

# Galaxy Rotation Curve Validation of Resonant Field Theory: A Zero-Tuning Blind Test

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## Galaxy Rotation Curve Validation of Resonant Field Theory: A Zero-Tuning Blind Test

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### Abstract

We present a blind validation of the Resonant Field Theory (RFT) computational solver against rotation curve observations from the SPARC database (McGaugh, Lelli, & Schombert 2016). Under a strict zero-tuning protocol ( $k = 0$  per-galaxy parameters), the RFT Galaxy Rotation Curve

Solver achieves a 58.8% pass rate on 34 blind TEST galaxies, compared to 52.9% for global NFW and 23.5% for canonical MOND. Statistical tests confirm the Solver is competitive with NFW (McNemar  $p = 0.69$ ) and significantly outperforms MOND ( $p = 0.004$ ). Low surface brightness galaxies show the starkest contrast (RFT Solver: 66.7%; global NFW: 0%), consistent with the Solver’s acceleration-gated mechanism activating in weak-field regimes where baryonic matter alone is insufficient.

**Keywords:** galaxy dynamics, rotation curves, dark matter, modified gravity, MOND, predictive modeling

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## 1. Introduction

The discrepancy between the observed rotational velocities of galaxies and the gravitational potential generated by their visible baryonic mass remains one of the most significant challenges in modern astrophysics. Since the seminal work of Rubin et al. (1980), this “mass deficit” has predominantly been explained by the presence of Cold Dark Matter (CDM) halos. While the Navarro-Frenk-White (NFW) profile (Navarro, Frenk, & White 1997) provides the standard cosmological framework for these halos, it faces persistent challenges on galactic scales, particularly the “cusp-core” problem in Low Surface Brightness (LSB) galaxies (McGaugh et al., 2016).

Alternatively, Modified Newtonian Dynamics (MOND) (Milgrom, 1983) proposes a modification to the gravitational law itself. MOND has achieved remarkable success in fitting rotation curves with minimal free parameters. However, in practice, even MOND analyses typically require the variation of the stellar mass-to-light ratio ( $M_*/L$ ) as a nuisance parameter to achieve optimal fits (Li et al., 2018). This introduces a “descriptive” degree of freedom ( $k \geq 1$ ) that complicates the assessment of the theory’s purely “predictive” power.

In this work, we present a rigorous blind validation of Resonant Field Theory (RFT), a geometry-only framework that generates the “missing” acceleration through a resonant interaction term rather than dark matter halos. To evaluate the theory without the confounding variable of parameter tuning, we developed **the RFT Galaxy Rotation Curve Solver**. This computational pipeline enforces a “Strict Zero-Tuning” ( $k = 0$ ) protocol: all theoretical parameters are fixed globally on a training set and evaluated blindly on a distinct test cohort from the SPARC database.

By locking distance, inclination, and mass-to-light ratios to their catalog values, the Solver isolates the intrinsic predictive accuracy of the model. We demonstrate that under these rigid conditions, the RFT Solver achieves a 58.8% pass rate ( $\text{RMS} \leq 20\%$ ), significantly outperforming canonical MOND (23.5%) and competing with global NFW predictions. Crucially, the Solver reveals a mechanistic dominance in the LSB regime, suggesting that the theory’s “acceleration gating” mechanism correctly identifies the dynamic transition in weak-field limits.

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## 2. Methodology

### 2.1 The RFT Solver Algorithm

The core logic of the RFT Galaxy Rotation Curve Solver computes a geometric acceleration tail,  $g_{\text{tail}}$ , which is added to the standard Newtonian baryonic acceleration  $g_b$ . The Solver implements the following predictive equation:

$$g_{\text{tail}}(r) = A_0 \left( \frac{r_{\text{geo}}}{r} \right)^\alpha \cdot \left[ 1 + \left( \frac{g_b}{g_*} \right)^\gamma \right]^{-1} \cdot \left[ 1 - e^{-(r/r_{\text{turn}})^p} \right]$$

where: -  $r_{\text{geo}}$ : Geometric radius scale derived from disk properties -  $g_b$ :

Baryonic acceleration computed from observed stellar and gas distributions - **Radial decay**:  $(r_{\text{geo}}/r)^\alpha$  controls outer falloff -

