Optimal mix of nano-additives with SAE10W30 lubricant oil for enhanced performance

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Abstract:
This article focuses on enhancing the performance of SAE10W30 lubricant oil for desirable lubricant properties, mixing with three different nano-additives. An artificial neural network, trained with data from 810 samples, was employed to predict the properties for 8,000 combinations of nano additives. This analysis identified the optimal mix that minimized wear and friction while ensuring desirable viscosity, density, and thermal stability. The blend was validated through real-time testing on a crankshaft-bearing assembly.

Keywords:
Nano additives, lubricant properties, optimal mix, factorial design, artificial neural network.

1. Introduction:
Wear is the gradual deformation of material from a surface due to mechanical action, such as sliding, rolling, or impact, in contact with another surface. This process leads to the degradation of components, affecting their performance, efficiency, and lifespan. Surface deposition of lubricants enriched with nanoparticles significantly reduces wear rates. Research has explored the effects of different nano-additive lubricants, such as SiO_2 TiO_2, and Al_2O_3, on wear and the coefficient of friction (CoF). Silicon dioxide (SiO_2), Aluminum oxide (Al_2O_3), and Titanium dioxide (TiO_2) nanoparticles play a crucial role in enhancing the performance of lubricants by improving their thermal, tribological, and rheological properties [1]. SiO_2 nanoparticles significantly enhance the thermal conductivity and stability of base oils while increasing their load-carrying capacity and reducing friction, leading to improved energy efficiency and lower wear. Al_2O_3 nanoparticles contribute to superior thermal and tribological properties, enabling lubricants to withstand high temperatures and pressures, thereby minimizing friction and wear while extending engine durability [2]. TiO_2 nanoparticles offer excellent anti-wear and friction-reducing characteristics by forming protective layers on metal surfaces, which improves machinery lifespan, fuel efficiency, and overall thermal stability [3]. The integration of these nanoparticles into lubricants presents a promising approach for optimizing lubrication performance, reducing energy consumption, and enhancing the longevity of mechanical systems [4].

2. Ann model:
ANN has become popular because they can model intricate non-linear relationships between input variables and output properties [5]. ANNs can be trained on experimental data to predict multiple material properties simultaneously, making them highly efficient for optimizing compositions. In this study, an ANN model is developed to predict six critical properties of oxide-based materials: Specific Wear Rate, CoF, Flash Point, Density, and Kinematic Viscosity, based on three input parameters: the weight percentages of SiO_2, TiO_2, and Al_2O_3 The goal is to demonstrate the effectiveness of ANN models in accurately predicting these properties and to explore how different optimization techniques can enhance the model's performance [6].
In this study, MATLAB's Neural Network Toolbox was utilized to develop and train an ANN model for predicting tribological, thermal, and rheological properties of nanocomposite materials. The dataset comprised 27 unique samples, each characterized by three input variables such as SiO_2, TiO_2, and Al_2O_3 nanoparticles and six output variables, including specific wear rate, coefficient of friction, flash point, fire point, density, and kinematic viscosity with the desirable quality metrics [7]. Each sample underwent 30

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repeated observations, yielding a total of 810 data points for training the ANN model. The trained ANN then generated 8000 virtual samples, enabling a broader exploration of property variations beyond physical experimentation. Backpropagation, a key learning algorithm, was employed to optimize weights and biases, minimizing the error between predicted and actual values. By leveraging ANN, the study identified optimal compositions for each material property, selecting six top-performing samples for further analysis.

The proposed ANN model is structured with three key components such as an input layer, multiple hidden layers, and an output layer, as illustrated in Figure 1. It is designed to process input data, learn complex patterns, and accurately predict lubricant performance properties. The input layer consists of three neurons corresponding to the weight percentages of SiO_2 TiO_2, and Al_2O_3 which define the composition of lubricant additives. The model incorporates 20 hidden layers, each applying weights and biases to capture nonlinear interactions between input parameters and output properties. This layered approach enhances the ANN's ability to model intricate relationships within the dataset. The output layer comprises five neurons, each predicting a key lubricant property such as specific wear rate, coefficient of friction, flash point, density, and kinematic viscosity. By training on these inputs and outputs, the ANN effectively models and predicts lubricant performance, aiding in the optimization of additive compositions.

