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ORIGINAL ARTICLE

A well-trained artificial neural network for predicting the optimum conditions of MWCNT–ZnO (10:90)/ SAE 40 nano-lubricant at different shear rates, temperatures, and concentration of nanoparticles

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SAE 40-nano lubricant;
ZnO;
Least square method

Abstract Fluid limitation in various industries due to their poor thermal conductivity has led to the improvement of the properties of the base fluid as a new method. With the development of nanofluid research, nanofluids are produced by adding metal nanoparticles and multi-walled carbon nanotubes (MWCNT). Due to the inability of theoretical models to predict the viscosity of nano-lubricants (μ_{nf}), mathematical models, especially artificial neural networks (ANNs), investigate the effect of various parameters on the properties of nanofluids and have replaced most of the usual statistical methods. This study investigates the effect of temperature, shear rate (SR), and volume fraction of nanoparticles (φ) on μ_{nf} of MWCNT –ZnO (10:90)/ SAE 40 nano-lubricant. Also, a non-linear polynomial with terms up to power 3 is fitted in the experimental data, and its accuracy is compared to that of ANN in MATLAB. It was proposed that the ANN model has high accuracy (slightly better concerning nonlinear polynomial) for estimating the present study, the μ_{nf} of MWCNT–ZnO (10:90)/SAE 40 nano-lubricant. This ANN achieves 0.9995 and 0.00048 values for R^2 and MSE, while the nonlinear polynomial showed 0.9983 and 4.0223 values, respectively,

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Nomenclature

$T\ (^oC)$	*temperature*	$\mu_{nf}(cP)$	*Dynamic viscosity of nanofluid*
R^2	*Correlation Coefficient*	φ	*Volume fraction*
$\dot{\gamma}\ (rpm)$	*Shear rate*		

for the same parameters, which shows the good training status of the ANN. According to obtained results, the temperature and SR significantly influence the output. The experimental results showed that by increasing the temperature from 25 to 50 ℃, the μ_{nf} of the nano-lubricant decreased from 397.5 to 90.5 cP (at φ = 1 % and SR = 400 rpm). So, the results show that with increasing temperature to 50 ℃, the viscosity of the nano-lubricant decreases by about 77 %. With increasing SR from 400 to 1000 rpm(at T = 50 ℃ and φ = 1 %), the viscosity of the nano-lubricant decreases from 90.5 to 85.3 cP. On the other hand, φ has a direct but negligible effect on μ_{nf}. In other words, the nanoparticle fraction change from 0 to 1 %, changes the μ_{nf} from 150 cP to around 200 cP. This model can be used as a design tool in future research or as an objective function in optimization problems.

1. Introduction

It may be safe to say that in the last two decades, significant changes have been made in many engineering sciences and techniques, and a major part of these changes is related to nanotechnology and the research conducted in this field (Sun et al., 2021; Keshtegar et al., 2020; Safa et al., 2020; Bagheri et al., 2020; Zhang et al., 2015; Zhang et al., 2018; Cui et al., 2022; Zhang et al., 2016). Scientists and researchers in the field of nanotechnology conducted their research on nanofluids, nanopowders, nanosheets, and nanoscales in general, and found interesting results (A, c., k, s., s, k., 2021; Issa, 2022; Chen and Marco, 2022; Giahi et al., 2021; Mansouri et al., 2017; Suhad et al., 2021; Domyati, 2022; Dwijendra et al., 2022). The most important fields of application of nanotechnology are fluid mechanics and heat transfer. Fluids have many applications in different fields such as lubrication, heat transfer, etc. in different devices (Wang et al., 2022; Wangjian et al., 2021; Narimani, 2022; Yang et al., 2019; Yang et al., 2017), and their rheological and thermal properties are very important. Fluid limitation in various industries due to their poor thermal conductivity has led to the improvement of the properties of the base fluid as a new method. So that the idea of dispersing solid particles in base fluids, which started with millimeters and micrometers, was completed with the use of nanoparticles, and today nanofluids as fluids with high heat transfer capacity are a good alternative to conventional fluids like water, ethylene glycol (EG), and oil (Das et al., 2007). With the development of nanofluid research today, nanofluids can be prepared by adding metal nanoparticles and multi-walled carbon nanotubes (MWCNT) (Ghalandari et al., 2020). $\mu_{nf}$is an important parameter in fluid transfer. Determination of nanofluid viscosity is necessary to accurately calculate the rate of increase in production, pumping power, convective heat transfer coefficient, etc. Studies show that the volume fraction of nanoparticles, nanofluid temperature, type of base fluid, shear rate, etc., affect the viscosity of all nanofluids, including hybrid nanofluids (Ahammed et al., 2016; Mishra et al., 2014; Alarifi et al., 2019).

Experimental results of researchers; like Fedele et al. (Fedele et al., 2012); Minakov et al. (Minakov et al., 2021), Nguyen et al. (Nguyen et al., 2007), show that the increase in $\mu_{nf}$is better than the increase in their thermal conductivity, and various factors such as nanoparticle concentration, temperature, and SR affect the μ_{nf}. Afshari et al. (Afshari et al., 2018) investigated the effect of concentration and temperature on the μ_{nf} of MWCNT–alumina/water (80 %)– EG (20 %) nanofluid. Their results show that μ_{nf} has a direct relationship with the φ. Goodarzi et al. (Goodarzi et al., 2019) investigated the effects of temperature and nanoparticle concentration on the μ_{nf} of ZnO-MWCNT/SAE 10 W40 engine oil hybrid nanofluid. The results show that the nanofluid has Newtonian behavior at all φ and temperatures. With increasing the φ, the μ_{nf}increases. Also, the μ_{nf}decreases with increasing temperature at a constant φ. High costs, time-consuming laboratory tests, and the need for complex equipment are the most problems of such tests. Due to the difficulty in laboratory methods, using mathematical models, especially ANNs, investigated various parameters' effects on the charachteristics of different systems considered by researchers (Zepeng et al., 2021; Yufei et al., 2021; He et al., 2020). The use of ANNs is a cheaper, more efficient, and highly reliable alternative for estimating nanofluids' properties. The advantage of ANNs compared to conventional traditional methods is high speed and complex relationship solving. When ANN has been trained, it can predict the required output parameters using the given input parameters (Tian et al., 2021). Researchers like Akhgar et al. (Akhgar and Toghraie, 2018) and Alrashed et al. (Alrashed et al., 2018) used the ANNs to predict the properties of nanofluids, including MWCNT nanoparticles. They showed that adding these materials to the base fluid improves the nanofluid properties.Table 1.

