Physics-Augmented Meta-ANN for Cross-Alloy Surface Roughness Prediction in Laser-Polished LPBF Metals: A Proof-of-Concept Study

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Abstract

Surface roughness remains a critical challenge in Laser Powder Bed Fusion (LPBF), where laser polishing is often required to achieve the surface quality needed for functional applications. Conventional prediction approaches are frequently alloy-specific or empirical, which can limit their transferability across different materials. This study presents a compact physics-augmented Meta-ANN for predicting surface roughness after laser polishing of LPBF metals. The framework incorporates energy density (ED = P/v) and nonlinear terms as physically meaningful features to enhance the representation of laser–material interactions. The model is trained using a heterogeneous literature-derived dataset comprising 60 samples from four commonly used LPBF alloys: AlSi10Mg, Ti6Al4V, Inconel 718, and SS316L. The proposed model achieves encouraging predictive performance, with R^2 values above 0.96 across the evaluated datasets. Given the limited dataset size and heterogeneous data sources, the results are interpreted as preliminary proof-of-concept evidence rather than definitive validation of cross-alloy generalization. Nevertheless, the findings indicate that physics-augmented feature representation may improve data efficiency and provide a practical basis for developing more generalizable machine-learning approaches for laser-polished LPBF surfaces.

Keywords: Laser Powder Bed Fusion (LPBF); Laser Polishing; Surface Roughness Prediction; Physics-Augmented Neural Networks; Cross-Alloy Prediction; Low-Data Machine Learning

1. Introduction

Laser Powder Bed Fusion (LPBF) is a widely used metal additive manufacturing (AM) technology because of its ability to fabricate complex geometries with high dimensional accuracy. Its applications extend across aerospace, biomedical, energy, and other advanced engineering sectors. Despite these advantages, LPBF components commonly exhibit relatively high surface roughness because of the layer-wise manufacturing process, partially melted powder particles, spatter, and melt-pool instabilities. Such surface irregularities can adversely affect fatigue performance, corrosion resistance, and wear behaviour, limiting the direct use of as-built components in demanding applications (DebRoy et al., 2018; Hofele et al., 2021; Chen et al., 2021). Laser polishing (LP) provides an attractive post-processing route for improving the surface quality of LPBF components. During laser polishing, controlled laser-induced remelting enables surface asperities to redistribute, thereby reducing surface roughness without relying on conventional mechanical finishing. However, the resulting surface condition depends on several interacting factors, including laser power, scanning speed, initial surface morphology, material characteristics, and polishing strategy. Consequently, the relationship between processing conditions and the resulting surface roughness is strongly nonlinear and can vary substantially between alloys (Li and Zuo, 2021; Ali et al., 2023; El Hassanin et al., 2024). Machine learning (ML) has increasingly been investigated as a means of modelling such complex relationships. Neural-network approaches have demonstrated potential for predicting surface quality and process responses in laser-based manufacturing because of their ability to represent nonlinear parameter interactions (Yousef et al., 2003; Pitschke et al., 2008). In particular, recurrent and feed-forward neural networks have been applied to laser-polished surface-quality prediction, demonstrating the feasibility of data-driven modelling for this type of process (Wu and Bordatchev, 2021; Wu et al., 2022). However, many existing approaches are developed for specific materials or relatively narrow processing conditions. This limits their direct applicability when the target alloy or processing regime differs from those represented in the training data. A further challenge arises from the availability of experimental data. Developing reliable ML models for laser polishing can require substantial datasets covering different materials, processing parameters, and surface conditions. Such datasets are often difficult to assemble because laser-polishing studies are distributed across different experimental investigations and frequently use different processing windows and measurement conditions. Physics-guided feature representation provides one possible way of extracting additional information from limited datasets. Recent research in physics-informed machine learning for additive manufacturing has highlighted the potential of incorporating physical knowledge into data-driven frameworks to improve interpretability and learning efficiency (Farrag et al., 2025; Faegh et al., 2025). Energy density is one of the simplest descriptors available for representing laser–material interaction. In the present work, linear energy density is defined as (ED=P/v), where (P) is laser power and (v) is scanning speed. Energy-density-based approaches have been widely considered in laser-processing research because changes in energy input influence melting, material redistribution, and the resulting surface morphology. Recent studies have specifically examined the role of energy density in laser polishing of LPBF Ti6Al4V and related processing systems (Lu et al., 2024). However, the use of energy-density descriptors within a compact neural-network framework for **cross-alloy prediction of laser-polished surface roughness** remains relatively limited. To address this gap, the present study develops a compact **physics-augmented Meta-Artificial Neural Network (Meta-ANN)** for predicting surface roughness ((Ra)) following laser polishing of LPBF metals. The framework incorporates energy density and simple nonlinear transformations as physically meaningful input descriptors alongside the primary processing variables. The model is trained using a heterogeneous literature-derived dataset containing 60 observations from four representative LPBF alloys: AlSi10Mg, Ti6Al4V, Inconel 718, and SS316L. By combining data from different alloy systems within a single modelling framework, the study investigates whether physics-guided feature representation can provide useful predictive capability under low-data conditions.

