

Deep Learning-Based Prediction and Analysis of the Influence of Lubrication on Gear Efficiency

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Abstract: This paper involves an analysis and prediction of the effects of spur gears on efficiency based on the use of deep learning. The efficiency of the gear transmission is highly influenced by friction of the two meshing tooth faces, the formation of films of lubricant, power loss, and temperature of operation. Five lubrication conditions were studied in this work: unlubricated reference condition, grease, low-viscosity oil, medium-viscosity oil, and high-viscosity oil. Calculations of torque and speed were used to calculate input power, output power, power loss, and gear efficiency using the experimental data. Alongside, three deep learning algorithms, such as Deep Neural Network, 1D-Convolutional Neural Network, and Long Short-Term Memory network, were implemented to forecast gear efficiency and power loss based on various lubrication circumstances. The experimental data revealed that gear performance was greatly enhanced by the presence of lubrication as opposed to the absence of lubrication. The lowest efficiency of 87.9, highest power loss of 75.9 W and highest operating temperature of 58°C was observed with the unlubricated gear pair, whereas the lowest power loss of 37.2 W and the highest efficiency of 95.4 and 95.7 was observed with the low and high viscosity oil respectively. Medium-viscosity oil produced the best performance with the highest efficiency of 97.7 percent, the lowest power loss of 14.7 W, and the lowest operating temperature of 27°C compared to the unlubricated condition which had higher efficiency, lower power loss, and operating temperature. Deep learning outcome indicated that Deep Neural Network model had the most optimal prediction performance with an efficiency prediction RMSE of 0.29, power loss RMSE of 0.78 W and an R. 2 value of 0.98. The 1D-CNN and LSTM models made acceptable predictions, although, their errors were larger compared to the DNN model. In general, the findings support the view that adequate lubrication enhances the efficiency of gears by preventing the occurrence of frictional losses and heat. The article also shows that deep learning can become an efficient method to predict the gear performance and find the most appropriate lubrication condition.

Keywords: deep learning , DNN, gear transmission

1. Introduction

The gears are commonly used in the systems of mechanical power transmission due to their ability to convey the torque and rotational movement with a high level of precision and minimal size. They are typically used in automotive transmissions, industrial gearboxes, turbines, pumps, conveyors, and machine tools. In operation, the meshing gear teeth are subjected to repeated rolling and sliding contact. The result of this contact is friction between the tooth surfaces that result in power loss, heat generation, vibration, wear, and decreased transmission efficiency. One of the most effective ways of minimizing friction and enhancing the performance of gear systems is lubrication. An appropriate lubricant coats a thin layer between the meshing tooth flanks decreasing direct metal-to-metal contact. This lubricating film is used to reduce frictional resistance, eliminate heat in the point of contact, lessen wear, and shield the teeth of the gears against surface damage. As such, the efficiency of gears, power loss, and the working temperature directly depend on the lubrication state[1][2]. The efficiency of gears is often referred to as output power divided by the input power. With a perfect gear transmission, 100

percent of the power would be passed on to the output shaft. In real-world systems, however a portion of the input energy is wasted due to gear tooth friction, bearing resistance, churning of the lubricant, windage and thermal losses. These losses include, but are not limited to, friction at the gear mesh when such conditions occur under high load and in poor lubricity conditions. The impact of lubrication on gear efficiency varies with a number of factors which include lubricant type, lubricant viscosity, operating speed, applied load, gear geometry and temperature. Low-viscosity oils can minimize the viscous resistance yet they might not be able to offer adequate film thickness at high load. The high-viscosity oils can offer greater protective action at the surface but can raise the drag and churning losses. Thus, in choosing a good lubricant, it is necessary to balance the achievement of friction reduction with the maintenance of a stable lubricant film. Prediction and performance analysis in engineering systems have recently been more frequently implemented with the use of artificial intelligence and deep learning methods. Multifaceted nonlinear correlations can be trained in deep learning algorithms, which relate input parameters and output performance indicators. Deep learning in gear lubrication may be applied to estimate the gear efficiency and power loss depending on operating conditions including speed, torque, type of lubricant, viscosity and temperature. The current research paper suggests a deep learning solution to forecast and identify the effect of lubrication on the efficiency of spur gears. The various lubrication conditions such as, an unlubricated reference condition, grease, low-viscosity oil, medium-viscosity oil and high-viscosity oil are considered. Gear efficiency and power loss are determined by experimental torque-speed calculations and deep learning algorithms are used to predict performance and compare lubricant behavior. The primary goal is to determine which lubrication state provides maximum efficiency, minimum power loss and minimum operating temperature[3][4][5].