Results from the μ_{nf}study of MWCNT-carbon/SAE 10 W40-SAE 85 W90, in which the temperature and concentration of nanoparticles define as the ANN input, shows that the effect of temperature on $\mu_{nf}$is better. According to the recommended value of R^2, ANN has a good performance in predicting the μ_{nf}(Maddah et al., 2018). Toghraie et al. (Toghraie et al., 2020) considered temperature, SR, and concentration as inputs and effective factors for predicting the $\mu_{nf}$of WO_3-MWCNTs / Engine Oil hybrid nanofluid in the ANN model. The results showed that the ANN method is suitable for predicting the properties of this nanofluid so that the proposed model fits the experimental data with a R^2 = 0.99. Hemmat et al. (Esfe and Toghraie, 2021) predicted the $\mu_{nf}$of Al_2O_3/engine oil using ANN.the results showed that the ANN estimates laboratory data more accurately.

Parashar et al. (Parashar et al., 2021) investigated the dynamic viscosity of MXene palm oil. Their results show that the μ_{nf} decreases with increasing temperature. The mean square error, mean average percentage error, and correlation coefficient (R^2) were 4.733E-05, 0.507 %, and 0.99975, respectively. Mohammadian et al.

Table 1 Effect of training functions on the ann performance.

Training function	Training Algorithm	Performance
trainbfg	BFGS Quasi-Newton	42.523
trainbr	Bayesian regularization back propagation	0.32
traincgb	Conjugate Gradient with Powell/Beale Restarts	22.85
traincgf	Fletcher-Powell Conjugate Gradient	20.41
traincgp	Polak-Ribiére Conjugate Gradient	30.37
traingda	Gradient descent with adaptive learning rate back propagation	180.83
traingdx	Variable Learning Rate Back propagation	70.04
trainrp	Resilient Back propagation	12.99
trainscg	Scaled Conjugate Gradient	23.21
trainlm	Levenberg-Marquardt	0.63

(Mohamadian et al., 2018) proposed a model for predicting the $\mu_{nf}$of Ag/water nanofluid using an ANN. Temperature, φ and nanoparticle size was defined as model input variables. The values were obtained for the R^2 are 0.9996, which indicates the complete accuracy of the proposed model. Their results show that the use of ANN leads to better results. The results of other researchers also confirm these results (Esfe and Toghraie, 2021; Toghraie et al., 2019; Shahsavar et al., 2019; Longo et al., 2017).

According to the review of previous articles, the ANN method is suitable for predicting nanofluid properties. As a result, in this paper, the effect of temperature, the volume fraction of nanoparticles, and shear rate on the viscosity of the hybrid lubricant (taken from Hemmat Esfe et al. 2017), which contains SAE 40 as the base fluid and a combination of multi-walled carbon nanotubes and zinc oxide (ZnO) as added nano particles, was investigated using the ANN and nonlinear fitting polynomial. In this work, a new modeling network with the highest accuracy is implemented for the prediction of Nanofluid dynamic viscosity and compared with the 3-dimensional nonlinear fitting function in MATLAB Measurements were performed in the temperature range of 25 to 50 ℃, the volume fraction of nanoparticles in the range of 0 to 1 %, and different shear rates (50 to 1000 rpm). This model can be used as a design tool in future research or as an objective function in optimization problems.

2. Material and methods

2.1. ANN construction

Artificial intelligence has found great attention due to its potential and abilities in contrast to statistical methods such as Taguchi or determinant of optimal design methods (Sadr et al., 2017). For example, curve fitting of experimental data for optimization (Babajamali et al., 2022), classification of raw information, and prediction of signal future using time series prediction are some of the capabilities of these intelligent systems. In this manuscript, various topologies for ANN are investigated to obtain the optimum model for predicting the μ_{nf} of MWCNT –ZnO (10:90)/ SAE 40 nano-lubricant. To this end, a multi-layer Perceptron (MLP) network is implemented with different neurons in the hidden layer. To investigate the performance of ANN, various indexes can be used (Esfe et al., 2022; Esfe et al., 2022; Xia et al., 2022), and here, Mean Square Error (MSE) and R^2 are used as performance indexes to assess different network performances and determine the optimum network for μ_{nf} prediction. According to the random nature of ANNs, the ANN is trained 10 times in each case, and the best situation is selected for comparison to other constructions. Due to the *nonlinear relation of input–output parameters*, the transfer function of hidden layer neurons must be of nonlinear type tangant hyperbolic sigmoid or Logarithm sigmoid (*tansig* or *logsig*) (Esfe et al., 2022; Moshayedi et al., 2022; Xie et al., 2022). Based on previous experiences of the authors, the *tansig* function has better performance (Esfe et al., 2021). Hence, this function is used for hidden layer neurons, while this paper uses a linear one for the output layer (Tian et al., 2021; Esfe and Toghraie, 2021; Azimi et al., 2017). As the training function, there is a variety of algorithms used. In this paper, several algorithms were used, and their performance is compared in Table 2. Among these trainig functions, the Levenberg-Marquart (LM) shows acceptable results and performance with low computation efforts for small-medium size ANNs. Also, this algorithm had reasonable performance among the others. Hence, this algorithm (*trainlm*) is used to investigate ANN further. The schematic configuration of this ANN is presented in Fig. 1.