The present work is intentionally formulated as a **proof-of-concept study**. The relatively small dataset and differences among the underlying literature sources limit the statistical strength with which broad cross-alloy generalization can be established. Therefore, the objective is not to claim universal predictive transferability, but rather to examine the feasibility of using a lightweight physics-augmented neural network to capture surface-roughness trends across multiple LPBF alloys. The findings can subsequently support more extensive investigations using larger experimental datasets, standardized processing conditions, and additional descriptors such as thermophysical properties, melt-pool characteristics, and cooling-related parameters. The contribution of this study lies in combining **cross-alloy modelling, physics-guided energy-density features, nonlinear feature representation, and a compact neural-network architecture** within a low-data setting for laser-polished LPBF metals. The resulting framework provides an initial computational approach for investigating whether physically meaningful descriptors can improve the transferability and data efficiency of surface-roughness prediction across different alloy systems.

2. Materials and Methods

2.1 Dataset Collection

The dataset used in this study comprises 60 validated observations extracted from peer-reviewed studies reporting surface roughness (R_a, μm) following laser polishing of LPBF-fabricated metallic alloys. Only studies providing complete laser-processing parameters together with corresponding post-polishing measurements were considered. Four alloys AlSi10Mg, Ti6Al4V, Inconel 718, and SS316L were selected to provide a heterogeneous dataset representing materials with different processing and thermophysical characteristics. The input variables included laser power (P), scan speed (v), laser operating mode (continuous-wave or pulsed), and alloy type, while the measured post-polishing surface roughness (R_a) was used as the target variable. This dataset structure incorporates both process-level and material-level variations, enabling an initial assessment of physics-augmented feature representation for cross-alloy prediction. Given the relatively small dataset size, the study is formulated as a proof-of-concept investigation rather than a statistically exhaustive predictive study. The dataset was curated to minimize duplicate or incomplete observations and to maintain representation across the four alloy systems. Cross-validation and comparisons with baseline models were subsequently used to assess the consistency and usefulness of the proposed feature representation.

Table 1. Summary of dataset structure and parameter ranges.

Parameter	Minimum	Maximum	Units	Description
Laser power	30	500	W	Laser power used during polishing
Scan speed	50	1500	mm/s	Laser scanning speed
Laser mode	CW	Pulsed	—	Binary encoded operating mode
Surface roughness	0.2	5.0	µm	Post-polishing roughness measured by profilometry

The parameter ranges summarize the diversity of the collected observations across the four alloy systems. The variation in laser power, scan speed, and operating mode provides the basis for subsequent feature engineering and neural-network modelling.

2.2 Feature Engineering

To introduce physically meaningful information into the predictive framework, linear energy density (ED) was calculated from laser power and scan speed as

$$ED = \frac{P}{v}$$

where P is the laser power (W) and v is the scan speed (mm/s). The resulting descriptor represents the linear energy input associated with the laser scanning process and provides a compact representation of the relationship between the principal processing variables.

Additional nonlinear descriptors were introduced to increase the representational capacity of the model. These included the squared energy density (ED^2) and squared scan speed (v^2). Laser operating mode was binary encoded, with continuous-wave (CW) operation assigned a value of 0 and pulsed operation assigned a value of 1. Alloy identity was one-hot encoded to avoid imposing an artificial ordinal relationship between the different materials.