**Acceleration gate**:  $\left[ 1 + \left( \frac{g_b}{g_*} \right)^\gamma \right]^{-1}$  activates in low- $g_b$  environments -

**Onset function**:  $\left[ 1 - e^{-(r/r_{\text{turn}})^p} \right]$  provides smooth turn-on at small radii

The Solver utilizes a frozen parameter set  $\{A_0, \alpha, g_*, \gamma, r_{\text{turn}}, p\}$  derived solely from the training cohort. **No per-galaxy optimization is performed during the test phase.**

**Frozen Parameter Values:** -  $A_0 = 1000 \text{ km}^2/\text{s}^2/\text{kpc}$  -  $\alpha = 0.6$  -  $g_* = 1000 \text{ km}^2/\text{s}^2/\text{kpc}$  -  $\gamma = 0.5$  -  $r_{\text{turn}} = 2.0 \text{ kpc}$  -  $p = 2.0$

### 2.2 Ensuring Parameter Parity ( $k = 0$ )

A critical methodological insight emerged during baseline development: **parameter budget must be controlled.** Initial NFW comparisons allowed per-galaxy halo fitting ( $k = 2$  free parameters:  $\rho_s, r_s$ ), yielding 82.4% pass rate—dramatically higher than the RFT Solver’s 58.8%.

However, this comparison was methodologically invalid. NFW had 68 total parameters ( $2 \times 34$  galaxies) versus the RFT Solver’s 6 global parameters. To ensure fairness, we implemented:

**Global NFW Baseline:** 1. Fit a single  $(\rho_s, r_s)$  on TRAIN cohort ( $n = 65$ ) 2. Apply frozen parameters to TEST cohort ( $n = 34$ ) with no per-galaxy tuning 3. Identical evaluation: 1-30 kpc radius window,  $\text{RMS\%} \leq 20\%$  pass criterion

**Result:** NFW<sub>global</sub> achieves 52.9% on TEST—below the RFT Solver’s 58.8%.

### 2.3 The Computational Audit Framework

To ensure rigor, we developed an automated evaluation pipeline—the RFT Galaxy Rotation Curve Solver. This framework ingests raw SPARC observation data (McGaugh, Lelli, & Schombert 2016) and computes theoretical velocities without human intervention. The pipeline enforces the Strict Zero-Tuning protocol by locking distance and inclination to catalog values.

**Key Features:** - Containerized artifact for independent verification - One-click RUNME.sh verification script - Full provenance (commit hash, data sources) - Public repository: <https://github.com/rft-cosmology/rft-v2-galaxy-rotations>

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## 3. Results

### 3.1 TEST Cohort Performance ( $n = 34$ , Blind Evaluation)

#### RFT Galaxy Rotation Curve Solver (Frozen Config)

- **Pass@20%:** 58.8% (20/34)
- **Pass@10%:** 8.8% (3/34)
- **RMS median:** 17.1%
- **Parameters:** 6 global,  $k = 0$  per-galaxy

#### NFW<sub>global</sub> (TRAIN-Fitted, TEST-Frozen)

- **Pass@20%:** 52.9% (18/34)
- **Pass@10%:** 11.8% (4/34)
- **RMS median:** 18.3%
- **Parameters:** 2 global,  $k = 0$  per-galaxy

#### MOND (Canonical $a_0$ )

- **Pass@20%:** 23.5% (8/34)
- **Pass@10%:** 0.0% (0/34)
- **RMS median:** 32.2%
- **Parameters:** 1 global ( $a_0 = 1.2 \times 10^{-10}$  m/s<sup>2</sup>),  $k = 0$  per-galaxy

### 3.2 Statistical Significance

#### McNemar Exact Test (Paired Analysis):

**RFT Solver vs NFW<sub>global</sub>:** - Concordant pairs: 28 (both pass or both fail) - Discordant pairs: 6 (RFT wins 4, NFW wins 2) - **p-value = 0.69** (NOT significant at  $\alpha = 0.05$ )

**Interpretation:** The observed difference is consistent with sampling noise. A larger TEST cohort would be needed to establish significance.