Fig. 1, W shows the weighting vector connecting the inputs to each neuron or the hidden layer neurons' output to the output layer neuron. The b values represent the bias values. This figure shows the input parameters with φ, T, and ST, representing the volume fraction of nanoparticles, temperature, and SR, respectively. The only output of the ANN is the μ_{nf} constructed using a linear activation function. Different values are considered for input parameters, and after experiments, the $\mu_{nf}$is obtained. This article used the experimental data of reference (Issa, 2022). The experiments were repeated at volume fractions of 0.05 %, 0.1 %, 0.2 %, 0.4 %, 0.6 %, and 0.8 %, with temperature range of 5–55 °C, and shear rates from 666.5 to 13,330 s^{-1}. The viscosity of the hybrid nano lubricant was measured using the Brookfield digital viscometer (CAP2000). The φ is in the range of 0 to 1 % with 9 levels, the temperature is chosen between 25 and 50 ℃ with 6 levels,

Table 2 Polynomial coefficients and standard deviation.

Nonlinear term	coefficient	Standard deviation
ϕ^3	−103.4333	12.5865
$T.\phi^2$	−1.8509	0.3987
$SR.\phi^2$	0.0021	0.0145
ϕ^2	245.2420	22.7036
$T^2.\phi$	0.0624	0.0158
$SR.T.\phi$	−0.0010	0.0007
$T.\phi$	−4.1721	1.0974
$SR^2.\phi$	0.0000	0.0000
$SR.\phi$	0.0162	0.0240
ϕ	19.6426	22.2098
T^3	−0.0105	0.0007
$SR.T^2$	0.0000	0.0000
T^2	1.5357	0.0764
$SR^2.T$	0.0000	0.0000
$SR.T$	0.0026	0.0021
T	−80.7641	2.6758
SR^3	0.0000	0.0000
SR^2	0.0001	0.0000
SR	−0.1330	0.0323
1	1593.4006	31.2158

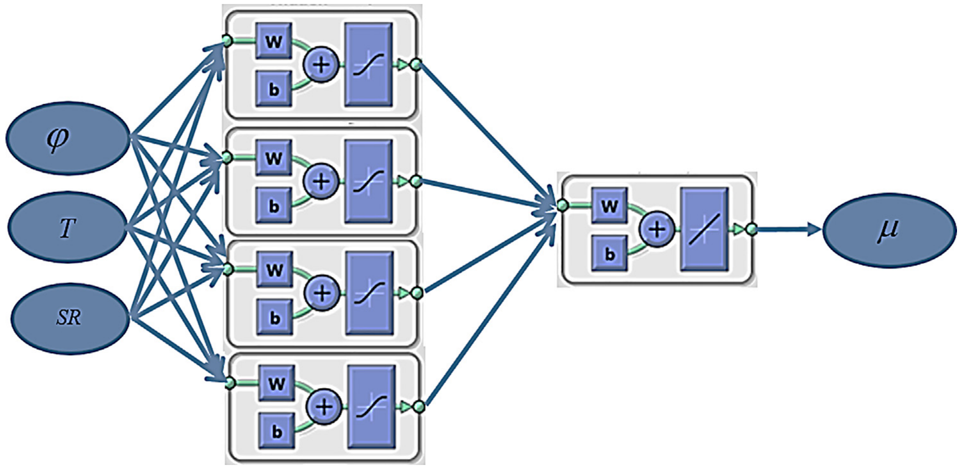

Fig. 1 Schematic configuration of used ANN for prediction of μ_{nf}.

and the SR is considered in the range of 50 to 1000 rpm in 10 different levels. After obtaining the samples from experiments, the first step is to train the ANN. Usually, 70 % of data is used for training, 15 % for validation, and the rest for testing. Therefore, 192 samples were used for training and 41 for validation and test. It is worth mentioning that these portions of data are selected randomly in each training iteration by the algorithm.

To assess the effect of various training functions on the ANN performance, 10 different training algorithms were used, and their performance is compared in Table 1 as follows.

2.2. Nonlinear curve fitting method

This method is developed and programmed based on QR factorization and general least squares by John R. D'Errico (D'Errico, 2005). *Polyfitn* is a powerful and simple algorithm for determining polynomial coefficients using the linear least-squares technique. Also, the chosen method of solution gives standard errors of the coefficients. The theory can be found in Draper and Smith's research (Draper and Smith, 1998).

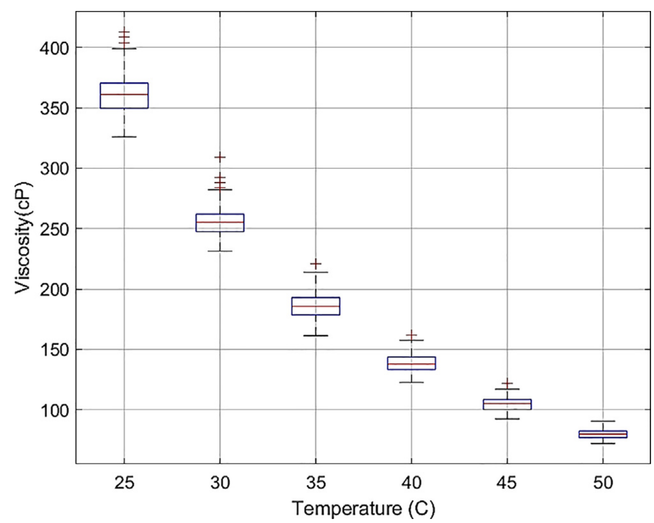

Fig. 3 Effect of temperature on the μ_{nf}deviation.

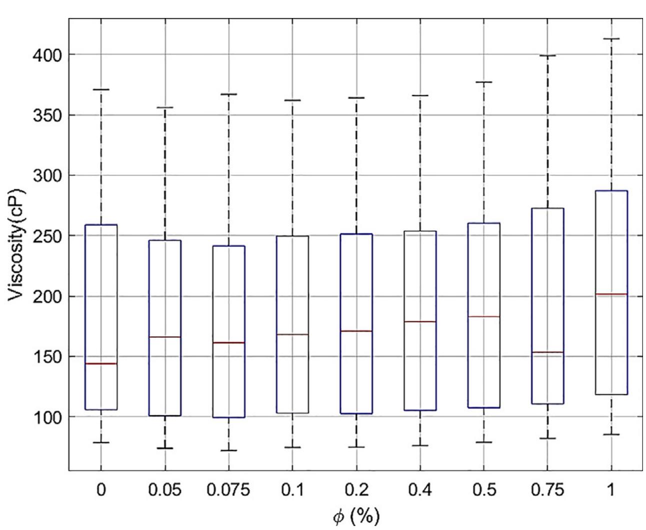

Fig. 2 Effect of φ on the μ_{nf} deviation.

