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# Al-6061 Composites Reinforced with Recycled Steel Chips: Mechanical Behaviour, Dry Sliding Wear, and an ANN-Aided Design Workflow

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#### **Abstract**

This paper reports the fabrication of aluminium 6061 (Al-6061) metal-matrix composites (MMCs) reinforced with recycled steel machining chips (40–60 µm) at 5 and 10 wt.% via stir casting, followed by tensile, hardness, and dry sliding wear evaluation. Relative to monolithic Al-6061, the MMCs exhibited increased ultimate tensile strength and hardness, with a moderate reduction in ductility. A normalized wear index decreased with reinforcement fraction, indicating improved wear resistance in the examined range. To support design decisions, a compact artificial neural network (ANN) workflow is outlined to estimate wear index from readily measurable inputs (reinforcement fraction, UTS, hardness). The results present an environmentally and economically favourable pathway to valorize machining waste into functional Al-based MMCs.

**Keywords:** Al-6061; recycled steel chips; stir casting; tensile strength; hardness; dry sliding wear; artificial neural networks.

#### 1. Introduction

Al-6061 and related 6xxx series alloys are widely used owing to their weldability and corrosion resistance. However, their wear resistance and strength are often insufficient for demanding sliding contacts. Metal-matrix composites (MMCs) with particulate reinforcements have been shown to enhance hardness and strength and to reduce wear rates under dry sliding. Simultaneously, manufacturing streams generate substantial volumes of steel machining chips, the disposal of which poses environmental and cost challenges. By upcycling machining chips as reinforcements, the present work seeks to improve Al-6061 performance while addressing waste valorization. In addition to experimental characterization, a compact ANN workflow is introduced to assist in mapping composition and properties to wear response, serving as a design aid alongside standard testing.

#### 2. Background and Related Work

Classical reviews establish the processing–microstructure–property relationships for particle-reinforced aluminium MMCs and emphasize challenges such as porosity, interfacial bonding, and particle clustering [Hashim 1999; Surappa 2003; Tjong & Ma 2000; Miracle 2005; Lloyd 1994]. Tribology studies report that harder reinforcement and higher composite hardness generally reduce wear rates under dry sliding [Prasad & Rohatgi 1993; Esmailzadeh et al. 2011; Hemanth 2008]. Recycling-oriented efforts demonstrate that machining chips can act as effective reinforcements when properly dispersed [Iglesias et al. 2013]. For predictive tools, feedforward neural networks have long been used in materials modelling, grounded in universal approximation theory and standard training algorithms [Hornik et al. 1989; Haykin 1999; Bishop 2006].

#### 3. Materials and Methods

Commercial Al-6061-T6 was selected as matrix. AISI-1060 steel machining chips were cleaned, sieved, and ball-milled to 40-60  $\mu m$ . Composite batches targeted 5 and 10 wt.% reinforcement;

monolithic Al-6061 provided a baseline. Melting was carried out at 650 °C; reinforcement powder was preheated to ~200 °C and stirred into the melt at ~300 rpm for ~5 min. The melt was poured into  $100 \times 100 \times 10$  mm moulds and cooled in air. Plates were EDM-sectioned into tensile and tribology coupons. Dog-bone tensile specimens followed a standardized geometry, and testing conformed to ASTM E8M-04. Vickers hardness was measured from ten indents per condition. Dry sliding wear was evaluated on a rotary pin-on-disc tribometer (track diameter 100 mm, normal load 2.5 kg, 382 rpm, 1000 s, ~23 °C). Wear index (WI) was computed from mass loss per unit time.

**Table 1:** Pin-on-disc wear test parameters.

Track diameter	100 mm	
Normal load	2.5 kg	
Rotational speed	382 rpm	
Duration	1000 s	
Temperature	≈23 °C	
Environment	Dry sliding	

#### 4. Results

Tensile strength increased with reinforcement, while ductility decreased. Hardness rose with reinforcement and normalized wear index declined, indicating improved wear resistance in the investigated range (0–10 wt.%). Representative trends are summarized below.

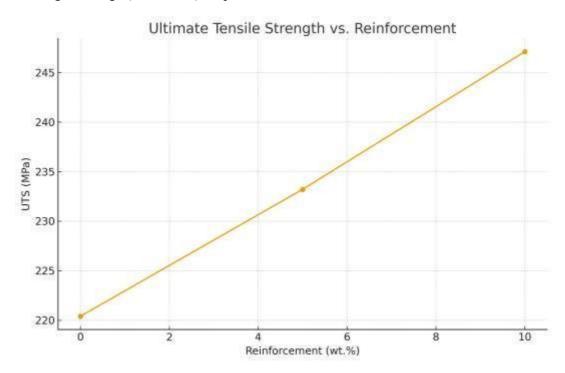


Figure 1: Ultimate tensile strength vs. reinforcement fraction.