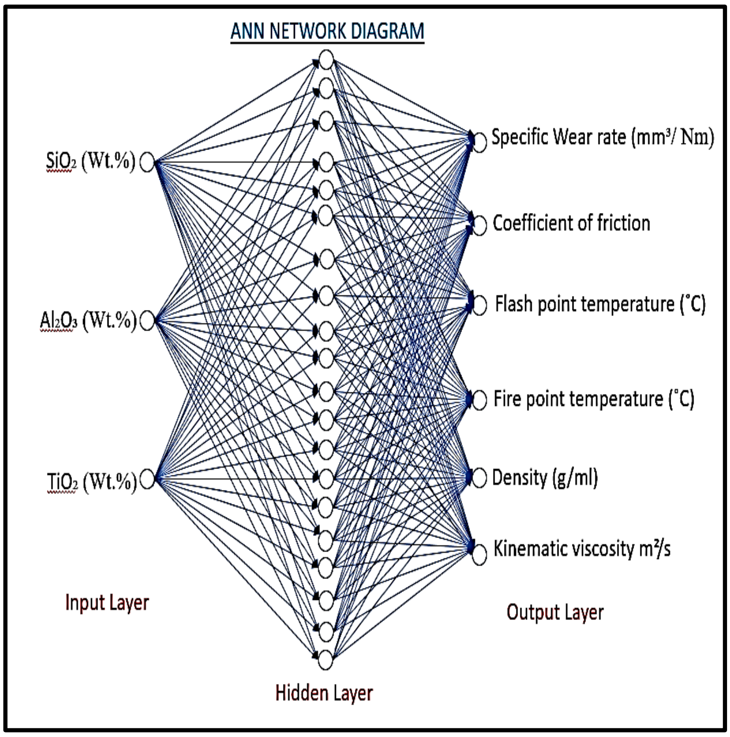

Figure. 1: ANN Network diagram

The ANN model is trained using a dataset containing various samples with known input compositions and corresponding output properties. During training, the model adjusts the weights and biases in the hidden layers through back-propagation, an iterative process that minimizes the error between predicted and actual values. The network architecture includes an input layer with three neurons representing the input variables, a single hidden layer with ten neurons, and an output layer with six neurons corresponding to the predicted material properties, as illustrated in Fig. 2.

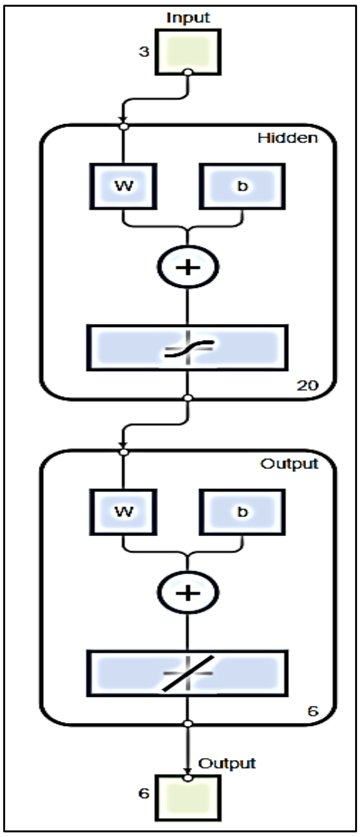

Fig. 2. Function Fitting Neural Network

The dataset used for training is detailed in Fig. 3. MATLAB's built-in training algorithm is utilized to optimize the network parameters, refining the synaptic weights and biases to enhance prediction accuracy.

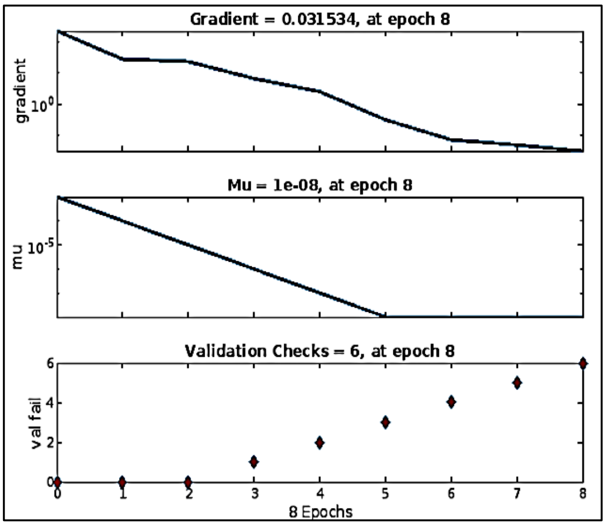

Fig. 3. Training State

After training, the performance of the ANN model is evaluated using testing data, which was not used during training. Performance metrics such as MSE and Regression value are computed to assess the accuracy of the predictions. These are shown in Fig. 4 & 5 respectively.