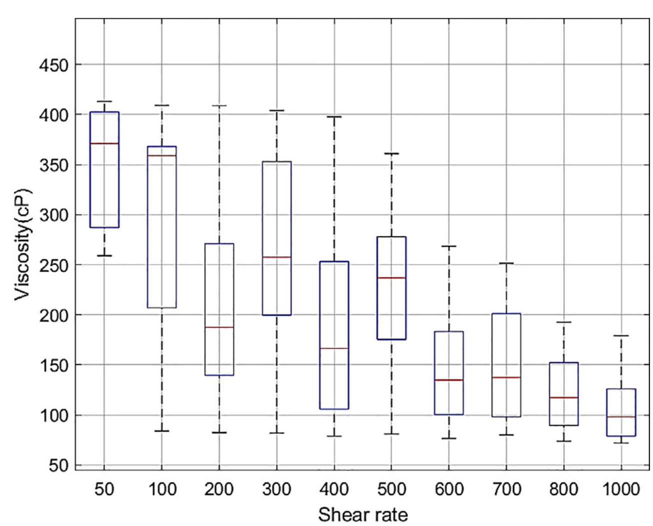

Fig. 4 Effect of SR on the μ_{nf}deviation.

To have a more stable algorithm, the QR factorization with pivoting is used for solving the system. Because it is much more stable concerning simple and pivoted QR version. Moreover, automatic variable scaling is used for illconditioning prevention.

With the experimental data presented in Table 1, a nonlinear polynomial based on three input parameters is assumed to predict the dynamic viscosity of Nanofluid as below.

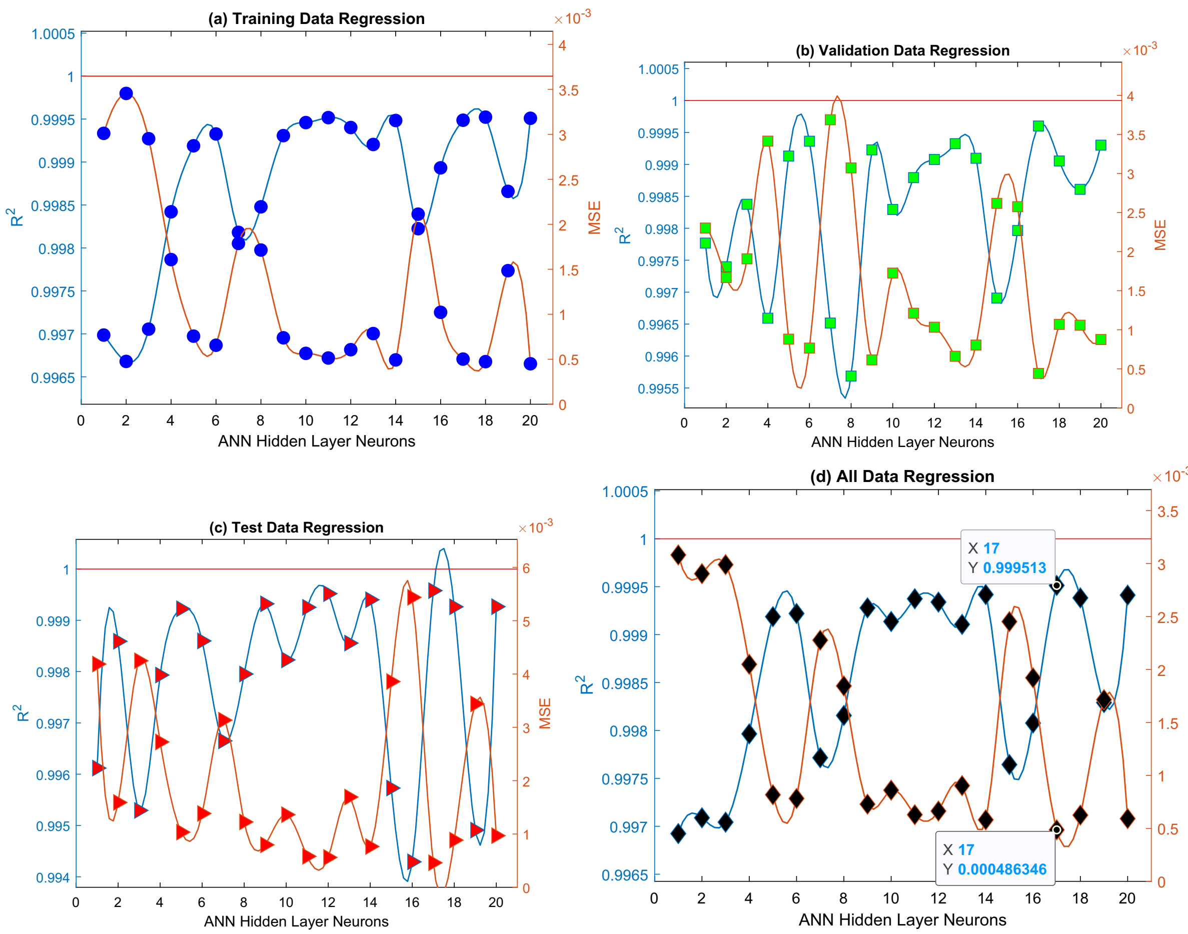

Fig. 5 MSE and R^2 of different ANN topologies for (a) Training data, (b)Validation data, (c) Test data, and (d) All data.

