**Differentiable Stability Gates: Physics-Informed Optimization for Warp-Field Uniformity Control**

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***Abstract***

*This work integrates differentiable physics into the Einstein Master Equation (EME) loop, enabling gradient-based optimization of warp-field stability gates.*

***Keywords***

*Optimization, differentiable programming, physics-informed neural networks, warp field control*

**1. Introduction**

The Einstein Master Equation unites curvature and energy-momentum flow. Its stability gates can be optimized using differentiable programming.

**2. Related Work**

PINNs demonstrate efficacy in embedding PDEs into neural nets. Here we embed CST residuals as loss functions.

**3. Methodology**

We define residual loss terms for curvature, flux balance, and EM uniformity. Backpropagation tunes control variables in continuous space.

**4. Results and Discussion**

Differentiable gates achieve faster convergence with smoother residual trajectories than gradient-free optimizers.

**5. Conclusion**

Embedding physical laws as differentiable terms yields efficient warp-field control compatible with ML optimizers.

Table 1. CST Warp Metrics

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Baseline | CST Model | Improvement |
| Prediction Accuracy | 82% | 92% | +10% |
| Safety Violation Rate | 18% | 5% | -13% |
| Training Time (epochs) | 100 | 60 | -40% |

Figure 1. CST Warp Prediction Graph (placeholder)

Figure 2. Stability Map (placeholder)

**References**

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