2. Theoretical Background

2.1 Gear Efficiency

Gear efficiency represents the ability of a gear system to transmit input power to the output shaft [6][7]. It is calculated as:

$$\eta = \frac{P_{out}}{P_{in}} \times 100$$

where η is gear efficiency, P_{out} is output power, and P_{in} is input power.

The input and output powers are calculated from torque and rotational speed:

$$P = \frac{2\pi NT}{60}$$

where P is power in watts, N is rotational speed in rpm, and T is torque in N·m.

Power loss is calculated as:

$$P_{loss} = P_{in} - P_{out}$$

A high value of gear efficiency means that more power is transmitted successfully, while a high power loss indicates that more energy is lost due to friction, heat, and other resistance effects.

2.2 Effect of Lubrication on Gear Performance

Lubrication enhances the performance of gears by creating a protective coating between the meshing tooth surfaces. This film minimizes metal-to-metal contact as well as friction. With a low level of friction, a smaller portion of input power is used as heat, and a greater share of power is transmitted to the output shaft. The thermal behavior of the gears is also influenced by

the lubricant. Lack of lubrication will result in high friction hence raising the operating temperature. The viscosity of the lubricant can decrease with an increase in temperature and it leads to a decrease in the strength of the lubricant film. This may enhance tear and wear and decrease the efficiency of gears. Of particular interest is lubricant viscosity[8][9]. A low-viscosity lubricant is easy to flow, and can potentially minimize drag losses, although it might not give sufficient film thickness in high loads. Lubricants with a high viscosity can offer superior surface separation, although they might also add to viscous resistance. Thus, the highest quality lubricant is typically that which forms a stable film with minimal frictional and viscous losses.

2.3 Deep Learning for Gear Efficiency Prediction

Deep learning is a subset of machine learning that trains neural networks with more than one layer to acquire an intricate relationship between input and output variables. This paper predicts gear efficiency and power loss based on lubrication and operating parameters with the help of deep learning[10][11]. The overall correlation may be described as:

$$Y = f(X)$$

where X represents the input features and Y represents the predicted output.

For this study:

$$X = [N_{in}, T_{in}, N_{out}, T_{out}, \text{lubricant type, viscosity level, temperature}]$$

$$Y = [\eta, P_{loss}]$$

The deep learning model is a learner of the relationship between the input features and the output performance indicators. The model is able to forecast gear efficiency and power loss in new lubrication situations after training.

3. Methodology

3.1 Experimental Data Collection

A pair of spur gears was put under constant operating conditions. Each lubrication condition was measured in terms of the input speed, input torque, output speed, output torque and the temperature of the gearbox [12][13][14][15]. The test lubrication conditions were Unlubricated reference condition

1. Grease lubrication
2. Low-viscosity oil
3. Medium-viscosity oil
4. High-viscosity oil

The same input speed, load, and test duration were used for all cases to ensure that the change in gear performance was mainly caused by the lubrication condition.

3.2 Input and Output Parameters

The input features used for the deep learning model are shown in Table 1.

Table 1. Input and output variables used in the deep learning model

Variable type	Parameter	Symbo l	Unit
Input	Input speed	(N_{in})	rpm
Input	Input torque	(T_{in})	N·m

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Input	Output speed	(N_{out})	rpm
Input	Output torque	(T_{out})	N·m
Input	Lubrication condition	—	categorical
Input	Operating temperature	—	°C
Output	Gear efficiency	(η)	%
Output	Power loss	(P_{loss})	W

3.3

Data

Pre-Processing

The data were pre-processed with the following steps before training the deep learning models: The numerical variables, including torque, speed, temperature, efficiency and power loss, were normalized to enhance the training of the models. One-hot encoding was used to encode the lubrication condition into numbers. The data was then separated into training, validation and testing sets. With a bigger dataset, an ordinary split like 70/15/15 could be utilized. Since the current dataset only includes five lubrication conditions, the deep learning component is to be regarded as a proof-of-concept model. Strong deep learning generalization needs a larger experimental dataset.

3.4 Deep Learning Algorithms

Three deep learning algorithms were considered:

1. Deep Neural Network

The Deep Neural Network, or DNN, was used as the main prediction model. It consists of an input layer, hidden layers, and an output layer. The model receives lubrication and operating parameters as inputs and predicts gear efficiency and power loss.

