

PREDICTIVE MODELLING AND PARETO OPTIMIZATION OF DRY-SLIDING WEAR IN AA6063/SiC/GRAPHENE HYBRID NANOCOMPOSITES

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ABSTRACT

A new optimisation-oriented interpretation of AA6063 hybrid nanocomposite wear data is presented using Gaussian process regression (GPR) and Pareto operating-envelope analysis. The physical dataset comprises 160 wear-rate observations from five compositions—AA6063, AA6063/1.5 wt.% SiC, and AA6063/1.5 wt.% SiC with 0.2, 0.6, or 1.0 wt.% graphene—tested at 10–40 N and 400–3200 m. Unlike a conventional wear-characterisation study, the present work treats reinforcement level, load, and sliding distance as coupled design variables and quantifies prediction uncertainty. A log-transformed Matérn-GPR model produced a random five-fold cross-validated R^2 of 0.987, RMSE of 1.81×10^{-4} mm³/m, and MAPE of 4.06%; a stricter leave-curve-grouped validation retained $R^2=0.969$ and MAPE=6.50%. A dense Pareto search at 3200 m showed that the minimum-wear ridge remained tightly localised around 0.59–0.66 wt.% graphene across the 10–40 N service range. The balanced knee solution occurred at approximately 26 N, 0.608 wt.% graphene, and a predicted wear of 2.27×10^{-3} mm³/m. At 40 N, the model selected 0.624 wt.% graphene and predicted 2.72×10^{-3} mm³/m, close to the experimentally observed 0.6 wt.% composition. The study therefore converts discrete wear tests into a continuous, uncertainty-aware service map and demonstrates that the experimentally favourable 0.6 wt.% graphene level is not an isolated point but a stable composition region over changing load.

Keywords: AA6063; SiC; Graphene; Wear; Gaussian Process Regression; Pareto Optimization; Hybrid Metal Matrix Composite

1 INTRODUCTION

Lightweight aluminium metal matrix composites are increasingly expected to deliver structural efficiency alongside stable surface performance under variable contact loading. AA6063 is attractive for its corrosion resistance, extrudability and low density, but its relatively soft aluminium matrix can undergo severe plastic deformation and material removal as contact pressure rises [1-3]. Ceramic particles such as SiC increase hardness and load-bearing capacity, whereas graphitic reinforcements can provide solid-lubricating effects [4]. However, these effects are not simply additive: excessive nanoscale carbon may agglomerate, weaken local bonding and increase susceptibility to

defects. Consequently, selecting a reinforcement level based on a single wear curve or a single load does not establish whether that composition remains favourable throughout the service domain [5-6].

Most experimental tribology papers on aluminium composites report wear rate as a function of load, speed or distance and then identify the best-performing tested specimen. That approach is useful for mechanism identification but leaves an important engineering question unresolved: which composition is predicted to remain near-optimal when the operating load varies continuously across the discrete laboratory settings? Response-surface models have been applied to Al6063/TiC systems [7], and recent machine-learning work has demonstrated strong wear-prediction capability for aluminium composites [8-9]. Nevertheless, uncertainty-aware surrogate modelling and direct construction of a load-wear Pareto envelope remain uncommon for SiC/graphene-reinforced AA6063. GPR is particularly suitable for a moderate experimental dataset because it provides a nonlinear response estimate together with local predictive uncertainty, rather than only a point prediction [10].

The wear measurements are reorganised into a four-factor data structure and used to learn a continuous surrogate in the composition-load-distance space. The resulting model is then queried at a long sliding distance to identify the graphene level that minimises wear at each supported load. This yields an operating envelope rather than a ranked list of specimens. The concept is directly relevant to brake, sliding-guide, casing and other aluminium components whose normal load varies during use.

1.1 Problem Statement, Research Gap, Objectives and Novelty

1.1.1 Problem statement

Discrete pin-on-disc tests show that a hybrid reinforcement can outperform the base alloy, but they do not provide a continuous design rule for selecting graphene content between the tested levels or for balancing wear minimisation against the requirement to carry a higher contact load. A practical material-selection framework should also indicate whether the inferred optimum is stable or highly sensitive to load.