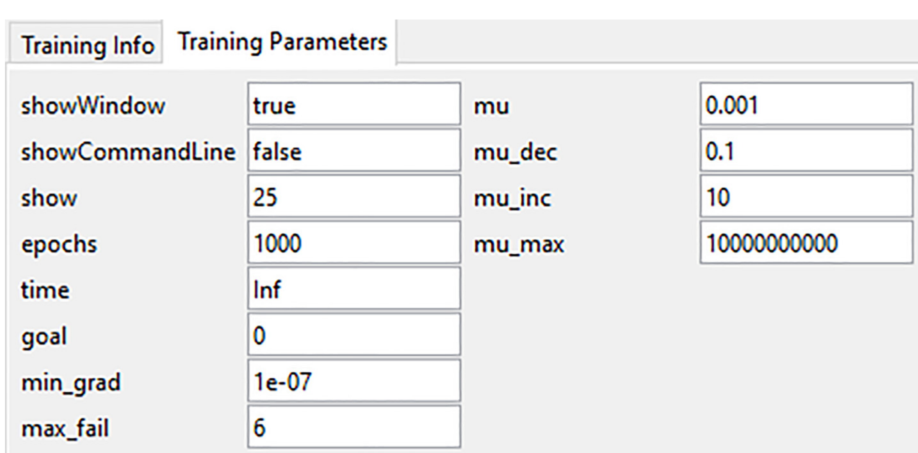

Fig. 6 ANN training parameters.

$$\mu(SR,T,\phi) = a_{30}\phi^3 + a_{31}T^3 + a_{32}SR^3 + a_{33}SR.T.\phi + a_{34}T.\phi^2 + a_{35}SR.\phi^2 + a_{36}T^2.\phi + a_{37}SR.T^2 + a_{38}SR^2.T + a_{39}SR^2.\phi + a_{20}\phi^2 + a_{21}T^2 + a_{22}SR^2 + a_{23}T.\phi + a_{24}SR.\phi + a_{25}SR.T + a_{10}\phi + a_{11}T + a_{12}SR + a_{00}$$

The coefficients a_{ij} must be determined using the least square method. In the implemented notation, the first indexes show the variables' power, and the second defines the term number in the equation. The next section compares the obtained fitting equation and its accuracy to the ANNs results.

3. Results

To have better insight into the raw data, the deviation of μ_{nf} is plotted against three input parameters in Figs. 2-4. Fig. 2 shows that this nano lubricant's viscosity does not change much (increases slightly) with increasing volume fraction. The results of Fig. 3 show that the viscosity of the present nano lubricant decreases with increasing temperature from 25 to 50 ℃ (Chu et al., 2021). This is due to the weakening of molecular attractions between lubricant molecules and hybrid nanoparticles. The results obtained from Fig. 4 show that the viscosity of the nano-lubricant generally decreases significantly with increasing shear rate (Li et al., 2020). Increasing the shear rate reduces the interaction of molecules and nanoparticles. And the free space between most molecules and the particle also increases; Finally, the viscosity of this nano-lubricant decreases.

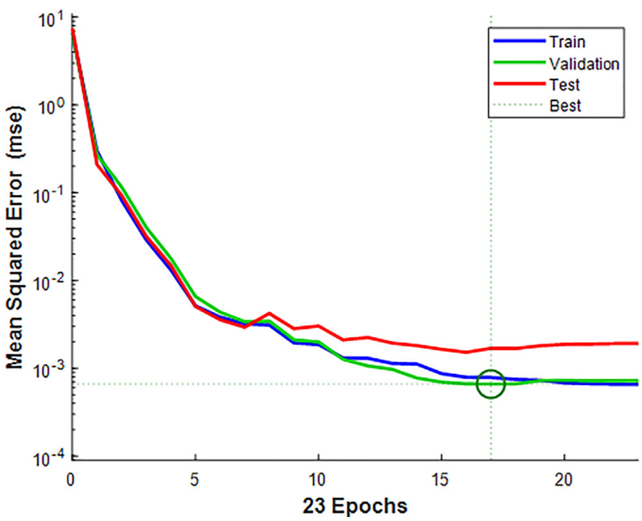

Fig. 7 Performance of ANN with 17 neurons in the hidden layer.

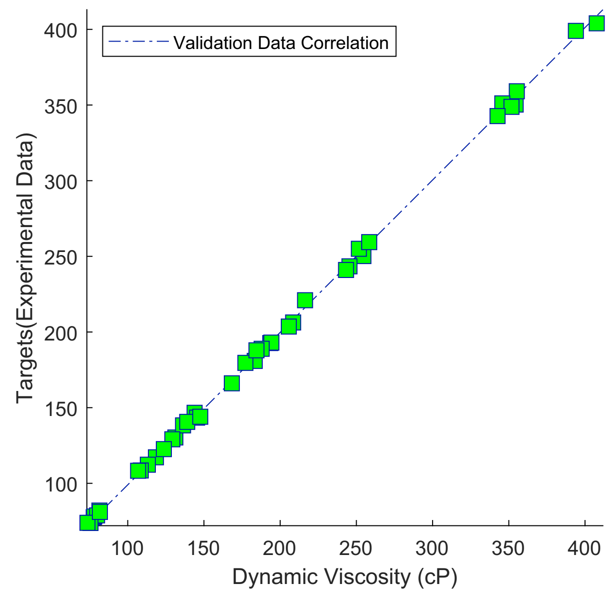

Fig. 9 Correlation plot of validation data for the optimum ANN.

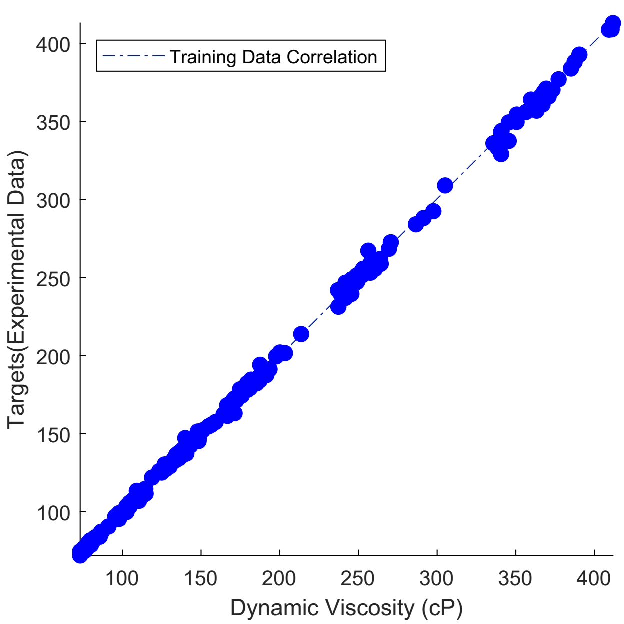

Fig. 8 Correlation plot of training data for the optimum ANN.