Additionally, a visual inspection of predicted versus actual values is performed to qualitatively validate the model's performance. In Figure 4, the value of mse is higher in the 1st epoch after training for 8th epoch the value of mse is reduced. This shows improvement in the performance. Figure 5 compares the predicted response values of the test set to the actual response values. A well-performing model will have predictions clustered close to the line.

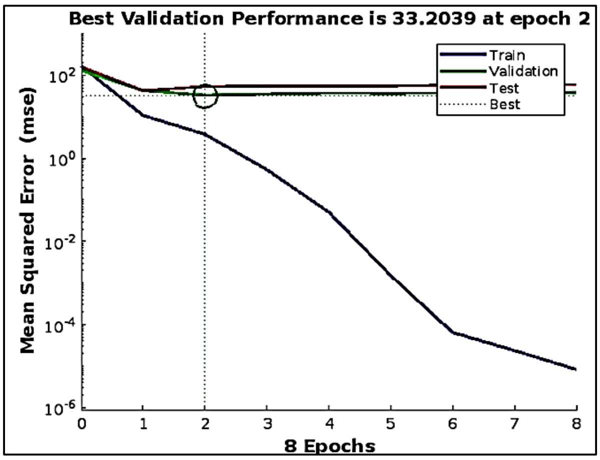

Fig. 4. Performance of ANN model

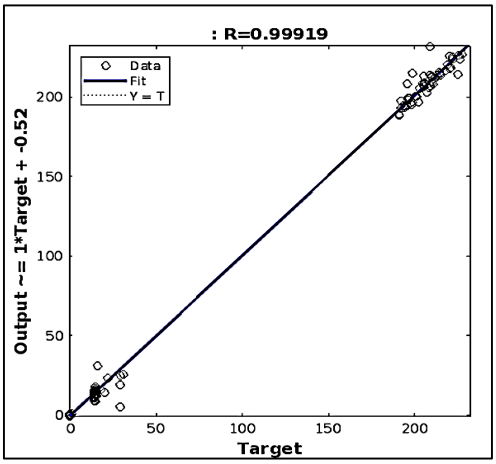

Fig. 5. Regression

Figure 6 illustrates the distribution of errors from neural network predictions on testing instances. Typically, for each output variable, a normal distribution centred on zero is expected. The trained ANN model demonstrated promising performance in predicting material properties based on chemical composition data.

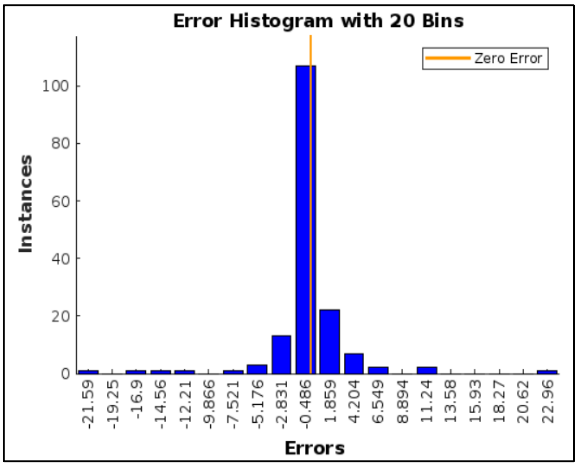

Fig. 6. Error Histogram

The Neural Network training and R^2 values indicated a good fit between predicted and actual values as shown in Table. 2 & 3, suggesting that the model effectively captured the underlying relationships in the dataset. Visual inspection of predicted versus actual values further confirmed the model's ability to capture the trends and variations in the data [8].