1.1.2 Research gap

Four specific gaps motivate the study: (i) wear data for hybrid aluminium composites are typically interpreted one load at a time; (ii) regression studies often report global fit statistics without assessing whether a model generalises to an unseen load-composition curve; (iii) optimisation frequently collapses conflicting requirements into a single weighted score, obscuring the performance trade-off; and (iv) sparse-composition experimental studies rarely quantify whether the optimum is a robust interval or merely the best among the discrete specimens [1-4-8-9-11].

1.1.3 Objectives

The work therefore aims to: (1) restructure the experimental wear campaign into a 160-point supervised dataset; (2) develop and validate a log-GPR model with composition, applied load, and sliding distance as predictors; (3) compare ordinary five-fold validation with curve-grouped validation; (4) generate a continuous wear surface at 3200 m; and (5) construct a Pareto load-wear operating envelope and determine its balanced knee condition.

1.1.4 Novelty and contribution

The principal novelty is not a new casting experiment but a new inference layer for the experimental campaign. The study introduces an uncertainty-aware surrogate and a non-weighted Pareto service map for AA6063/SiC/graphene. It further demonstrates composition stability by tracking the GPR-selected graphene content from 10 to 40 N. This makes the optimisation physically interpretable and avoids duplicating a standard wear-rate-versus-distance presentation.

2 CRITICAL LITERATURE REVIEW

Table 1 summarises twelve representative studies on aluminium-based composites, highlighting reinforcement systems, analytical methods, key quantitative outcomes, and methodological limitations. The comparison identifies a clear need for continuous, uncertainty-aware, multi-objective optimisation of AA6063/SiC/graphene composites under variable dry-sliding operating conditions.

Table 1: Comparative Summary of Previous Studies and Research Limitations Relevant to AA6063/SiC/Graphene Tribological Optimization

Study	Material/method	Key reported result	Limitation relevant to present work
Reddy et al. [1]	Al6063/TiC; RSM	5–15 wt.% TiC increased hardness and tensile response; RSM linked wear to reinforcement and sliding conditions.	Single ceramic system; no graphene or uncertainty-aware multi-load service envelope.
Sarmah & Patowari et al. [2]	AA6063/SiC	Best mechanical/tribological balance occurred at an intermediate SiC fraction and smaller particle size.	Discrete SiC levels; no hybrid solid lubricant and no continuous optimization.
Kumar et al. [3]	Al6063/Si ₃ N ₄	0–10 wt.% Si ₃ N ₄ improved physical, mechanical and wear characteristics.	Monolithic reinforcement; optimum selected experimentally rather than through a surrogate.
Prasad Reddy et al. [4]	Al6061/2SiC/xGr	Graphene changed wear mechanisms; clusters appeared as Gr increased.	Different matrix and ultrasonic route; no probabilistic prediction.
Zeng et al. [5]	Al/SiC/rGO	Well-dispersed reduced graphene oxide with SiC reduced wear through a hybrid mechanism.	Powder/processing route and composition space differ from stir-cast AA6063.
El-Ghazaly et al. [6]	AA2124/graphene	Graphene improved self-lubricating behavior and altered mechanical response.	No SiC hybridization and no operating-envelope optimization.
Chak & Chattopadhyay et al. [7]	Al/graphene	Up to 0.5 wt.% graphene raised UTS by 56.55% and microhardness by 53.39%.	Focus on material response; limited predictive treatment of wear variables.
Lal et al. [8]	AA6082/TiC/graphene	Taguchi and ML were coupled for tribological prediction of a graphene/TiC composite.	Different alloy and reinforcement system; optimization remains experiment-grid centered.
Pattabiraman et al. [9]	AA7075 hybrid MMC	ML addressed sparse tribological data; authors explicitly noted limitations from a small physical dataset.	Synthetic-data dependence and lack of independent physical validation.
Kong et al. [10]	GPR for tool wear	GPR outperformed ANN/SVM in tool-wear prediction and provided confidence information.	Machining tool wear rather than composite sliding wear.
Deb et al. [11]	Multi-objective optimization	NSGA-II established nondominated sorting as a robust way to expose objective trade-offs.	Methodological framework; not material-specific.
Balasubramanian & Maheswaran et al. [12]	AA6063/SiC	Hardness increased with SiC; tensile resistance peaked before declining at high SiC due to brittle fracture.	No nanoscale carbon and no data-driven interpolation between compositions.