**RFT Solver vs MOND:** - Concordant pairs: 18 - Discordant pairs: 16 (RFT wins 14, MOND wins 2) - **p-value = 0.004** (HIGHLY significant)

**Interpretation:** The RFT Solver demonstrates superior predictive accuracy in the zero-tuning regime.

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## 4. Discussion

### 4.1 The Low-Acceleration Regime: LSB Dominance

The starkest contrast in performance appears in the Low Surface Brightness (LSB) cohort. Standard CDM halos (NFW) famously suffer from the “cusp-core” problem in these systems (de Blok 2010). Under our zero-tuning protocol, global NFW models failed to fit a single LSB galaxy (**0% pass rate**). In contrast, the RFT Solver achieved a **66.7% pass rate**.

Cohort	RFT Solver	NFW <sub>global</sub>	Mechanism
<b>LSB galaxies</b>	<b>66.7% (4/6)</b>	<b>0% (0/6)</b>	Acceleration gate activates in low- $g_b$ environments
<b>HSB galaxies</b>	55% (16/28)	68% (18/28)	Baryonic dominance reduces tail contribution

This suggests that the RFT Solver’s acceleration gate ( $G(g_b) = [1 + (g_b/g_*)^\gamma]^{-1}$ ) correctly identifies the dynamic transition in weak-field limits where baryonic matter alone is insufficient. The mechanism naturally favors LSB galaxies—precisely where dark matter halos struggle most.

## 4.2 Methodological Discrepancies in Baseline Comparisons

We note that the low performance of the MOND baseline (23.5%) is largely attributable to the strict structure of the zero-tuning protocol, which locks the Mass-to-Light ratio ( $M_*/L$ ) to catalog defaults. While standard MOND analyses typically treat  $M_*/L$  as a nuisance parameter to be fitted, this study isolates the intrinsic predictive power of the acceleration law itself.

The fact that the RFT Solver achieves 58.8% accuracy under the same rigid constraints suggests a higher degree of robustness to mass-model uncertainties. This is not a criticism of MOND—which performs excellently when allowed per-galaxy  $M_*/L$  freedom—but rather a demonstration that the RFT Solver’s geometric tail mechanism provides additional predictive power in the zero-tuning regime.

## 4.3 Comparison to Descriptive Fits

When NFW is allowed  $k = 2$  free parameters per galaxy (per-galaxy halo fitting): - **Pass@20%**: 82.4% (28/34) - **Total parameters**: 68 ( $2 \times 34$  galaxies)

This demonstrates that local dark matter halos outperform universal parametric models—an expected result, not a controversial claim. However, such fits are **descriptive** rather than **predictive**. The relevant comparison for theory testing is the  $k = 0$  regime, where the RFT Solver provides the most accurate no-tuning baseline.

Penalized comparisons (BIC, AIC) would favor the RFT Solver’s parameter efficiency:  $k = 0$  versus NFW’s  $k = 2 \times N_{\text{gal}}$ .

## 4.4 Systematic Uncertainties

We observe that significant outliers (RMS > 30%), such as IC2574, are often systems where non-circular motions or high inclinations introduce systematic errors in the observational data, affecting all solver types. Future work should incorporate kinematic modeling beyond circular velocities to address these edge cases.

Additionally, the RFT Solver currently assumes a simple baryonic model (exponential stellar disk + gas). Improved fits may be achievable with more sophisticated mass decompositions, though this would increase the per-galaxy parameter count beyond our strict  $k = 0$  protocol.

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## 5. Conclusions

Under a strict zero-tuning protocol ( $k = 0$  per-galaxy parameters), the RFT Galaxy Rotation Curve Solver achieves a 58.8% pass rate on blind TEST data, compared to 52.9% for global NFW and 23.5% for canonical MOND. While the advantage over NFW is modest and not statistically significant with  $n = 34$  ( $p = 0.69$ ), the Solver significantly outperforms MOND ( $p = 0.004$ ).

The LSB cohort results (66.7% vs 0%) provide evidence that the acceleration-gated mechanism activates where baryonic gravity is weakest—consistent with the geometric tail formulation. This demonstrates that the RFT Solver offers a viable alternative to dark matter halos in the zero-tuning regime.

The Solver's computational framework ensures full reproducibility: containerized code, frozen configurations, and one-click verification scripts are publicly available. This rigorous methodology isolates predictive accuracy from descriptive curve-fitting freedom, providing a fair baseline for future theoretical comparisons.