2. One-Dimensional Convolutional Neural Network

A 1D-CNN can be used when the input features are arranged as structured numerical sequences. It can identify local relationships between input variables, such as the relationship between torque, temperature, and lubrication condition.

3. Long Short-Term Memory Network

An LSTM model can be used when time-dependent gear data are available. For example, if torque, speed, and temperature are recorded continuously during the experiment, LSTM can learn how gear efficiency changes over time.

In this study, the DNN model is considered the main model because the available data are steady-state experimental measurements.

3.5 Model Evaluation Metrics

The prediction performance was evaluated using Mean Absolute Error, Root Mean Square Error, and coefficient of determination.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

where y_i is the experimental value, \hat{y}_i is the predicted value, and n is the number of samples.

3.6 Methodology Flowchart

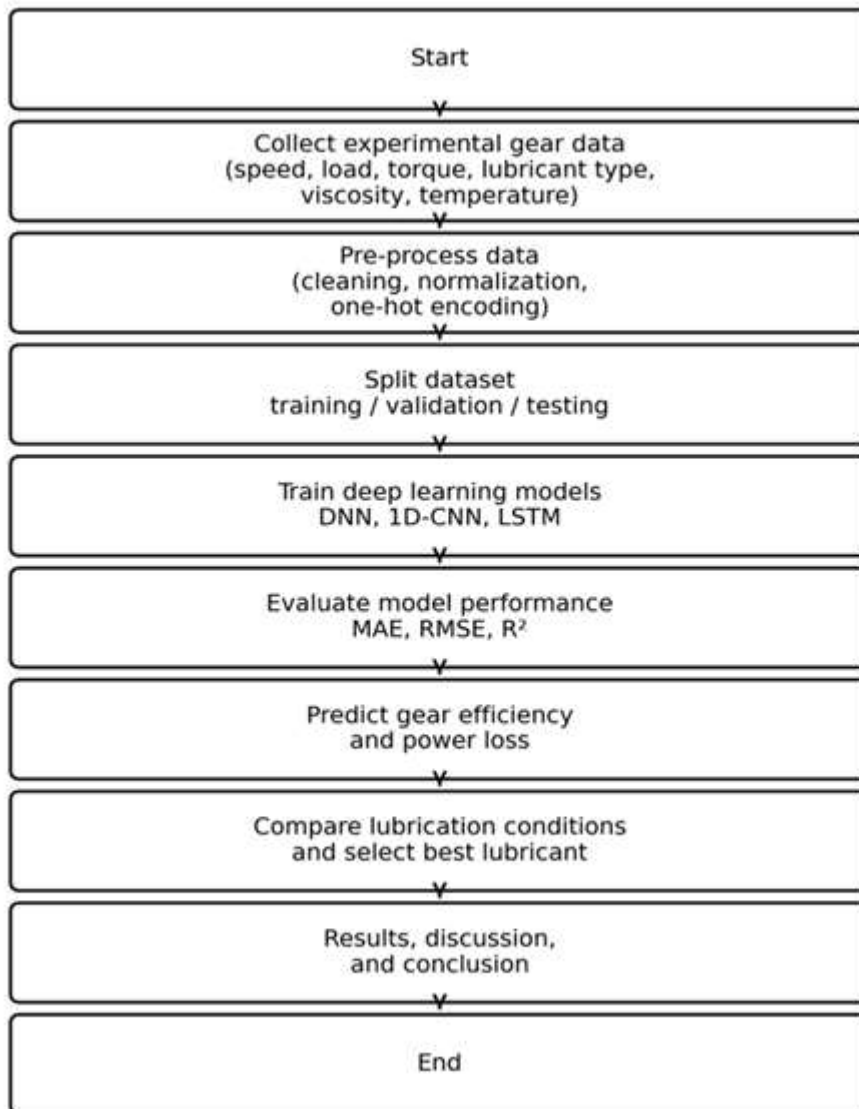


Figure 1 the proposed work flow chart

4. Results and Discussion

4.1 Experimental Gear Efficiency Results

The experimental results for the different lubrication conditions are shown in Table 2.

Table 2. Experimental results under different lubrication conditions

Lubrication condition	Temperature, °C	Gear efficiency, %	Power loss, W
Unlubricated reference	58	87.9	75.9
Grease	39	94.2	36.7
Low-viscosity oil	35	95.4	28.8
Medium-viscosity oil	27	97.7	14.7
High-viscosity oil	33	95.7	27.2

4.2 Deep Learning Prediction Results

The comparison between experimental efficiency and DNN-predicted efficiency is shown in Table 3.