The resulting input representation was defined as

$$X = \left[P, v, \text{Mode}, \text{Alloy}_1, \text{Alloy}_2, \text{Alloy}_3, \text{Alloy}_4, ED, ED^2, v^2\right]$$

This hybrid representation combines experimentally reported process variables, categorical material information, and physics-augmented nonlinear descriptors. The resulting feature space was used as the input to the proposed Meta-ANN.

2.3 ANN Architecture and Training

The Meta-ANN was implemented using MATLAB's Neural Network Toolbox. A compact architecture was selected to limit model complexity relative to the available dataset size. The network consisted of an input layer representing the engineered feature vector, two hidden layers containing 5 and 3 neurons, respectively, and a single output neuron for prediction of surface roughness (R_a, μm). Leaky ReLU activation functions were employed in the hidden layers. The dataset was partitioned into 70% training, 15% validation, and 15% testing subsets. Because of the limited number of observations, early stopping was employed to reduce unnecessary model fitting, with training terminated after 20 consecutive validation epochs without improvement or after a maximum of 300 epochs. Comparative training trials were also conducted using Levenberg–Marquardt and Adam optimization strategies. The objective of this modelling procedure was to evaluate the feasibility of combining physics-augmented descriptors with a compact neural-network architecture under low-data conditions. The resulting framework was therefore assessed primarily as a proof-of-concept rather than as a fully optimized predictive system. The overall modelling workflow and ANN architecture are presented in Figure 1.

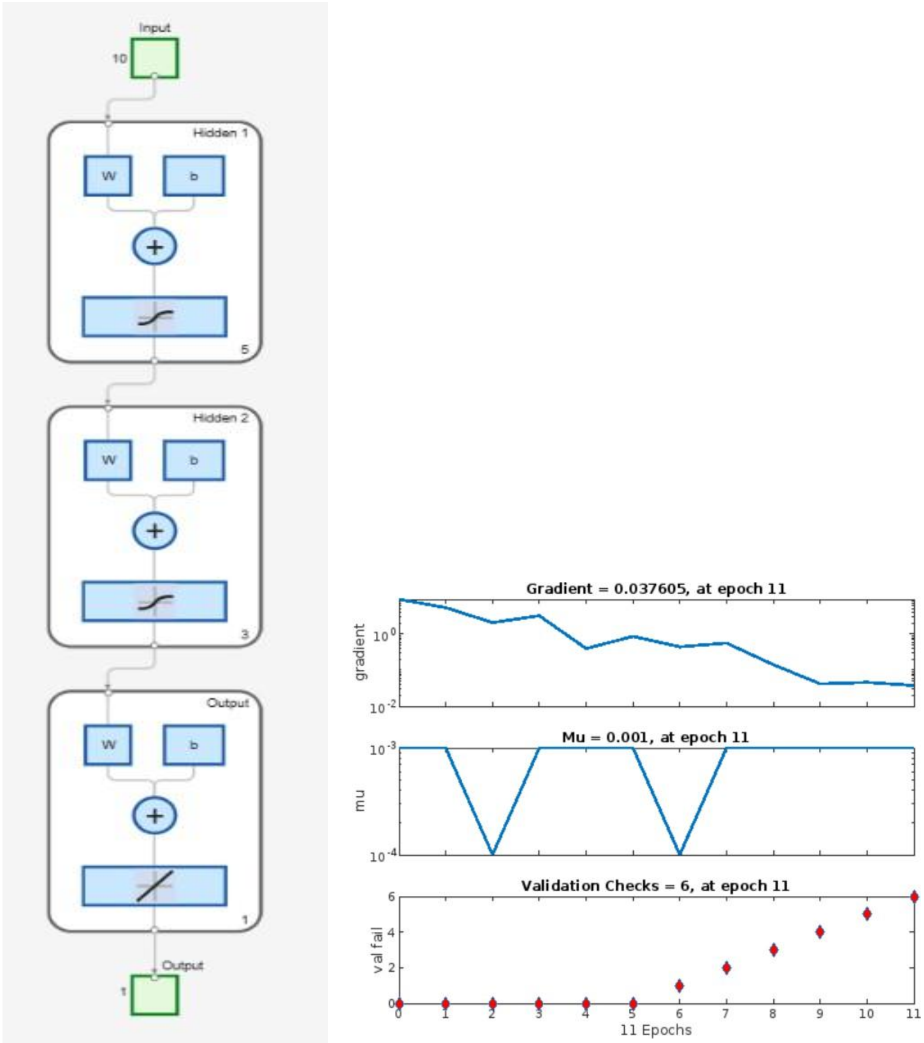

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Figure 1. Meta-ANN architecture and training diagnostics.