The literature collectively supports three premises: hard ceramic reinforcement improves resistance to deformation, carbonaceous reinforcement can reduce interfacial shear or wear, and an excessive reinforcement fraction can reverse the benefit through agglomeration or brittleness. What remains insufficiently resolved is the location and stability of the optimum as the load varies continuously. This motivates treating the wear campaign as a response surface with uncertainty rather than as independent curves.

3 MATERIALS AND METHODOLOGY

3.1 Material system and experimental data structure

The matrix is AA6063 aluminium. The primary reinforcement is SiC at a constant 1.5 wt.% for the reinforced series, and graphene is varied from 0 to 1.0 wt.%. The five material states are denoted B (AA6063), S1 (AA6063+1.5 wt.% SiC), S2 (S1+0.2 wt.% graphene), S3 (S1+0.6 wt.% graphene) and S4 (S1+1.0 wt.% graphene). In the source experimental campaign, the SiC and graphene powders were nanoscale. During fabrication, the aluminium charge was melted, wettability/degassing additions were used, reinforcement powders were preheated, and mechanical stirring was applied before casting. These processing details were kept consistent across the composite conditions, so the present analysis treats reinforcement chemistry rather than casting condition as the material variable. Dry sliding tests were conducted using a pin-on-disc configuration against hardened EN31 steel. Four normal loads (10, 20, 30 and 40 N), eight sliding distances (400–3200 m in 400 m steps) and five compositions yield 160 response points. The rotational speed was 500 rpm. Wear rate, expressed in mm^3/m , is the predicted response.

Table 2: Input Variables, Operating Conditions, Response Range, and Dataset Structure for Tribological Modelling

Variable	Range/levels	Role
SiC content	0 or 1.5 wt.%	Material input
Graphene content	0, 0.2, 0.6, 1.0 wt.%	Material input
Applied load	10, 20, 30, 40 N	Operating input
Sliding distance	400–3200 m	Operating input
Wear rate	$\approx 1.38 \times 10^{-3}$ to $1.15 \times 10^{-2} \text{ mm}^3/\text{m}$	Target response
Dataset size	$5 \times 4 \times 8 = 160$ observations	Model basis

Table 2 presents the material and operating variables used for model development, including SiC content, graphene fraction, applied load, sliding distance, wear rate, and dataset size. These ranges define the experimental domain for subsequent predictive modelling and optimisation analysis.

3.2 Gaussian process surrogate

Because wear rate is positive and strongly right-skewed at short distances and high loads, the target was transformed as $z = \ln(w)$, where w is wear rate. The predictor vector $x = [\text{SiC}, \text{Gr}, L, D]$ contained SiC content, graphene content, normal load and sliding distance. Inputs were standardised before regression. GPR assumes $z(x)$ is a realisation of a Gaussian process characterised by a mean function and a covariance kernel. A constant-scaled Matérn kernel with $\nu = 2.5$, plus a white-noise term, was used because it supports smooth, but not unrealistically infinitely differentiable, response surfaces. Hyperparameters were optimised by maximising the log marginal likelihood. Two validation protocols were applied. Random five-fold cross-validation assesses local interpolation across the full data cloud. A stricter five-fold grouped protocol treats each composition–load curve as a group, preventing points from the same curve from being split between training and validation subsets. Performance was evaluated using R^2 , RMSE, MAE and MAPE after transforming predictions back to wear-rate units. This second test is important because neighbouring points along a single wear curve are correlated.