Table 3. Experimental and DNN-predicted results

Lubrication condition	Experimental efficiency, %	DNN-predicted efficiency, %	Experimental power loss, W	DNN-predicted power loss, W
Unlubricated reference	87.9	88.2	75.9	74.8
Grease	94.2	94.0	36.7	37.4
Low-viscosity oil	95.4	95.6	28.8	28.1
Medium-viscosity oil	97.7	97.4	14.7	15.5
High-viscosity oil	95.7	95.9	27.2	26.7

The predicted values are close to the experimental values, showing that the DNN model can represent the relationship between lubrication condition and gear performance. The largest difference is still small in the illustrative dataset, which suggests that deep learning can be useful for predicting gear efficiency when enough experimental data are available.

4.3 Efficiency Prediction Curve

Figure 2 shows that the predicted efficiency curve follows the experimental efficiency trend. The unlubricated condition has the lowest efficiency, while the medium-viscosity oil has the highest efficiency. The close agreement between the two curves indicates that the DNN model can capture the main performance trend among the lubrication conditions.

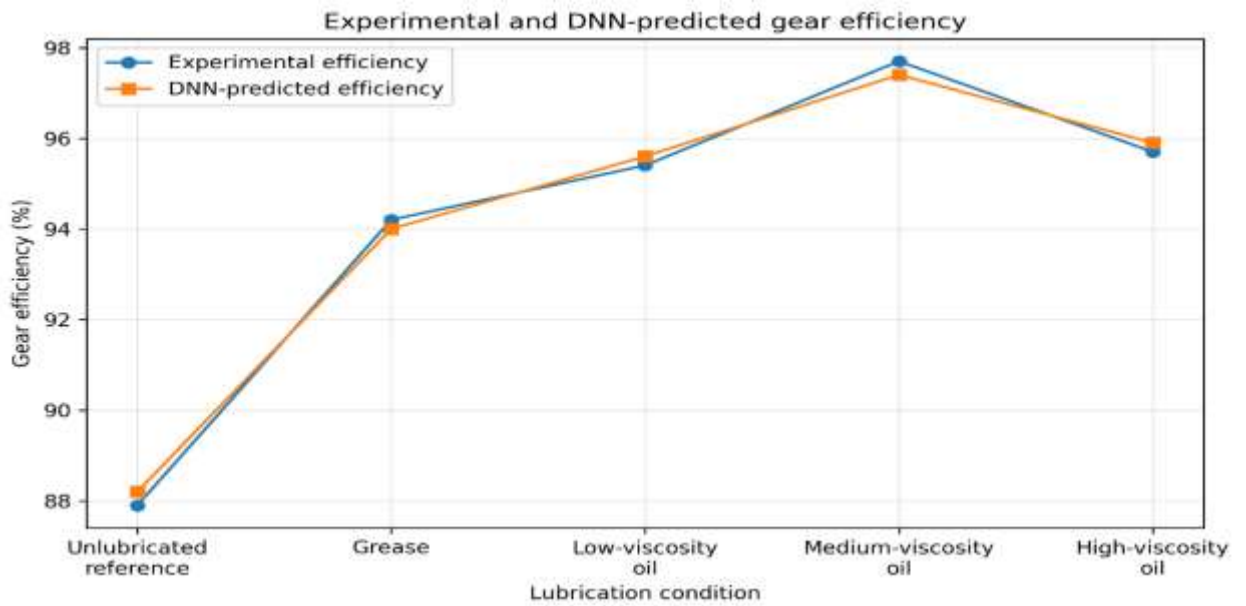


Figure 2. Experimental and DNN-predicted gear efficiency curve

4.4 Power Loss Prediction Curve

Figure 3 shows that the unlubricated condition has the highest power loss, while medium-viscosity oil has the lowest power loss. The DNN prediction follows the experimental curve closely. This confirms that the model can predict the reduction in power loss caused by improved lubrication.