(a) Schematic representation of the proposed Meta-ANN, comprising ten input features, two hidden layers with 5and 3neurons, respectively, and a single output node for predicting surface roughness (R_a). Physics-augmented descriptors (ED, ED^2, and v^2) are included to enrich the input representation. **(b)** Training diagnostics showing the evolution of the training gradient, adaptive learning parameter (μ), and validation checks over successive epochs, illustrating the convergence behaviour of the network and the application of early stopping to limit overfitting.

3. Results and Discussion

3.1 Model Performance

The proposed Meta-ANN, consisting of two hidden layers with 5 and 3 neurons, respectively, demonstrated strong predictive agreement with the measured surface-roughness values within the available dataset. The model achieved R^2 values of approximately 0.99 for the training/testing data and 0.97 for the validation set. The corresponding mean absolute error (MAE) and root mean square error (RMSE) were 0.06 μm and 0.08 μm, respectively, indicating close agreement between the predicted and measured R_a values. The inclusion of physics-augmented descriptors, particularly ED^2 and v^2, provided additional nonlinear representations of the processing variables and improved the model's ability to capture variations in surface roughness. These features complement the primary process variables by enabling the network to represent nonlinear relationships that may not be adequately captured using laser power and scan speed alone. Despite the high predictive metrics, the results should be interpreted cautiously because the model was developed using a relatively small and heterogeneous dataset. High R^2 values obtained from limited observations can be sensitive to the specific data partition and may not necessarily indicate robust generalization to previously unseen alloys or processing conditions. Early stopping and separate training, validation, and testing subsets were therefore employed to reduce the likelihood of excessive fitting. Nevertheless, the present results should be regarded as proof-of-concept evidence of predictive feasibility rather than definitive evidence of cross-alloy generalization. Within these limitations, the results indicate that incorporating physically meaningful descriptors into a compact neural-network framework can provide useful predictive representation under low-data conditions. The regression relationships between measured and predicted surface roughness for the training, validation, and testing subsets are presented in Figure 2.

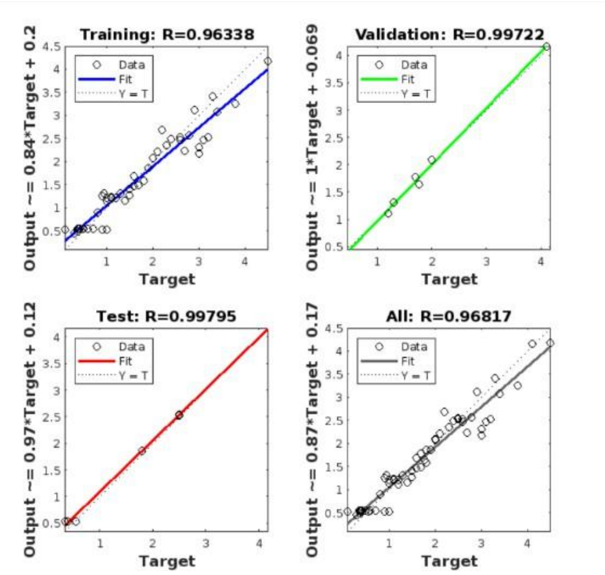


Figure 3. Regression plots for Meta-ANN surface-roughness prediction. Comparison between measured (R_a) and predicted surface roughness for the training, validation, testing, and overall datasets. The fitted regression lines show strong agreement between predicted and measured values, with correlation coefficients of $R = 0.96338$ for training, $R = 0.99722$ for validation, $R = 0.99795$ for testing, and $R = 0.96817$ for the complete dataset. The dotted line represents the ideal $Y = T$ relationship.

