Dry sliding wear behavior of aluminum graphene nanoplatelet (GNP) composites

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Article Information

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Conventional aluminum (Al) and its alloys have been replaced by aluminum matrix composites (AMCs) due to their superior properties in the recent years. There are several attractive candidates as reinforcement for aluminum composites such as Al_2O_3, B_4C and SiC. Nowadays, carbon based materials such as graphite, carbon nanotubes (CNTs) and graphene have attracted much attention owing to their above mentioned mechanical and physical properties. In this study, the wear behavior of Al graphene nanoplatelets (GNPs) composites reinforced with up to 2 wt.-% GNP were investigated. The addition of graphene up to 1 wt.-% decreased coefficient of friction. Experimental data were used to develop linear and nonlinear models. The experimental results are in good agreement with the results of the simulations based on the identified models.

The wear and friction resistances of pure aluminum (Al) are low during operation. Different attempts have been made to improve strength and wear characteristics of Al materials. Metal matrix composites (MMCs) play an important role to improve wear resistance of pure aluminum in relatively moving mechanical parts at dry sliding condition.

There are various studies dealing with carbon nanotube (CNT) reinforced Al alloys in the literature. Al-CNT composites provide lightweight, high stiffness, strength, improved wear and friction resistance, if uniform dispersion is succeeded [1, 2]. So many efforts have been made to overcome agglomeration problem by using ball milling and melting processes. However, CNTs are not suitable for milling process because milling process can cause breakage [3-6]. Graphene has a higher surface area than those of other carbon nanostructures, hence better interface adhesion with metal matrix can be obtained [7]. It was stated that its dispersion in different kinds of matrices is easier than dispersion of CNTs [8]. In recent years, most of the studies have focused on the investigation of mechanical properties of the produced Al graphene nanoplatelets (GNPs) composites [1, 3, 9]. In the literature, several studies investigating the wear behavior of Al-GNPs composites can be found. However, only a few studies on the estimation of the wear behavior of Al-GNPs have been reported. The estimation of wear behavior is very important in machine parts at dry sliding condition in order to predict component lifetime and wear damage [10-12]. Various intelligent modeling techniques are highly effective in understanding the prediction of wear behavior of composites [13-16].

In the present work, three types of models for the estimation of wear behavior of Al-GNPs composites have been developed. The modeling utilized in this study was based on the wear test of the composites at constant wear load and distance.

Experimental procedure

Materials. The powder blends of Al and GNPs at 0, 0.5, 1 and 2 wt.-% were mechanically alloyed (MA'd) in a planetary ball mill (FritschTM, Pulverisette 6) at 300 rpm for 1 hour. As blended and MA'd powders were compacted in a hydraulic press (MSE™ PE-30) with 30 ton capacity to obtain cylindrical preforms with a diameter of 20 mm under a uniaxial pressure of 625 MPa. These compacts were sintered at 630 °C for 1 hour in a tube furnace (MSE™ T-1600-74-450) with a heating and cooling rate of 5 K × min^{-1} under Ar gas flow.

Wear tests. The wear data of the produced Al-GNPs composites were collected by using pin-on-disk equipment shown in Figure 1. The wear tests were conducted against cast iron counter body (hardness: 526 HV) in ambient air at room temperature. Normal load of 9.81 N was employed during the tests. All the tests were performed at a sliding speed of 4.10^{-2} m × s^{-1} and the total sliding distance was 500 m. The wear rate K was calculated using the Equation (1):