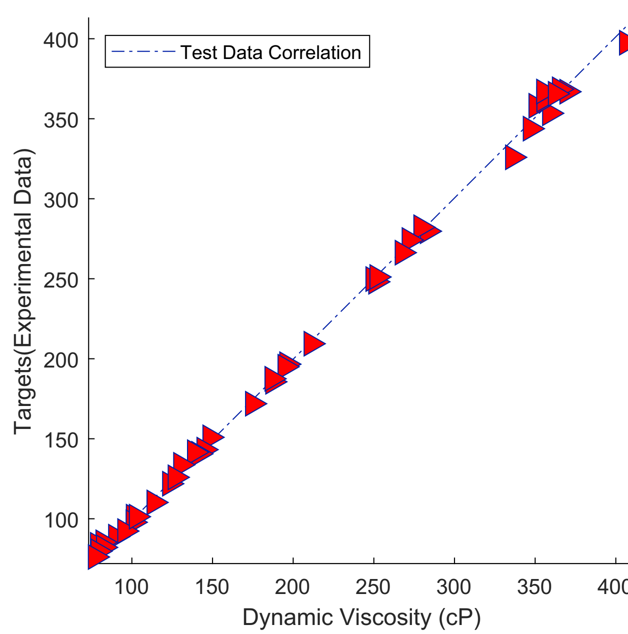

Fig. 10 Correlation plot of test data for the optimum ANN.

3.1. ANN results

Using 274 samples, different ANNs with various neurons from 1 to 20 in the hidden layer were trained. The results are presented in Fig. 5 for training, validation, and test data with different colors. The x-axis shows the number of neurons in the hidden layer in each figure. The y-axis presents two parameters, R^2 and MSE, in the left and right hand of the graph, respectively. To determine the best ANN topology, the MSE and R^2 of each network are computed for each portion of data. These indexes are computed as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\mu_{Exp} - \mu_{output}\right)^2 \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(\mu_{Exp} - \mu_{output}\right)^2}{\sum_{i=1}^{N}\left(\mu_{Exp} - \bar{\mu}\right)^2} \quad (2)$$

The training parameters are shown in Fig. 6.

ANNs training starts from the random condition, hence increasing the network complexity will not necessarily increase its performance. According to these figures, increasing the number of hidden layer neurons will generally increase network performance alongside decreasing the MSE value. Among the investigated topologies, the network with 17 neurons in a hidden layer showed the highest R^2 value as 0.9995 and the lowest MSE equal to 0.0005. Therefore, this network is considered for modeling the input–output relationship of $\mu_{nf}$for this nano-lubricant. In Fig. 7, the performance of this ANN is depicted for three different data portions. The training data are plotted in blue, validation data in green, and the test data in red. The best condition of the network is determined in this graph with a green circle on the 17th epoch. This point is

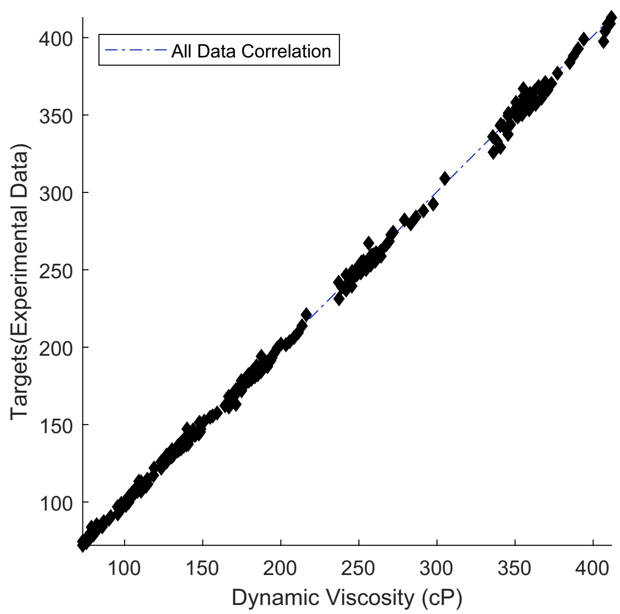

Fig. 11 Correlation plot of all data for the optimum ANN.

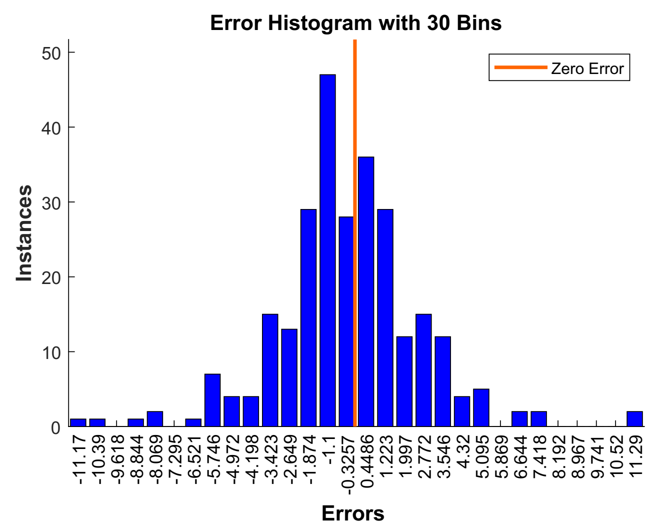

Fig. 13 Error histogram for μ_{nf}.

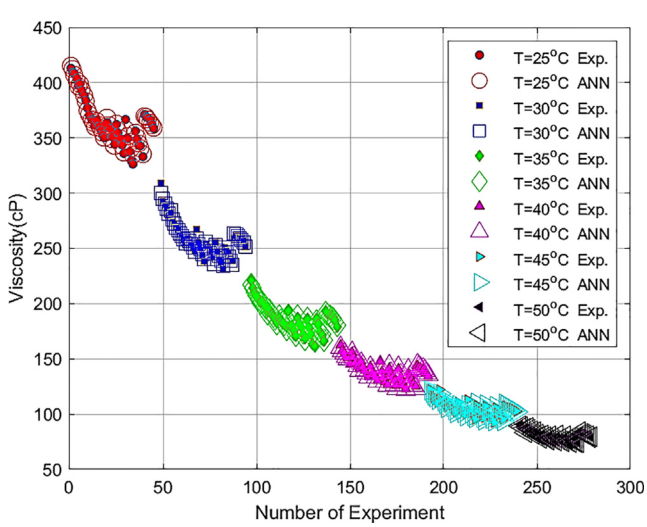

Fig. 12 Comparison of experimental data and the real output of the ANN.