3.2 Effect of Physics-Augmented Features

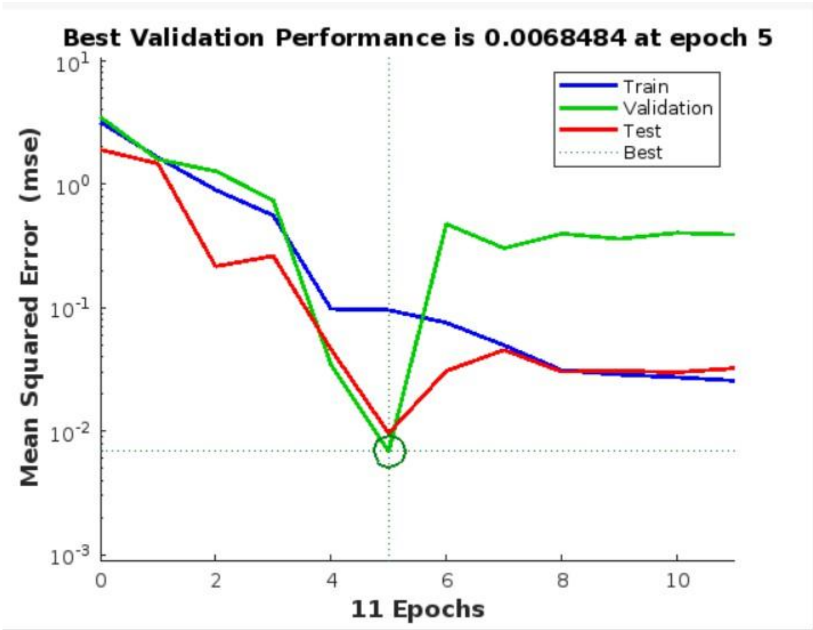
The inclusion of physics-augmented features produced a measurable improvement in the predictive performance of the neural-network model. In particular, incorporating linear energy density ($ED = P/v$) and its nonlinear representation (ED^2) increased the coefficient of determination from approximately $R^2 = 0.91$for the conventional feature set to $R^2 = 0.99$for the physics-augmented model, while reducing the mean absolute error (MAE) by approximately 35%. This improvement indicates that the derived energy-density descriptors provided additional information beyond the original laser power and scan-speed variables and helped the network represent the nonlinear response of surface roughness to laser-processing conditions. The contribution of the engineered features was also reflected in the feature-influence analysis. The combined contribution of $ED$and ED^2accounted for more than 40%of the estimated feature influence, indicating that energy-density-related information played a substantial role in the model response. Alloy identity and scan speed also showed appreciable influence, which is physically reasonable because differences in alloy characteristics and laser–material interaction conditions can affect melt-pool behaviour, material redistribution, and the resulting surface morphology. An important aspect of this result is that the physics-augmented descriptors were derived directly from experimentally available process variables rather than requiring additional measurements or complex physical simulations. This provides a relatively simple means of introducing process-related information into a low-data learning framework. The improvement from the baseline representation to the physics-augmented representation therefore suggests that appropriate feature engineering can partially compensate for limited data availability by providing the network with descriptors that have a direct relationship to the underlying laser-processing conditions. Nevertheless, the magnitude of the improvement should be interpreted with caution. The comparison was performed using a relatively small dataset, and therefore the observed performance gain may depend partly on the specific composition and partitioning of the available observations. The results do not establish that energy density alone governs surface roughness, nor do they demonstrate universal transferability across alloys. Instead, they provide proof-of-concept evidence that physics-augmented feature representation can improve the predictive behaviour of a compact neural network under low-data conditions. Further validation using larger, independently generated datasets and additional material- and process-specific descriptors is required to determine the robustness and generality of this effect.

