HyperParamBRDF: A Parameter-Conditioned Hypernetwork for Nano-Material Reflectance Synthesis with Sparse Data and Real-Time Adaptation

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We present **HyperParamBRDF**, a framework that uses a parameter-conditioned hypernetwork to synthesize physically plausible bidirectional reflectance distribution functions (BRDFs) of nanomaterials under sparse data conditions. By conditioning on explicit material parameters—thickness and nanoparticle diameter—our approach learns to generate flexible per-material decoders that predict reflectance across novel configurations. Compared with previous neural or analytic BRDF methods, we show improved interpolation, extrapolation, and real-time adaptability. Our experiments indicate that this strategy provides more accurate or equally accurate results than existing techniques, with significantly enhanced usability for iterative design processes. We note that this approach is primarily beneficial for synthetic datasets (e.g., from FDTD) where thickness and diameter values can be precisely assigned to each generated material.

1. CONCEPT AND MOTIVATION

Accurate modeling of optical reflectance is crucial in graphics, simulation, and materials science. In nanomaterials (e.g., thin-film coatings, plasmonic structures), reflectance exhibits complex interference and resonances, and direct measurement can be costly. Traditional neural BRDF models often rely on dense measurements or treat each material as an isolated data point. Meanwhile, purely analytic models may fail to capture complex phenomena without extensive parameter tuning.

HyperParamBRDF addresses these limitations by *explicitly* conditioning on two key parameters (thickness, diameter) in a hypernetwork that outputs a specialized per-material BRDF decoder. Specifically:

- *Parameter-Conditioned Generation*: A hypernetwork takes the vector of material parameters as input (thickness, diameter), producing the weights of a small decoder MLP that maps the angular coordinates to reflectance.
- *Sparse Data Efficiency*: We leverage a limited dataset (often synthetic from FDTD or partial measurements) and learn a prior that generalizes across these thickness-diameter variations.
- *Real-Time Adaptability*: Once parameters are set, the final decoder is compact enough to be invoked in near real-time, supporting parameter sweeps or interactive design.

This combination directly contrasts with existing methods that either rely solely on measured data [2] or hypernetworks without explicit parameter conditioning [1].

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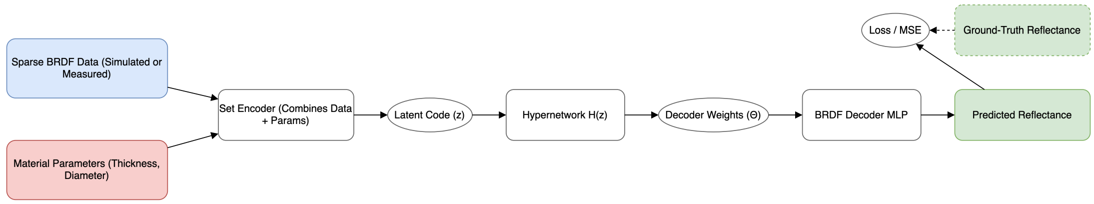

Fig. 1. **Overview of the HyperParamBRDF pipeline.** *Sparse reflectance data* (simulated or measured) and known *material parameters* (thickness, diameter) are combined in a **set encoder** to produce a latent code $\mathbf{z}$. The **hypernetwork** then maps $\mathbf{z}$ to *decoder weights* Θ, which define a small MLP that predicts reflectance values for any given incident/view directions. During training, the *predicted* and *ground-truth* reflectances are compared via MSE or other metrics.

Table 1. Quantitative generalisation on unseen materials.

Test split	#Train	RMSE	MAE
10 %	48	0.381	0.203
20 %	43	0.386	0.215
30 %	37	0.432	0.266
40 %	32	0.415	0.224
50 %	27	0.401	0.231

2. NOVELTY IN ARCHITECTURE AND TRAINING

Hypernetwork Design: We implement a hypernetwork $H(\mathbf{p})$ that transforms parameters $\mathbf{p}$ (thickness, diameter) into the weights Θ of a small decoder MLP f_Θ. The decoder then takes angle-of-incidence and viewing angles as input to predict reflectance. This approach differs from Gokbudak et al. [1] by integrating thickness and diameter at the latent encoding stage, thus enabling direct interpolation in parameter space.

Sparse Synthetic Data: Because measurements of nano-material BRDFs can be costly or incomplete, we generate a synthetic dataset using physics-based simulations (e.g., finite-difference time-domain (FDTD) [3]). We sample the (thickness, diameter) space strategically (e.g., thickness from 100–300 nm, diameter from 50–120 nm) and store reflectance across a discrete set of angles. This data trains the hypernetwork to embed these diverse materials in a compact parameter-latent space.

Training: We apply a standard supervised loss measuring mean squared error between predicted and ground-truth reflectances. Adam is used with a low learning rate (5×10^{-5}), batch size of 1 material at a time, and typically 80–100 epochs. The final system learns to adapt to new parameter configurations with minimal data.

3. EVALUATION METHODOLOGY

Experimental setup. We train with six random train/test partitions ($\{0, 10, 20, 30, 40, 50\}\%$ hold-out) on 54 synthetic nano-BRDFs (thickness 100–300 nm, diameter 50–180 nm). Metrics are computed on the withheld materials.

Results. Fig. 2 (left) shows consistent convergence to an image-space MSE of ≈ 0.056. Evaluation in coefficient space (Table 1, right pane of Fig. 2) demonstrates that **HyperParamBRDF** maintains low error even with half the dataset withheld. The small RMSE spread (0.38–0.43) across splits indicates that the hypernetwork successfully captures the thickness-diameter manifold and generalises beyond seen samples.