Table. 2: Neural Network training

Training Progress			
Unit	**Initial value**	**Stopped value**	**Target value**
Epoch	0	8	1000
Elapsed Time	-	00:00:04	-
Performance	166	8.3e-06	0
Gradient	224	0.0315	1e-07
Mu	0.001	1e-08	1e+10
Validation check	0	6	6

Data Division: Random dividerand
Training : Levenberg-Matquardt trainlm
Performance : Mean Squared Error mse
Calculations : MEX

Table. 3: R^2 value

R^2= 0.1358 Ans =					
0.0070	0.0251	0.0000	0.0518	0.0280	0.0018
0.0003	0.1454	0.0908	0.1137	0.0048	0.0153
0.0204	0.1778	0.1258	0.0376	0.0351	0.0222
0.0000	0.0605	0.0107	0.0852	0.0377	0.0003
0.0365	0.0091	0.0140	0.2254	0.3379	0.0842
0.0950	0.2487	0.1181	0.0369	0.2515	0.4422

The developed ANN model provides a valuable tool for predicting material properties based on chemical composition data. By harnessing the capabilities of machine learning, researchers and engineers can accelerate the material discovery and optimization process, facilitating the development of novel materials with customized properties for a wide range of applications [9].

3. Result analysis of the ANN generated samples:

Table 4 presents the optimum values of nanofluid parameters, among the 8000 samples generated by an ANN. Each sample shows a different mix of SiO_2, Al_2O_3, and TiO_2 additives, along with its specific wear rate (mm^3/mm), CoF, density (g/ml), flash point (˚C), fire point (˚C), and kinematic viscosity (m^2/s). For the first sample with 0.9 wt.% of SiO_2, 0.6 wt.% of TiO_2, and 0.3 wt.% of Al_2O_3, the nanofluid shows least specific wear rate of 0.000000060 mm^3/Nm, indicating potential improvement in wear resistance. The CoF is relatively low at 0.30869168, suggesting reduced friction between surfaces. The nanofluid also demonstrates a density of 1.025 g/ml, a flash point temperature of 188.8 ˚C, a fire point temperature of 196.5 ˚C, and a kinematic viscosity of 11.26 m^2/s.

Table 4. Optimum values of nanofluid parameters among 8000 ANN generated samples

ANN Sample	**SiO_2 (wt.%)**	**TiO_2 (wt.%)**	**Al_2O_3 (wt.%)**	**Specific Wear rate (mm^3/Nm)**	**CoF**	**Density (g/ml)**	**Flash point (˚C)**	**Fire point (˚C)**	**Kinematic viscosity @55˚C (m^2/s)**
ANN S1	9	0.6	0.3	0.000000060	0.3086917	1.025	188.8	196.5	11.26
ANN S2	3	0.9	0.8	0.001028567	0.0000161	0.966	204.5	221.6	11.12
ANN S3	4	0.6	0.35	0.001461324	0.2368572	0.897	189.3	211.6	14.59
ANN S4	05	0.75	0.55	0.0019968	0.2646728	0.990	217.9	218.0	4.57

				99					
ANN S5	3	1	0.05	0.0019278 05	0.0170795	0.980	206.4	232.6	15.51
ANN S6	05	0.6	0.55	0.0010061 77	0.2348986	0.982	213.1	218.5	3.08

4. Multi-objective polynomial optimization:

A multi objective polynomial optimization program [10] is developed with the input values taken from table 4. The optimization process involves three key steps are polynomial regression, optimization, and post-processing. in polynomial regression, input features are transformed into polynomial features of degree 2 to capture nonlinear relationships, followed by fitting a linear regression model for each output variable. The optimization step utilizes an objective function that balances minimizing specific outputs (y_1, y_2, y_3, y_6) while maximizing others (y_4, y_5) by minimizing the sum of the selected outputs and maximizing the negative sum obtained if any. Sequential least squares programming (slsqp), is employed using the minimize function from scipy.optimize to optimize the objective function while handling constraints [11]. In the post-processing stage, the optimized results are adjusted to the nearest allowed values within the specified range (0.05 to 1, at intervals of 0.05) to ensure compliance with predefined constraints.

5. Conclusion:

This experiment discussed the tribological, thermal, and rheological properties of 27 experimental samples, along with the predicted properties of 8000 samples from an ANN program and the values from the mop model. This comprehensive analysis validated the optimal weight percentage concentration for achieving the best material properties. The mop program utilizes the best six ANN sample nanoparticle weight percentages. In this method, the addition of 0.05 wt.% SiO_2, 1% wt.% TiO_2, and 0.05% wt.% Al_2O_3 to SAE10w30 base oil worked best for getting the right amount of mop nanoparticles to provide optimal performance characteristics in the oil blend.

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