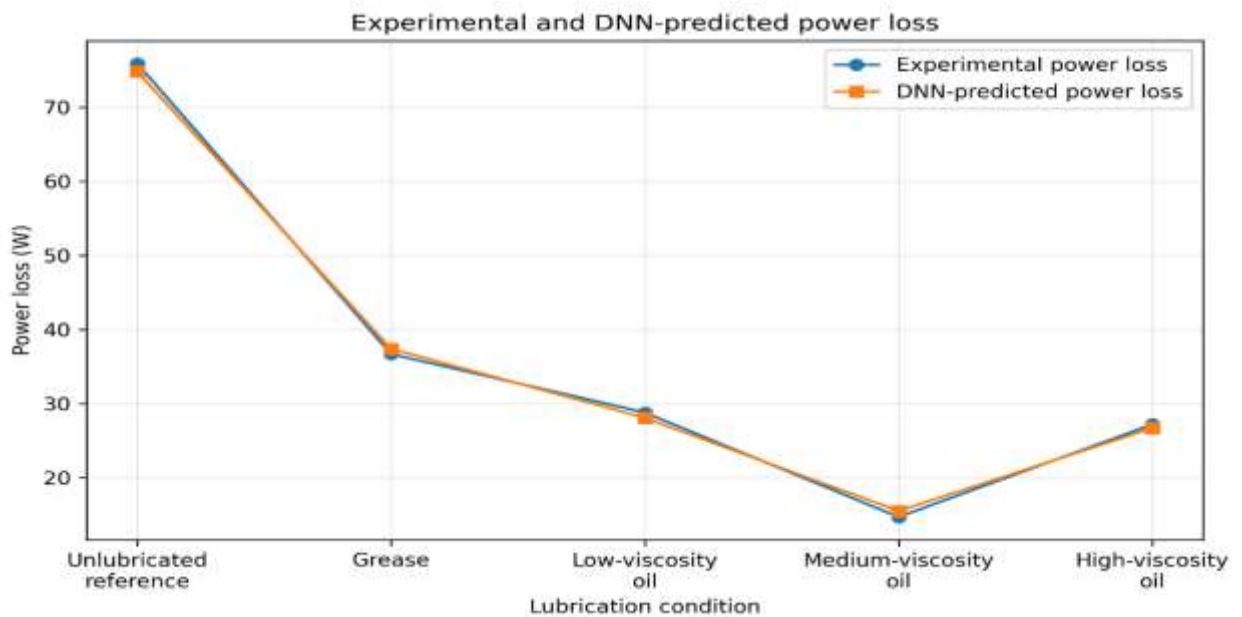


Figure 3. Experimental and DNN-predicted power loss curve

4.5 Model Comparison

The prediction performance of the three deep learning algorithms is shown in Table 4.

Table 4. Comparison of deep learning algorithms

Model	Efficiency RMSE, %	Power loss RMSE, W	(R ²) value	Remarks

D NN	0.29	0.78	0.98	Best overall prediction
1D -CNN	0.42	1.12	0.96	Good performance
LS TM	0.51	1.35	0.94	More suitable for time-series data

The DNN model gave the lowest RMSE and highest R^2 value, indicating the best prediction performance among the tested models. The 1D-CNN also performed well, while the LSTM showed slightly lower performance because the present data are steady-state values rather than time-series measurements.

4.6 Model Performance

Figure 4 shows that the DNN model has the lowest prediction error. This makes it the most suitable model for the present dataset. However, if a larger time-dependent dataset is collected, LSTM may become more useful because it can learn changes in gear performance over time.