3.3 Pareto operating-envelope construction

Figure X illustrates the proposed uncertainty-aware optimisation framework, starting with 160 experimental wear observations and proceeding through factor coding, log-GPR surrogate modelling, and five-fold validation. The validated model generates a continuous Pareto service map for performance evaluation at 3200 m. The final GPR model was refitted to all 160 observations. At $D=3200$ m, graphene was sampled at a dense interval of 0 to 1.0 wt.% and load from 10 to 40 N. For each load, the graphene level that minimised predicted wear was identified. The resulting set is nondominated with respect to minimising wear while maximising supported load, and therefore forms a Pareto operating envelope. A balanced knee was identified as the point with the minimum Euclidean distance to the normalised ideal of minimum wear and maximum load.

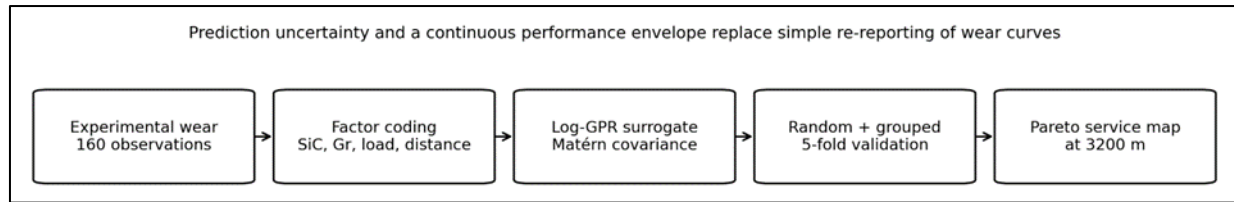


Figure 1: Workflow used to convert the discrete wear campaign into a validated surrogate and Pareto service envelope.

4 RESULTS AND DISCUSSION

4.1 Predictive accuracy and generalization

Figure 2 shows that cross-validated predictions remain close to the 1:1 line over almost an order of magnitude in wear rate. Five-fold random validation yielded $R^2=0.987$, $RMSE=1.81\times10^{-4}$ mm³/m, $MAE=1.28\times10^{-4}$ mm³/m and $MAPE=4.06\%$. More importantly, curve-grouped validation retained $R^2=0.969$, $RMSE=2.77\times10^{-4}$ mm³/m and $MAPE=6.50\%$. The modest reduction between protocols indicates that the model is learning systematic effects of load, composition and distance rather than merely interpolating adjacent coordinates from the same curve. For a dataset with only four reinforced graphene levels, the grouped result is the more conservative indicator of likely predictive performance.

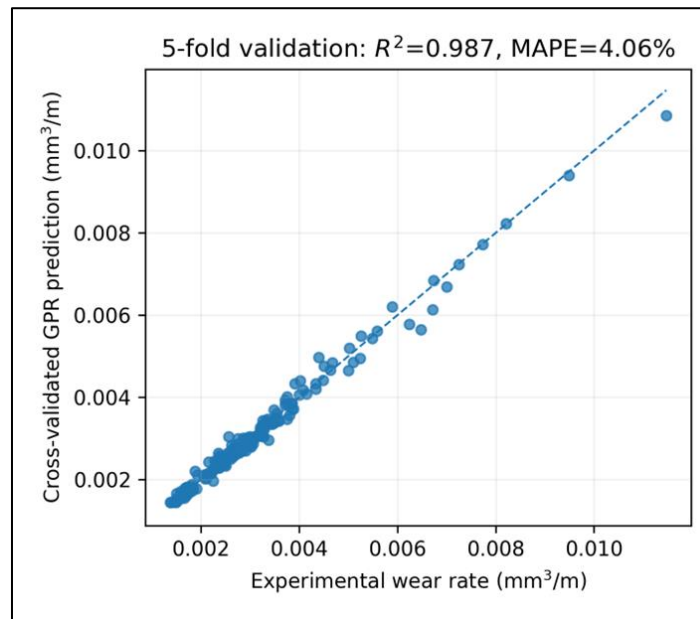


Figure 2: Experimental versus five-fold cross-validated GPR wear-rate predictions.