3.3 Cross-Alloy Generalization

A key objective of the proposed Meta-ANN is to examine whether a common feature representation can capture surface-roughness trends across different LPBF alloy systems. Unlike conventional single-material models, the present framework incorporates alloy identity together with process variables and physics-augmented descriptors, allowing the model to account for both shared processing trends and material-dependent behaviour. The alloy-wise evaluation produced values above 0.96 for AlSi10Mg, Ti6Al4V, Inconel 718, and SS316L within the available dataset. As an illustrative case, for a Ti6Al4V condition processed at 180 W and 300 mm/s in pulsed mode, the model predicted an value of 0.95 µm compared with the corresponding experimental value of 0.93 µm. This close agreement demonstrates that the model can reproduce individual observations within the range represented by the training dataset. The predictions also showed relatively close agreement with the experimental measurements across the four alloy groups. Some deviations were observed for Inconel 718, which may reflect the greater complexity associated with alloy-dependent laser–material interactions and differences in thermal response. Such deviations highlight an important characteristic of cross-alloy modelling: a common process descriptor such as energy density can provide useful information, but it cannot fully represent all material-specific phenomena governing surface evolution during laser polishing. Accordingly, the observed alloy-wise performance should not be interpreted as evidence of universal cross-alloy generalization. The dataset contains a limited number of observations and was compiled from heterogeneous literature sources, meaning that differences in experimental equipment, initial surface condition, measurement procedures, and processing strategies may contribute to the observed variability. The present results therefore provide **preliminary evidence that physics-augmented feature representation can support prediction across multiple LPBF alloys**, while also demonstrating the need for larger and independently generated datasets to establish robust transferability. Overall, the cross-alloy analysis supports the feasibility of using a compact physics-augmented Meta-ANN as an initial modelling framework for heterogeneous laser-polishing data. Future validation should evaluate the model using alloy-wise holdout or leave-one-alloy-out testing to more rigorously determine whether the learned relationships can generalize to an alloy that is completely excluded from model training.

```
% Define your new input parameters
Power_input = 310;        % in Watts
Speed_input = 800;        % in mm/s
Mode_input = 0;           % 0 = CW, 1 = Pulsed
Alloy_type = 2;           % 1, 2, 3, or 4 (as per your training logic)

% Physics-based features
ED_input = Power_input / Speed_input;
ED2_input = ED_input^2;
Speed2_input = Speed_input^2;

% One-hot encoding for alloy
Alloy1 = double(Alloy_type == 1);
Alloy2 = double(Alloy_type == 2);
Alloy3 = double(Alloy_type == 3);
Alloy4 = double(Alloy_type == 4);

% Combine all inputs into a 10x1 column vector
Xnew = double([Power_input; Speed_input; Mode_input; ED_input; ED2_input; Speed2_input; Alloy1; Alloy2; Alloy3; Alloy4]);

% Normalize new input using settings from training
Xnew_norm = mapminmax('apply', Xnew, settings);

% Predict using trained ANN
Ra_pred = net(Xnew_norm);

% Display result
fprintf('\n✅ Predicted Surface Roughness (Ra) = %.4f µm\n', Ra_pred);

✅ Predicted Surface Roughness (Ra) = 0.9484 µm
```

a



b

Figure 4. Cross-alloy prediction and training performance of the Meta-ANN. (a) Predicted surface roughness (R_a) values grouped according to alloy type, illustrating the model's ability to reproduce surface-roughness values across AlSi10Mg, Ti6Al4V, Inconel 718, and SS316L. For the Ti6Al4V condition with $P = 180$ W, $v = 300$ mm/s, and pulsed operation, the predicted $R_a$was $0.9484\ \mu$m. (b) Training, validation, and testing performance of the Meta-ANN, represented by mean squared error (MSE) as a function of training epochs. The minimum validation MSE of 0.0068was obtained at epoch 5, after which early stopping was applied to limit further fitting and reduce the risk of overfitting.

4. Limitations, Future Directions and Technology Readiness

The present study has several limitations that should be considered when interpreting the results. The first and most important limitation is the relatively small dataset of 60 observations. Although the dataset provides sufficient information for an initial proof-of-concept assessment, its size limits the statistical confidence and the extent to which the model can be expected to generalize to new alloys and processing conditions. In addition, the data were collected from different literature sources, where differences in experimental equipment, initial surface condition, laser configuration, and measurement procedures may introduce additional variability. Such differences are particularly relevant in laser-polishing studies, where initial surface condition and processing parameters can substantially influence the achievable surface quality (Hofele et al., 2021; Li and Zuo, 2021).

A second limitation concerns the feature representation. The proposed framework primarily uses laser power, scan speed, alloy identity, and energy-density-based descriptors, together with simple nonlinear terms. These features provide a physically meaningful starting point, but they cannot capture the full complexity of laser–material interactions during polishing. Future models could incorporate additional descriptors such as thermal conductivity, absorptivity, melting temperature, viscosity, melt-pool dimensions, cooling rate, initial surface roughness, and other material- and process-dependent characteristics. Multiphysics modelling and physics-informed approaches provide potential routes for incorporating such information into surface-quality prediction (Pham and Tran, 2024; Faegh et al., 2025).