$$K = \frac{\Delta m}{l \cdot \rho \cdot F} \quad (1)$$

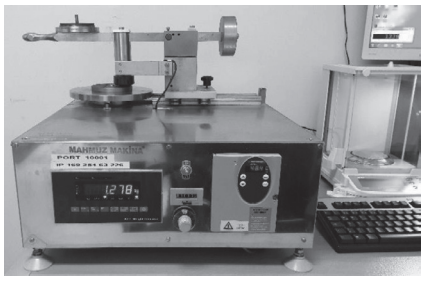


Figure 1: Pin-on-disk experimental setup



Figure 2: The input and the output of the wear process

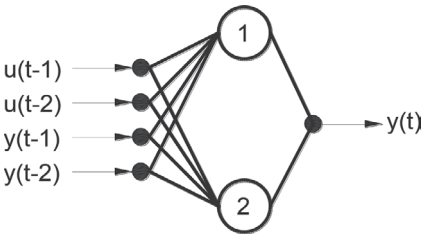


Figure 3: NARX model structure of the wear process

With: K is the wear rate ($mm^3 \times (N \times mm)^{-1}$), Δm is the mass loss of the test samples (g) during wear test, ρ is the density of test material ($g \times cm^{-3}$), l is the total sliding distance (m) and F is the normal force on the pin (N).

Identification of the wear process

In order to obtain linear and nonlinear models of the wear process, system identification was performed. Measured frictional forces were used as system input, whereas calculated wear rates were used as system output for the identification. Wear process is assumed to be a single input single output (SISO) system as illustrated in Figure 2.

Identification of all three models of the wear tests was done using Matlab® software. The first chosen model structure was the first-order continuous time model which is given in Equation (2):

$$G(s) = \frac{K_p}{1 + T_{p1}s} \quad (2)$$

For the identification of the transfer function model, nonlinear least squares were used.

As a second model structure, process model was utilized which is given in Equation (3):

$$G(s) = \frac{K_p}{1 + T_{p1}s} e^{-T_d s} \quad (3)$$

The Levenberg–Marquardt algorithm was used as a numeric minimization algorithm to compute the process model parameters.

For both models, G(s) is the transfer function of the wear process, K_p is the steady-state gain, T_{p1} is a time constant, s is the Laplace operator and T_d is the time delay in Equation (3).

Nonlinear autoregressive exogenous (NARX) model structure was selected as a third model. Identification of NARX models was done using Matlab® software. Sigmoid network with two units in one hidden layer was used to model wear behavior of Al composites which is shown in Figure 3.

The modeling of wear behavior by using training and validating data sets was based on a feed-forward network with sigmoid function and Levenberg-Marquardt algorithm was used as optimizing network weights.

For the given model structures, model parameters were estimated using experimental data. In this study, the three different models were obtained for each test material containing different amounts (0, 0.5, 1 and 2 wt.-%) of graphene. Models and related model parameters are tabulated in Table 1.

Results and discussion

Experimental data were pre-processed for the identification, which cover the training and the validation data sets. Recorded frictional forces were used as system input, whereas calculated wear rate was the system output. Following the identification procedure, three different model types were obtained. Table 1 shows the modeling results, in this regard, the simplest model is the transfer function. Coefficients of transfer functions for each material were very similar. Material contents cannot be predicted using these model coefficients. However, pairs of friction material may be predicted using these models.

Process model was an extension of the transfer function model. Process model coefficients differ by changing material content. Using these coefficients, material content can be predicted.

NARX models shown in the fourth column of Table 1 has two sigmoid activation functions in one hidden layer and indicate good estimation with experimental results. These models were suitable for simulations, however, they cannot predict the material content. On the other hand, they can be used for further simulations at different loading conditions without making time consuming and expensive tests. Accordingly, it has been reported that NARX model for Al-CNT composites predicted the wear rates between 93 and 98 % accuracy [16].

Figure 4 shows the friction forces and compares the wear rates between the experimental study and the three model responses of the Al-GNPs composites with different weight percentages of GNPs. It should be noted that with the addition of 1 wt.-% GNPs, the frictional force and the coefficient of friction (COF) decreased significantly compared to that of the pure Al. Whereas the GNPs content was increased to 2 wt.-%, the COF was observed to increase significantly to reach the value of 1.5.