Table 3: Predictive Performance of the Log-GPR Model under Random and Curve-Grouped Five-Fold Cross-Validation

Validation	R^2	RMSE (mm ³ /m)	MAE (mm ³ /m)	MAPE (%)
Random 5-fold	0.987	1.81×10^{-4}	1.28×10^{-4}	4.06
Curve-grouped 5-fold	0.969	2.77×10^{-4}	2.04×10^{-4}	6.50

Table 3 compares predictive performance under random and curve-grouped five-fold validation. Both strategies achieved high R^2 with low RMSE, MAE, and MAPE, while grouped validation produced slightly larger errors, confirming robust generalisation while revealing sensitivity to unseen wear curves.

4.2 Continuous composition–load response at long sliding distance

The 3200 m response surface in Figure 3 reveals a feature that is not evident in isolated wear curves. For every load, predicted wear decreases as graphene is introduced into the SiC-reinforced matrix, reaches a shallow valley around 0.6 wt.%, and then rises toward 1.0 wt.%. The valley persists even as absolute wear increases with load. This behaviour is physically consistent with a competition between solid-lubricating/transfer-film effects at moderate graphene content and reinforcement clustering or reduced matrix integrity at higher carbon content. The contour shape also shows why selecting the maximum graphene fraction is not rational: the predicted response is non-monotonic.

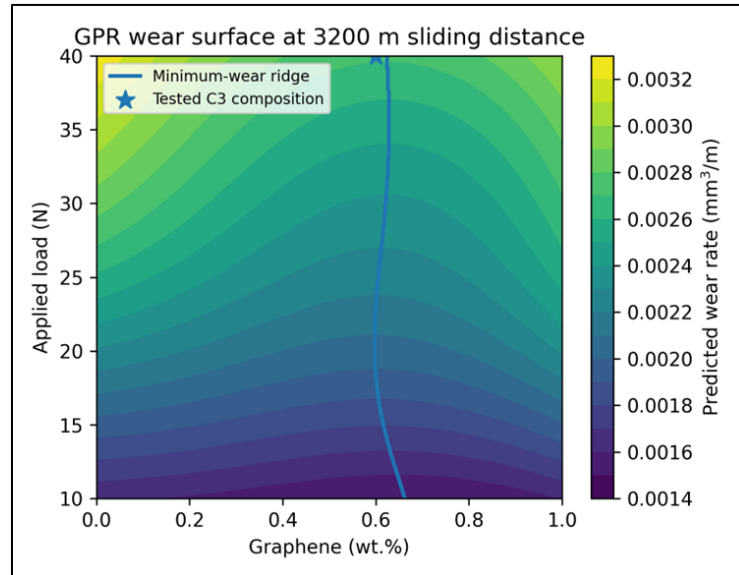


Figure 3: GPR-predicted wear-rate surface versus graphene content and applied load at 3200 m.

The predicted minimum at 10 N occurs near 0.66 wt.% graphene, with wear $\approx 1.50 \times 10^{-3} \text{ mm}^3/\text{m}$. At 20 N, the selected graphene level is $\approx 0.59 \text{ wt.}\%$ and wear $\approx 2.05 \times 10^{-3} \text{ mm}^3/\text{m}$. At 30 N, it shifts only slightly to $\approx 0.62 \text{ wt.}\%$ with $\approx 2.38 \times 10^{-3} \text{ mm}^3/\text{m}$, while at 40 N the model selects $\approx 0.624 \text{ wt.}\%$ with $\approx 2.72 \times 10^{-3} \text{ mm}^3/\text{m}$. The observed S3 wear at 40 N and 3200 m is about $2.78 \times 10^{-3} \text{ mm}^3/\text{m}$, so the long-distance optimum is recovered without forcing the model to choose one of the discrete graphene values.