The findings should therefore be interpreted as **proof-of-concept evidence rather than validation of an industrial-scale predictive system**. In particular, the high predictive performance obtained from the present dataset should not be interpreted as evidence of universal cross-alloy generalization. Independent experimental datasets and stricter alloy-wise validation strategies, such as leave-one-alloy-out testing, would provide a more rigorous assessment of transferability. Cross-alloy and physics-guided learning frameworks have shown the potential to address this challenge, but their reliability remains dependent on the diversity and quality of the available training data (Karkadakattil, 2025; Karkadakattil, 2026a; Karkadakattil, 2026b).

Future work should first focus on expanding the dataset through controlled experiments conducted under standardized conditions, complemented where appropriate by reliable open-access datasets. A larger and more systematically designed dataset would improve statistical reliability and provide a stronger basis for evaluating cross-alloy generalization. The framework could also be extended beyond surface roughness to other important quality characteristics, including porosity, residual stress, dimensional accuracy, and microstructural attributes. Machine-learning approaches have already demonstrated potential for predicting multiple quality-related characteristics in additively manufactured materials (Alamri et al., 2025).

Integration with **in-situ monitoring** is another promising direction. Optical, thermal, acoustic, or other process-monitoring signals could provide real-time information about the evolving polishing condition and enable the model to move beyond static prediction. In a more advanced implementation, the predictive framework could be coupled with adaptive control or reinforcement-learning strategies to support real-time adjustment of laser power, scan speed, or other processing parameters. Such developments could ultimately contribute to closed-loop laser-polishing systems capable of responding dynamically to changing surface conditions. The framework could also be extended toward **multi-objective process optimization**, where surface roughness is considered together with other engineering requirements such as material removal, productivity, fatigue performance, and corrosion resistance. This would provide a more realistic basis for process selection in applications where surface finish is only one component of overall part performance. Automated laser-polishing approaches have already demonstrated potential for improving surface finishing in practical manufacturing environments (Caggiano et al., 2021; Ali et al., 2023). From a technology-readiness perspective, the present study is best regarded as an **early-stage proof-of-concept**. The concept has been formulated and evaluated computationally using a limited heterogeneous dataset, corresponding broadly to the early stages of technology development. Progress toward laboratory-level validation would require larger datasets, controlled experiments, independent testing, and additional physics-based descriptors. Subsequent integration with in-situ monitoring and closed-loop control could support progression toward higher technology-readiness levels. However, industrial deployment would require extensive multi-alloy validation, standardized benchmarking, demonstrated process robustness, and testing under representative manufacturing conditions. Overall, the present work establishes a preliminary basis for **physics-augmented, low-data cross-alloy prediction of laser-polished surface roughness**. Its main value lies not in claiming a fully general predictive solution, but in demonstrating a practical modelling direction that can be systematically strengthened through larger datasets, richer physical descriptors, independent validation, and eventually real-time process control. The broader development of physics-guided neural networks and physics-regularized transfer-learning strategies further illustrates the potential of embedding physical information into data-driven models for improving prediction across heterogeneous manufacturing conditions (Karkadakattil, 2026a, 2026b; Farrag et al., 2025; Faegh et al., 2025).

Conclusion

This study developed a physics-augmented Meta-ANN for cross-alloy prediction of laser-polished LPBF surface roughness using energy density ($\mathrm{ED} = P/v$) and nonlinear descriptors. Trained on 60 observations spanning AlSi10Mg, Ti6Al4V, Inconel 718, and SS316L, the model achieved $R^2 > 0.96$, with $\mathrm{MAE} = 0.06\ \mu$m and $\mathrm{RMSE} = 0.08\ \mu$m. Incorporating ED and ED^2 reduced MAE by approximately 35% and increased R^2 from 0.91 to 0.99 relative to the conventional feature representation, while ED and ED^2 together accounted for more than 40% of the estimated feature influence. An illustrative Ti6Al4V condition ($P = 180$ W, $v = 300$ mm/s, pulsed mode) yielded a predicted R_a of $0.9484\ \mu$m, compared with an experimental value of $0.93\ \mu$m. Although these results demonstrate the feasibility of physics-augmented low-data modelling, the limited and heterogeneous dataset means that the findings remain proof-of-concept evidence, and larger independently generated datasets and stricter cross-alloy validation are required to establish robust generalization.

Conflict of Interest

The author declare that they have **no known financial or personal conflicts of interest that could have influenced the research, analysis, or conclusions presented in this manuscript.**

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