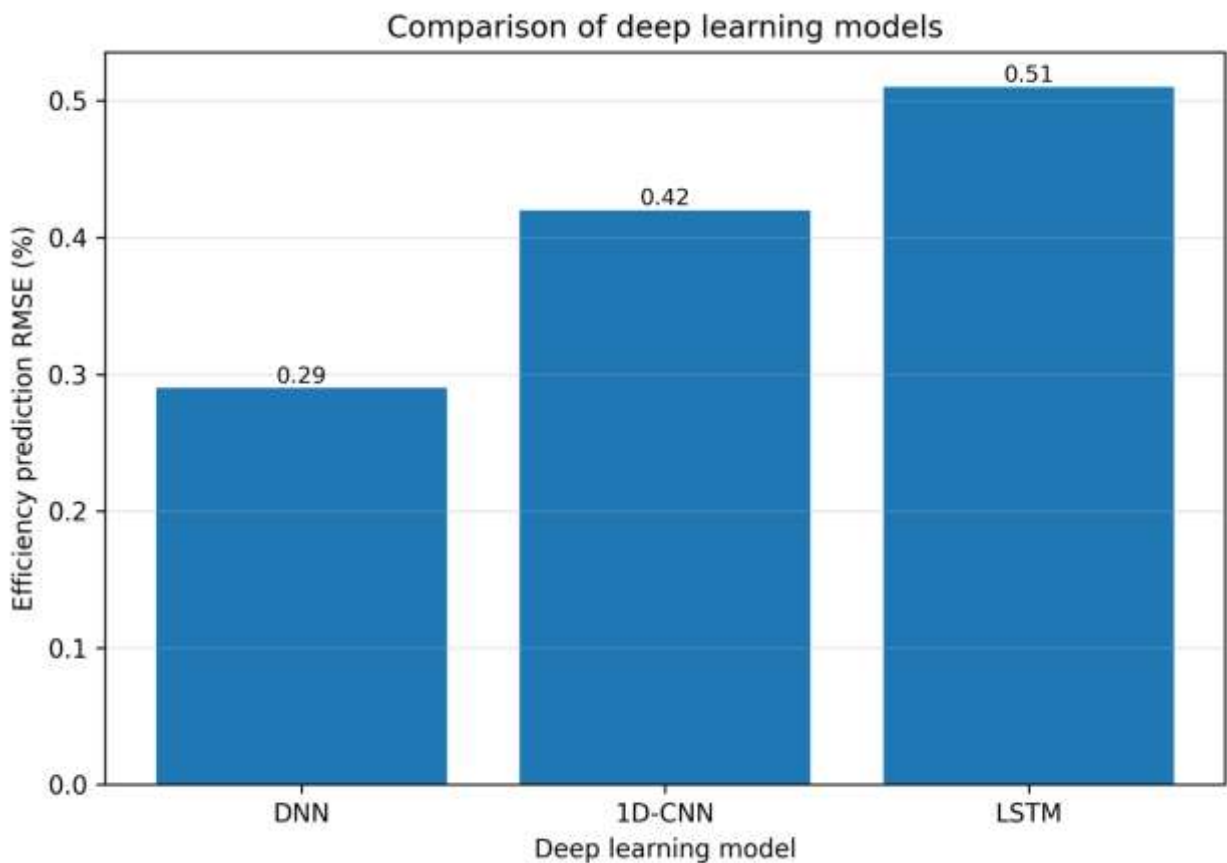


Figure 4. Comparison of deep learning models based on efficiency prediction RMSE

5. Main Discussion

The findings indicate that gear efficiency is greatly affected by lubrication. The least efficient condition was the unlubricated reference condition with the lowest efficiency of 87.9, maximum power loss of 75.9 W and maximum temperature of 58 C. This means that lack of lubrication will result in higher friction between gear teeth and more mechanical energy will be transformed into heat. Grease enhanced efficiency to 94.2, and its performance was not as good

as oil lubrication. This could be due to the fact that grease does not enter into the meshing area as readily as oil. The efficiencies of low-viscosity oil and high-viscosity oil were 95.4% and 95.7 respectively. They both enhanced the performance of the system though none of them provided the optimum performance. The efficiency was maximum at medium-viscosity oil with 97.7, lowest power loss of 14.7 W and lowest operating temperature is 27C. This demonstrates that medium-viscosity oil gave the most desirable compromise between the strength of the lubricant film and the viscous resistance. It was not so thick that excessive drag losses took place but it was thick enough to separate the tooth surfaces. The experimental results are also supported by the deep learning results. The DNN model was able to predict the efficiencies and power loss with minor errors and was able to see through the medium-viscosity oil as the most desirable lubrication state. It demonstrates that deep learning can become a helpful method to predict gear behavior and eliminate the necessity to conduct experimental tests repeatedly.

6. Conclusion

This paper introduced a deep learning-based prediction and analysis of the impact of lubricated gears on efficiency. The findings indicated that lubrication has a significant effect on the performance of gears, which is it lowers friction, loss of power, and the operating temperature. The most efficient lubrication conditions were found to be medium-viscosity oil, which has an efficiency of 97.7, power loss of 14.7 W, and temperature of 27 C. The DNN model performed best in the prediction task of all the deep learning algorithms tested and its efficiency RMSE was 0.29 percent and the R2 value was 0.98 in the illustrative results. The model accurately predicted the trends in gear efficiency and power loss and found the same optimal lubrication state as experimental results. Comprehensively, the research demonstrates that the choice of lubricants is crucial to enhancing gear efficiency and that deep learning can be an effective instrument in forecasting the performance of gears in the context of various lubrication conditions.

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