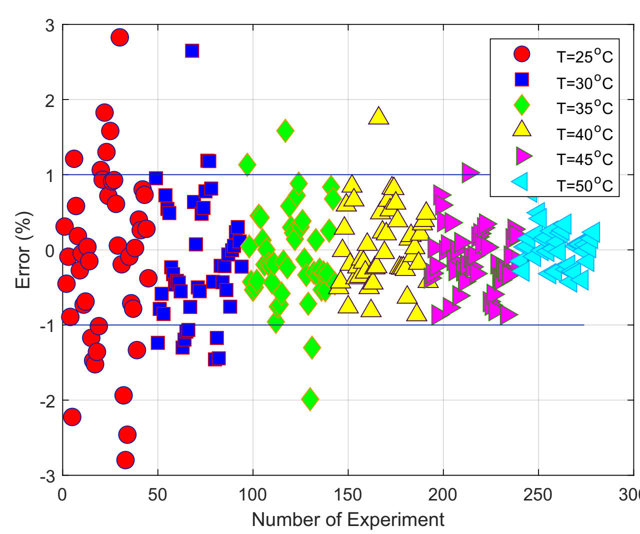

Fig. 14 Error percentage of network output data versus various temperatures.

determined according to the number of validation fails considered here equal to 6 times. In other words, when the ANN is getting to overlearn data, its number of validation fails increases, showing the network is not learning the overall data trend but only maintaining the MSE value as low as possible. Therefore, the best condition of ANN would be the epoch having the lowest validation error.

It is clear from Fig. 7 that the ANN performance is low at the initial iterations. Still, after several iterations, the MSE value decreases exponentially, showing the training condition of the network. To be sure about the training condition of the ANN, the correlation plot of training, validation, test, and all data are presented in Figs. 8-11, respectively. In these figures, different data are specified with different colors.

Targets and output values are shown on the vertical and horizontal axes. In a well-trained ANN, the output and target values should be coincident. In this situation, the line slope would be 1 with 0 bias. Based upon these figures, all data are almost located on the bisector of the plane. Hence there is a very good correlation between the real output of the ANN and target values (Experimental data) that proves the goodness of the trained ANN for predicting μ_{nf} versus three input parameters. In Fig. 12, the real output of the ANN is compared to the experimental data for various temperatures with different colors. Again, there is a good match between these data in this figure.

For another checkpoint, the error histogram is shown in Fig. 13. This graph shows that most samples have errors close to zero (orange line), and the normal distribution of errors proves a good experimental data set and a well-trained ANN.

Fig. 14 shows the error percentage of all samples for different temperatures.

This figure shows that most errors are in the ±1% margin, which is quite acceptable. Another important point is that the deviation of error is decreased with increasing temperature. In other words, the highest deviation is observed $T = 25^oC$ around ±3% while the lowest variation arises in $T = 50^oC$ lower than±0.5%. The reason for decreasing error deviation is that by increasing temperature, the viscosity value would decrease drastically and its error would also lower. According to Figs. 2-4, the significant temperature highly influences the viscosity. On the other hand, the nanoparticle volume fraction in the experimented range has the least effect on the output.

Table 3 Accuracy of nonlinear curve fitting.

R^2	Adj-R^2	MSE
0.9983	0.9981	4.0223

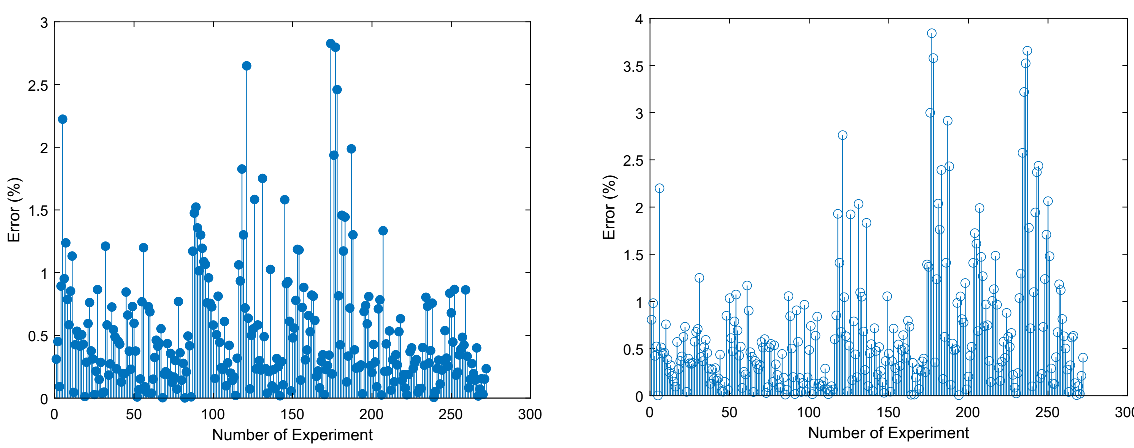

Fig. 15 Comparison of ANN error (Left) and nonlinear polynomial error (Right).