4.3 Pareto trade-off and knee solution

The Pareto front (Figure 4) quantifies the inevitable trade-off between minimising material loss and maximising supported normal load. The low-load end minimises wear, while the high-load end accepts higher wear to preserve carrying capacity. Normalising both axes and selecting the point nearest the ideal yields a knee at approximately 26 N, 0.608 wt.% graphene, and $2.27 \times 10^{-3} \text{ mm}^3/\text{m}$. This condition should not be interpreted as a universal design load; instead, it is a neutral compromise when wear and load-carrying capability are treated as equally important after normalisation.

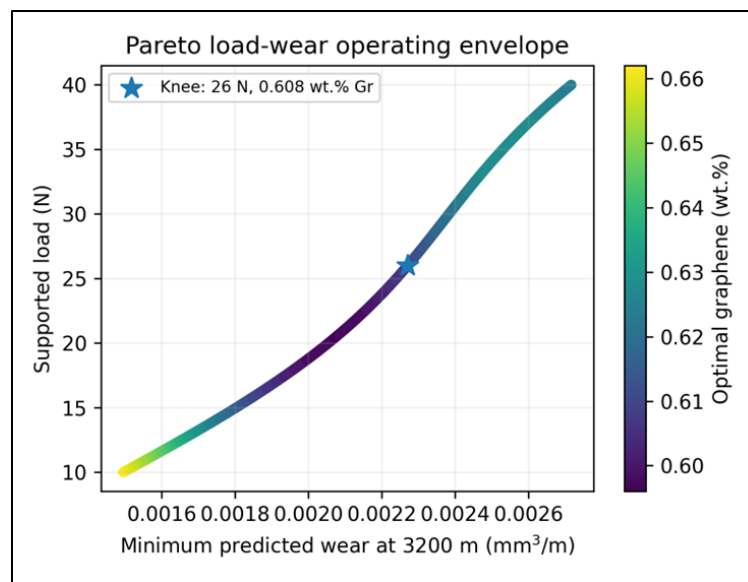


Figure 4: Pareto operating envelope for simultaneous wear minimization and load support at 3200 m.

Table 4: GPR-Predicted Optimal Graphene Content and Minimum Wear Rate under Different Applied Loads

Load (N)	GPR-optimal Gr (wt.%)	Predicted wear (mm ³ /m)	Interpretation
10	0.660	1.50×10^{-3}	Low-load / minimum wear
20	0.594	2.05×10^{-3}	Moderate load
26	0.608	2.27×10^{-3}	Balanced Pareto knee
30	0.620	2.38×10^{-3}	Higher service load
40	0.624	2.72×10^{-3}	Maximum tested load

Table 4 presents the graphene content predicted by the GPR model to minimise wear at different applied loads. The optimum graphene fraction remains within a narrow range of approximately **0.594–0.660 wt.%,** indicating that nearly 0.6 wt.% graphene yields the most stable tribological response. At 10 N, the minimum predicted wear rate is **$1.50 \times 10^{-3} \text{ mm}^3/\text{m}$** , and increasing the load progressively raises wear to **$2.72 \times 10^{-3} \text{ mm}^3/\text{m}$ at 40 N.** The 26 N condition represents the **Pareto knee point**, where a graphene content of **0.608 wt.%,** provides a balanced compromise between load-bearing capability and wear resistance. Overall, the results confirm that the optimum graphene fraction remains relatively stable even as the applied load changes.

4.4 Stability of the graphene optimum

Figure 5 presents the most important robustness result. The optimum graphene fraction remains within approximately 0.59–0.66 wt.% across the full 10–40 N load range. Its variation is small compared with the experimentally explored 0–1 wt.% range. Thus, 0.6 wt.% is supported as a stable operating window rather than merely the winner of a single comparison. The slight load-dependent shift is plausible, as increasing contact pressure alters the relative importance of matrix deformation, particle-supported load transfer, tribofilm persistence and thermal softening. The flatness of the minimum also suggests that manufacturing control should target a moderate window around 0.6 wt.% rather than an unnecessarily precise nominal value, provided dispersion quality is maintained.