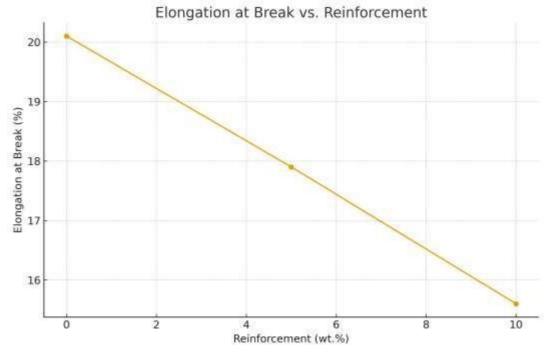


Figure 2: Elongation at break vs. reinforcement fraction.

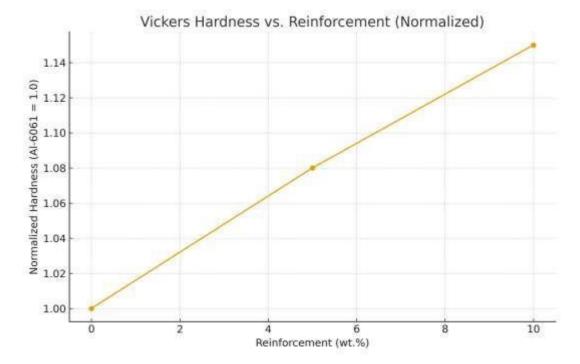


Figure 3: Normalized Vickers hardness vs. reinforcement fraction.



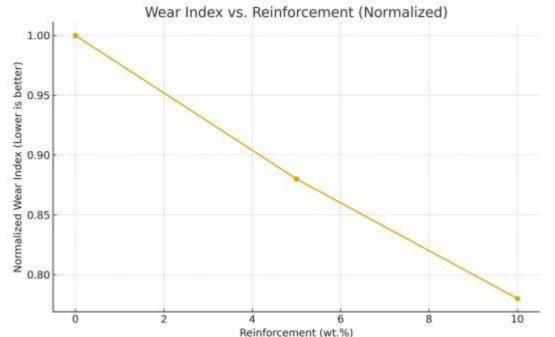


Figure 4: Normalized wear index vs. reinforcement fraction (lower is better).

**Table 2:** Summary of tensile properties for Al-6061 and steel-chip-reinforced composites.

Composition	UTS (MPa)	Elongation at break (%)
0 wt.% (Al-6061)	220.4	20.1
5 wt.% steel chips	233.2	17.9
10 wt.% steel chips	247.1	15.6

#### 5. Discussion

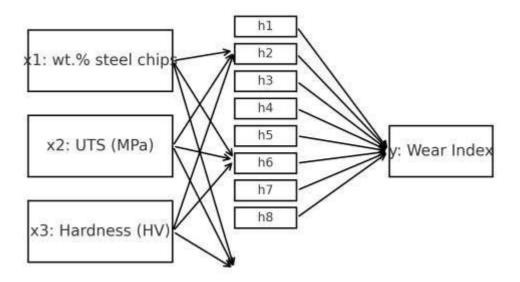
Strengthening is attributed to load transfer to stiff particles and local constraint of plastic flow, while ductility reduction arises from strain localization and micro-stress concentrations around particles. Improvements in wear resistance correlate with higher hardness and the stabilization of a mechanically mixed layer. Processing parameters (particle preheating, stirring speed/time, pouring temperature) influence porosity and interfacial bonding, which govern the magnitude of property changes.

Design implications include selecting reinforcement levels that meet strength and wear targets while retaining adequate ductility for forming and in-service deformation. Candidate applications include bushings, wear pads, and housings, where enhanced wear performance outweighs maximum elongation requirements.

### 6. ANN-Aided Predictive Workflow

Objective: estimate wear index (output) from measurable inputs to support rapid screening of compositions. Representative inputs include reinforcement fraction, UTS, and hardness. A feedforward multilayer perceptron with one hidden layer (e.g., eight neurons) suffices for compact datasets. Training minimizes regularized mean-squared error with early stopping or  $\ell 2$  regularization. Data standardization and k-fold cross-validation (e.g., k=5) are recommended. Model performance is summarized by RMSE/MAE and R²; variable influence can be probed via permutation importance or partial dependence.





**Figure 5:** Schematic of a compact MLP for wear index prediction.

#### 7. Environmental and Economic Considerations

Upcycling machining chips into reinforcements reduces waste and embedded energy relative to procuring virgin ceramic particles. Stir casting aligns with conventional foundry practice, minimizing capital expenditure. Local sourcing of chips shortens supply chains and may reduce cost variability.

#### 8. Limitations and Future Work

Further microstructural analysis (optical/SEM), porosity quantification, and interfacial characterization are needed to refine structure–property linkages. Parametric studies on particle size, morphology, surface treatment, and reinforcement level should be undertaken, alongside fatigue, impact, corrosion, and elevated-temperature testing. For the ANN, expanding datasets and incorporating microstructural descriptors are expected to improve generalization while maintaining compact architectures.

## 9. Conclusions

- Recycled steel machining chips (5–10 wt.%) in Al-6061 increased UTS and hardness relative to the base alloy.
- Ductility decreased with reinforcement, consistent with particulate strengthening mechanisms.
- $\bullet$  Normalized wear index decreased with reinforcement, indicating improved dry sliding wear resistance within 0–10 wt.% range.
- A compact ANN workflow can support property targeting from measurable inputs as a complement to experiments.

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