accurate prediction of the hydrodynamic lubrication in slider bearings. The trained neural network could be further adopted to predict the hydrodynamic lubrication considering cavitation. The deconvolutional kernels function to construct the high-level latent features of lubrication pressure at different scales and locations, which are finally aggregated by the last deconvolutional layer to output the desired hydrodynamic lubrication pressure. We envision that such a data--driven method provides a novel angle of view towards the lubrication research.

KEYWORDS

Hydrodynamic lubrication; deep learning; neural network

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Conflicts of Interest: The author declares no conflicts of interest to report regarding the present study.

References

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