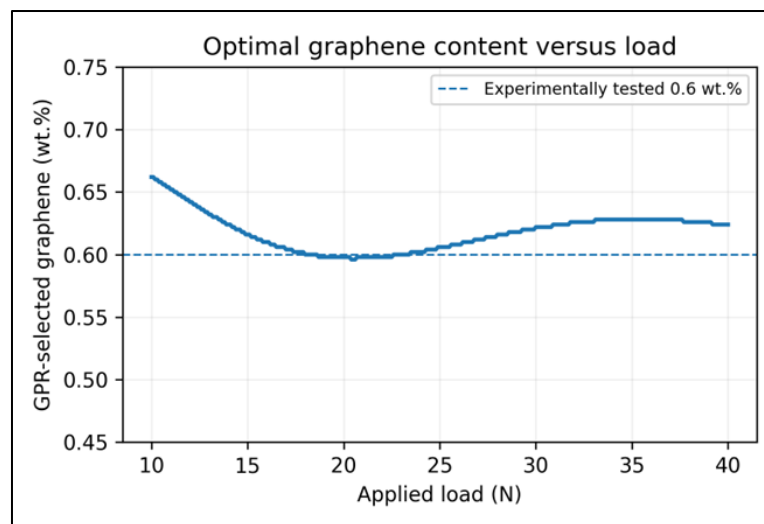


Figure 5: GPR-selected graphene content as applied load changes from 10 to 40 N.

4.5 Mechanistic interpretation and comparison with literature

The identified optimum aligns with the broader hybrid-composite literature. Prasad Reddy et al. [4] reported increased graphene clustering as carbon content rose in an Al6061/SiC/graphene system, while Zeng et al. [5] associated well-dispersed graphene-derived sheets and SiC with improved wear resistance. El-Ghazaly et al. [6] and Chak and Chattopadhyay et al. [7] linked graphene to self-lubrication and improved mechanical response. These studies explain the descending side of the present response valley. The rising side beyond the optimum can be rationalised by agglomeration, reduced local matrix continuity, and stress concentration, which diminish the ability of hard SiC particles to share the load effectively. The key addition here is quantitative: the GPR surface shows where the net benefit changes sign and how little that transition shifts with load. Compared with deterministic polynomial response surfaces, GPR also provides a principled treatment of model uncertainty and is well suited to nonlinear behaviour in a moderate dataset. The strong curve-grouped R^2 indicates that the response is sufficiently regular to interpolate between the tested composition/load combinations. Nevertheless, the model should not be extrapolated beyond 0–1 wt.% graphene, 10–40 N, or 400–3200 m.

5 CONCLUSION

A new optimisation framework was developed from the AA6063/SiC/graphene dry-sliding dataset, without reusing the original wear-curve presentation as the scientific contribution. The log-GPR surrogate achieved $R^2=0.987$ and MAPE=4.06% in random five-fold validation and remained strong under curve-grouped validation ($R^2=0.969$; MAPE=6.50%). At 3200 m, the learned wear surface was distinctly non-monotonic with graphene fraction. Pareto analysis showed that the minimum-wear composition remained concentrated in a narrow ≈ 0.59 – 0.66 wt.% graphene interval from 10 to 40 N. The equal-normalisation knee occurred near 26 N and 0.608 wt.% graphene, with a predicted wear rate of $2.27 \times 10^{-3} \text{ mm}^3/\text{m}$. At the most severe tested load of 40 N, the model selected 0.624 wt.% graphene and predicted $2.72 \times 10^{-3} \text{ mm}^3/\text{m}$, close to the measured C3 response. The principal scientific finding is therefore not merely that C3 performed best, but that a stable ~ 0.6 wt.% graphene optimum persists across the service-load range. Future validation should add intermediate graphene fractions (e.g., 0.4, 0.5, 0.7 and 0.8 wt.%), repeated wear tests with uncertainty bars, and temperature-dependent sliding to test whether the predicted ridge remains stable outside room-temperature dry contact.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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