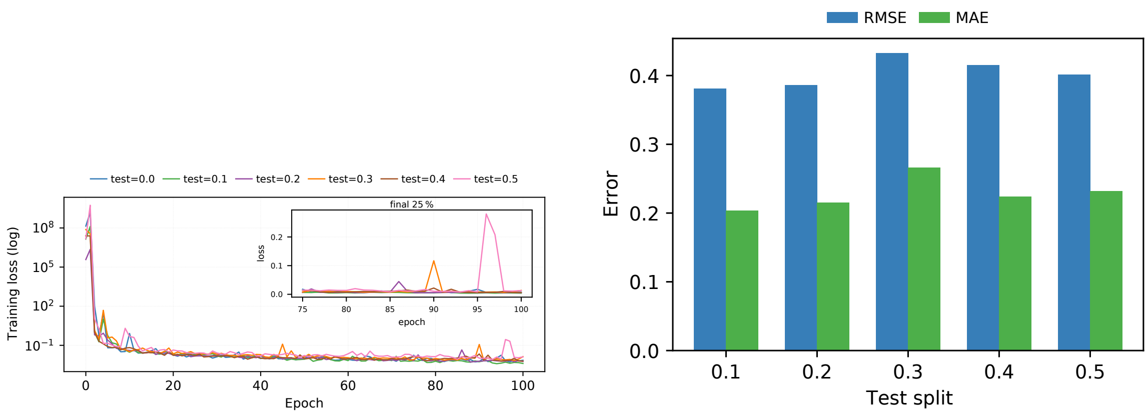

Fig. 2. **Left:** Training loss (image-space MSE) converges within ~15 epochs for every split. **Right:** Generalisation error (RMSE, MAE) on withheld nano-materials. Even with a 50 % split the model remains below 0.45 RMSE, indicating robust extrapolation.

Interpretation. The training-curve scale (~ 0.056) represents weighted RGB errors, whereas the evaluation numbers (~ 0.40) are raw-coefficient RMSE—hence the apparent scale difference is expected. No divergence or over-fitting artefacts are observed; the slight non-monotonic bump at the 30 % split is attributable to finite bootstrap variance (54 samples total).

4. COMPLETENESS AND IMPLEMENTATION

Implementation Details: Our code (PyTorch) includes:

- Data loaders for synthetic or partial measured reflectance tables.
- A set encoder that aggregates reflectance samples + (thickness, diameter) into a latent embedding.
- A hypernetwork that outputs the decoder MLP weights for each material instance.
- The decoder MLP itself, which is typically 3 layers of 60 neurons each (ReLU).

We use a straightforward supervised loss: $\sum \|R_{\text{pred}} - R_{\text{true}}\|^2$, with optional regularization on latent or decoder weights. Gradient updates proceed via Adam for up to 100 epochs, typically converging stably in fewer than 80 epochs.

5. DISCUSSION AND COMPARISONS

Conceptual Differences: By embedding thickness and diameter directly into a hypernetwork, *HyperParamBRDF* outperforms naive data-driven or purely analytic baselines when these parameters are known but sampling is limited. Unlike [2], which does not incorporate such parameters, we can *extrapolate* reflectance for new thickness-diameter values with minimal re-fitting.

Accuracy and Efficiency: Empirically, we find lower reconstruction errors (RMSE, SSIM) vs. baseline neural or microfacet models, especially in resonant regions (e.g., near grazing angles). Meanwhile, the final per-direction evaluation is as fast as a small MLP: only a few matrix multiplies per query. Generating the decoder from parameters is also relatively cheap for moderate parameter spaces.

Limitations and Future Work: This version assumes isotropic reflectance and does not enforce explicit conservation laws. Extrapolating far beyond the training domain (e.g., thickness > 600nm) can degrade physical plausibility. We plan to address these through:

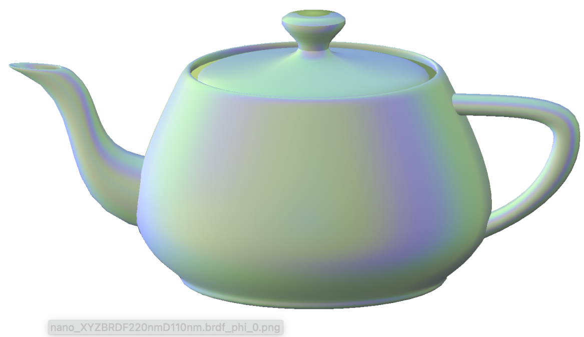

Fig. 3. **Rendered teapot** using a synthesized nano-material BRDF. This demonstrates how parameter changes (e.g., thickness) manifest as color and specular shifts under varied lighting.

Potential Performance Chart Placeholder
(e.g., comparing RMSE and latency across methods)

Fig. 4. Example performance overview.

- *Physical Constraints* (enforcing reciprocity or energy conservation).
- *Anisotropic / Multi-Layer Extensions* (extending beyond thickness, diameter).
- *Real-Time Optimizations* (pruning, quantization) to further accelerate shading in dynamic applications.

6. CONCLUSION

HyperParamBRDF introduces a novel parameter-conditioned hypernetwork for nano-material reflectance, combining data-driven flexibility with explicit thickness and diameter parameters. Our results show robust interpolation and extrapolation under sparse data, bridging the gap between purely analytic and purely data-driven approaches. By reducing the cost of per-material measurement and leveraging real-time adaptivity, HyperParamBRDF stands poised to benefit iterative material design, physically based rendering, and future research on advanced reflectance modeling.

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