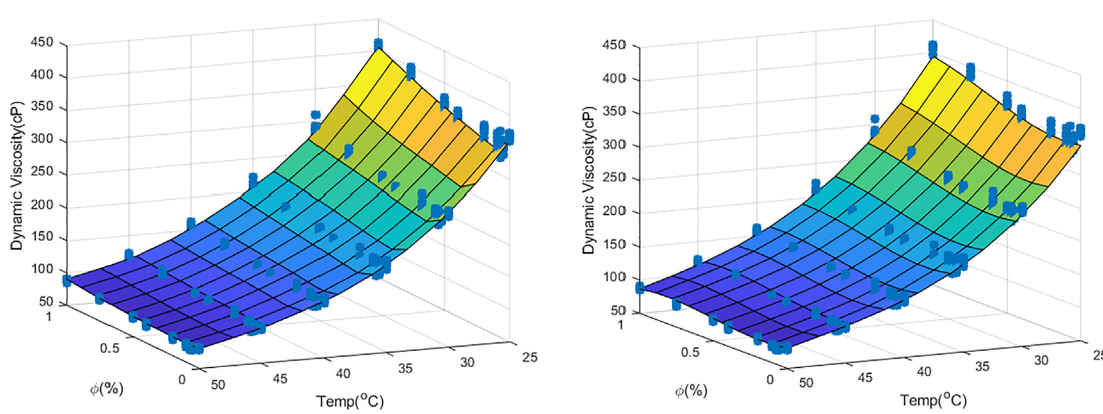

Fig. 16 Comparison of ANN prediction (Left) and nonlinear polynomial prediction (Right).

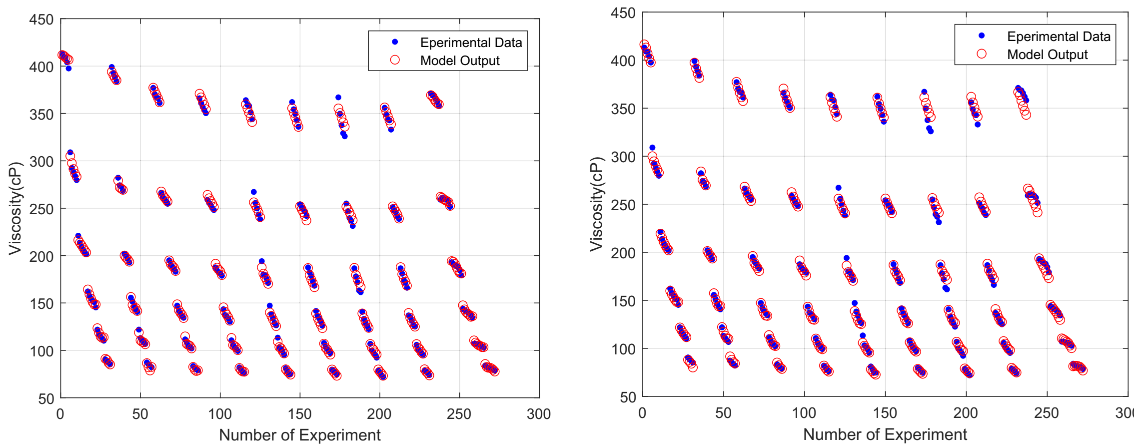

Fig. 17 Comparison of ANN output and targets (Left) and nonlinear polynomial output and targets (Right).

3.2. Nonlinear curve fitting results

Using the least square method, a nonlinear polynomial with the highest degree of 3 can predict the nonlinear relation of three inputs and the dynamic viscosity as the sole output. The obtained equation can be used for design and modeling systems using MWCNT –ZnO (10:90)/ SAE 40 nano-lubricant, likewise the optimized ANN. Also, this equation can be used for optimization as an objective.

The obtained equation is presented as follows:

$$\mu(SR,T,\phi) = -103.43\phi^3 - 0.0105T^3 + 1.5108e - 08SR^3$$
$$-0.0010SR.T.\phi - 1.8508T.\phi^2 + 0.0021SR.\phi^2 + 0.0624T^2.\phi$$
$$+5.6836e - 06SR.T^2 - 1.7457e - 06SR^2.T + 1.8868e - 05SR^2.\phi$$
$$+245.2420\phi^2 + 1.5357T^2 + 5.5572e - 05SR^2$$
$$-4.1721T.\phi + 0.0162SR.\phi + 0.0026SR.T$$
$$+19.6426\phi - 80.7640T - 0.1330SR + 1593.4005$$

To assess the presented models' accuracy, R^2, Adj-$R^{2,}$ and RMSE are computed as listed in Table 3:

To better compare ANN and nonlinear polynomials, the error of individual samples is depicted in Fig. 15 for both methods. ANN has slightly lower errors.

In Fig. 16, the 3D plot of dynamic viscosity versus temperature and nanoparticle volume fraction is presented.

According to this figure, both methods can accurately model the output, i.e., dynamic viscosity. As the last assessment, in Fig. 17, the predicted and target values for all samples are compared for both methods.

In Fig. 17, the real output of the two methods is depicted in red circles, and the experimental data points are shown in blue dots. Therefore, a higher coincidence of red circles and blue dots represent a lower error. Although both methods have acceptable predictions from the above figure, ANN generally has better predictions due to the better coincidence of dots and circles.

4. Conclusion

In this manuscript, three input parameters' influence is investigated on the μ_{nf} of MWCNT –ZnO (10:90)/ SAE 40 nano-lubricant. For this reason, two methods, including ANN and nonlinear polynomials, are used. Input parameters are considered to be φ, temperature, and SR. The following conclusions can be summarized based on the obtained results.

- The optimum topology for ANN has 17 neurons in the hidden layer with a tansig transfer function and 1 linear neuron in the output layer.
- This network achieved 0.9995 and 0.00048 values for R^2 and MSE, respectively, showing the network's good training status.
- Various indexes such as Error Histograms, correlation, and Error percentage plots proved the well-trained network's capability to predict the μ_{nf}.
- The temperature and shear rate significantly influence the output among the three input parameters. Moreover, their effect is inverse because increasing these parameters will lower the μ_{nf} of MWCNT –ZnO (10:90)/ SAE 40 nano-lubricant.
- On the other hand, the φ has a direct but negligible effect on μ_{nf}.
- To be more precise, increasing temperature from T = 25 to 50 ℃ changes the μ_{nf} from 350 cP to around 100 cP.
- Nonlinear polynomial coefficients with 20 terms of powers up to 3 were determined using the least square method. The R^2 and MSE values are equal to 0.9983 and 4.0223, respectively.
- Although both methods showed high prediction potential, ANN methods have slightly better accuracy.

By obtaining ANN or nonlinear polynomials, one can design systems based on nano lubricants or optimize the system as an objective function. Also, the attained results in this manuscript can be used by academics and industrial counterparts.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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