Conclusions

Aluminum matrix composites reinforced with 0.5, 1 and 2 wt.-% GNPs were pre-

GNP portion (wt.-%)	Transfer function models (fit to estimation data %)	Process models (fit to estimation data %)	Nonlinear ARX models (fit to estimation data %)	Coefficient of friction
0	$G_0(s) = \frac{-1.066 \cdot 10^{-10}}{s + 0.1927}$ (69.86%)	$G_0(s) = \frac{1.8895 \cdot 10^{-9}}{1 + 16.552s} e^{-9.3615 \cdot 10^{-6} s}$ (81.3%)	Sigmoid network with 2 neurons (95.72 %)	1.5
0.5	$G_0(s) = \frac{-2.175 \cdot 10^{-9}}{s + 0.1927}$ (69.85%)	$G_0(s) = \frac{4.201 \cdot 10^{-8}}{1 + 11.905s} e^{-0.27433s}$ (82.85%)	Sigmoid network with 2 neurons (95.1 %)	1.3
1	$G_0(s) = \frac{-1.849 \cdot 10^{-10}}{s + 0.1925}$ (69.98%)	$G_0(s) = \frac{3.4276 \cdot 10^{-9}}{1 + 11.754s} e^{-6.0593 \cdot 10^{-9} s}$ (82.45%)	Sigmoid network with 2 neurons (98.98 %)	1.1
2	$G_0(s) = \frac{-2.139 \cdot 10^{-10}}{s + 0.1924}$ (69.95%)	$G_0(s) = \frac{3.6968 \cdot 10^{-9}}{1 + 15.232s} e^{-1.8575s}$ (81.62%)	Sigmoid network with 2 neurons (97.32 %)	1.5

Table 1: Identified models and their parameters

pared by cold compaction and sintering techniques. Friction and wear behaviors of the composites with constant load and sliding speed were determined using pin-on-disk test setup. The identification process was performed by using frictional force as system input, whereas system output was wear rate. The following remarks can be obtained by the present study:

1. COFs of composites at 0.5 and 1 wt.-% were decreased from 1.5 for pure aluminum to 1.3 and 1.1, respectively. However, at 2 wt.-% graphene reinforcement, COF reached the maximum value of 1.5. This may indicate that uniform dispersion was not obtained at 2 wt.-% addition.
2. The first-order transfer function model can be used to identify friction pairs with about 70 % accuracy.
3. Coefficients of process model can be used to estimate wear behavior with approximately 80 % accuracy.
4. The simulation studies of wear behavior under different load and sliding distance conditions can be performed using the NARX models with almost 95 % accuracy.

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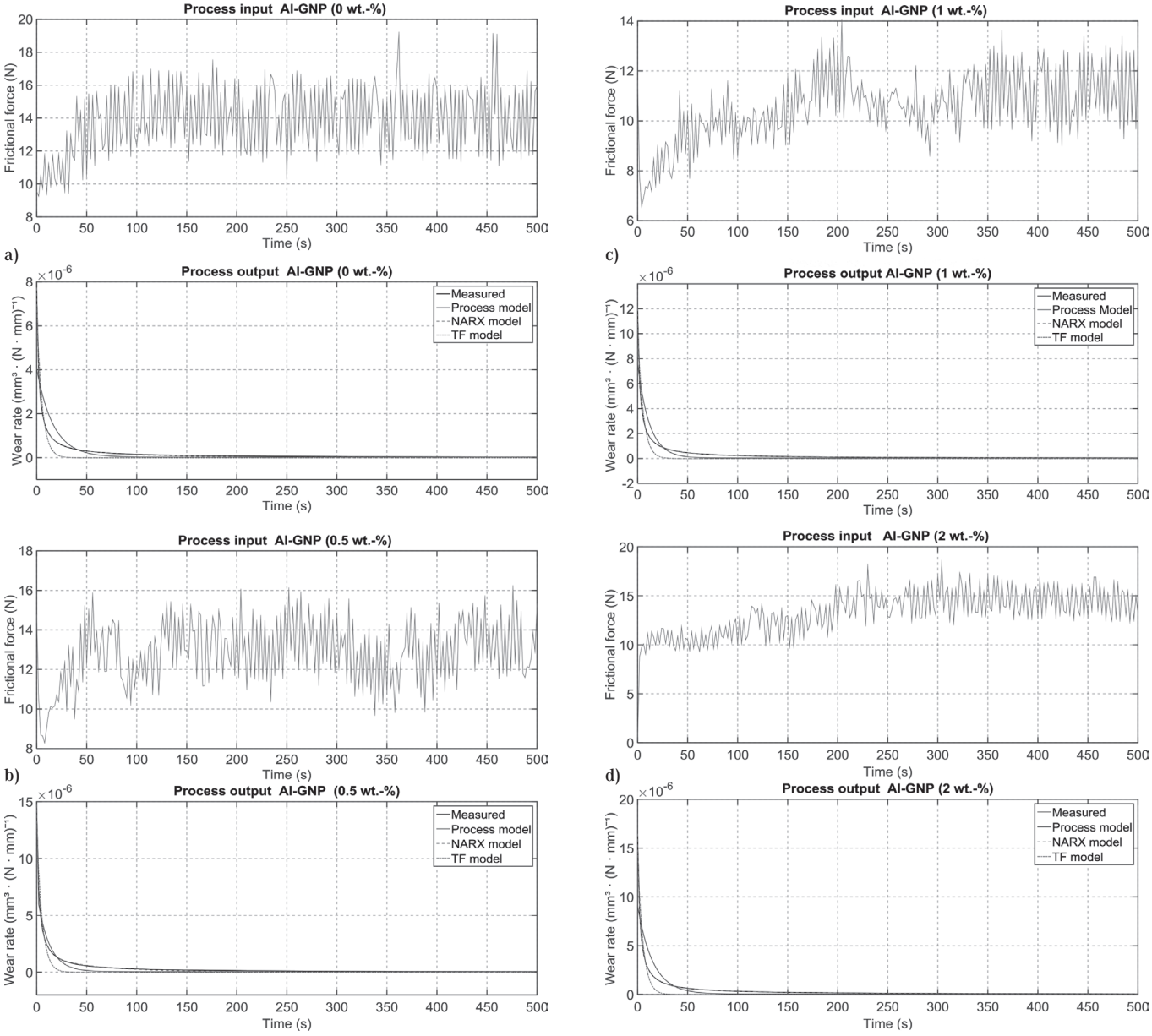


Figure 4: The inputs and the outputs of the wear process with identified model responses: a) pure aluminum, b) 0.5 wt.-% of GNP, c) 1 wt.-% of GNP, d) 2 wt.-% of GNP

Abstract

Trockenverschleißverhalten von Aluminium-Kompositen mit Graphen-Nanoplättchen (GNP). Konventionelles Aluminium (Al) und seine Legierungen wurden in den letzten Jahren durch Aluminiummatrix-Komposite (AMC) aufgrund ihrer hervorragenden Eigenschaften ersetzt. Für die Verstärkung der Aluminium-Komposite existieren verschiedene attraktive Komponenten, wie beispielsweise Al_2O_3, B_4C und SiC. Heute gewinnen kohlenstoffbasierte Materialien, wie beispielsweise Graphit, Carbon-Nanoröhrchen und Graphen eine hohe Beachtung wegen der oben erwähnten mechanischen und physikalischen Eigenschaften. In der diesem Beitrag zugrunde liegenden Studie wurde das Verschleißverhalten von Al-GNP Kompositen untersucht, die mit bis zu 2 wt.-% GNP verstärkt wurden. Die Zugabe von bis zu 1 wt.-% GNP verringerte den Reibkoeffizient. Die experimentellen Ergebnisse wurden verwendet, um lineare und nichtlineare Modelle zu entwickeln. Die experimentellen Ergebnisse sind in guter Übereinstimmung mit den Resultaten der Simulationen, die basierend auf den identifizierten Modellen durchgeführt wurden.

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