**Future work** should extend the Solver to lensing observables (galaxy cluster mass profiles) and cosmic microwave background predictions to test the RFT framework across multiple observational scales.

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## Data Availability

All data, configuration files, and solver code are publicly available at:  
**<https://github.com/rft-cosmology/rft-v2-galaxy-rotations>**

The containerized artifact includes: - SPARC database inputs (McGaugh, Lelli, & Schombert 2016) - Frozen RFT Solver configuration (JSON format) - Global NFW and MOND baseline generators - One-click RUNME.sh verification script - Full provenance (commit hash: 3428db0f, git tag: rc-v2-green-20pct)

**SHA256 checksums:** - .tar.gz:

33cd83cf2279132e42a54cc24745e997a482359e724b96c39387dd6807f78857 -

.zip:

14e2f9d9210034aa0554ec95c2d3873fab68e0299c56ebe08913edb8740b818

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## Acknowledgments

We thank the SPARC collaboration for making their rotation curve database publicly available. This work used computational resources designed for reproducibility: all results can be independently verified using the containerized solver package.

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## Appendix A: Stability Analysis and Parameter Grid Search

**Date:** November 2025 **Status:** Complete

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### A.1 Overview

To ensure the RFT Solver's results were not a product of fine-tuning, we conducted a post-hoc stability analysis exploring variations in the shape parameters  $\{p, \alpha, A_0, r_{\text{turn}}\}$  while holding the acceleration-gating parameters  $\{g_*, \gamma\}$  fixed. The grid search evaluated 81 configurations in a neighborhood of the frozen Solver parameters.

**Result:** The optimal configuration (selected by BIC on TRAIN) achieved identical TEST performance (58.8%) to the frozen baseline, confirming that the Solver's parameters represent a robust local optimum in shape parameter space.

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### A.2 Pre-Registration Protocol

To prevent overfitting and ensure methodological integrity, we pre-registered the following protocol before executing the grid search:

### Grid Definition

- $p \in \{1.5, 2.0, 2.5\}$  (onset smoothness)
- $\alpha \in \{0.5, 0.6, 0.7\}$  (radial decay exponent)
- $A_0 \in \{900, 1000, 1100\}$  km<sup>2</sup>/s<sup>2</sup>/kpc (amplitude normalization)
- $r_{\text{turn}} \in \{1.7, 2.0, 2.3\}$  kpc (onset radius)
- **Total:**  $3 \times 3 \times 3 \times 3 = 81$  configurations

### Selection Criterion

Minimum Bayesian Information Criterion (BIC) on TRAIN cohort ( $n = 65$ ):

$$\text{BIC} = n \cdot \ln \left( \text{RSS}/n \right) + k \cdot \ln ( n )$$

where  $n$  is the number of data points per galaxy,  $k = 6$  is the number of free parameters, and RSS is the residual sum of squares.

### Evaluation Protocol

1. Run all 81 configurations on TRAIN
2. Select configuration with lowest  $\text{BIC}_{\text{sum}}$  across TRAIN galaxies
3. Evaluate selected configuration **once** on blind TEST ( $n = 34$ )
4. **Stop rule:** Report winner, no post-hoc tuning

All steps were documented in a pre-registration file (committed before execution) to prevent researcher degrees of freedom.

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## A.3 Results

### TRAIN Phase ( $n = 65$ )

**Optimal configuration by BIC:** Config 003 - **Parameters:**  $p = 1.5$ ,  $\alpha = 0.5$ ,  $A_0 = 1000$  km<sup>2</sup>/s<sup>2</sup>/kpc,  $r_{\text{turn}} = 1.7$  kpc - **TRAIN performance:** 58.5% pass@20% (38/65) - **BIC<sub>sum</sub>:** 9714.1

**Comparison to frozen Solver configuration:** - Frozen:  $\alpha = 0.6$ ,  $p = 2.0$ ,  $A_0 = 1000$ ,  $r_{\text{turn}} = 2.0$  kpc - Config 003:  $\alpha = 0.5$ ,  $p = 1.5$ ,  $A_0 = 1000$ ,  $r_{\text{turn}} = 1.7$  kpc - **Interpretation:** BIC selected a configuration with slightly sharper radial decay ( $\alpha \downarrow$ ), faster onset ( $p \downarrow$ ), and earlier turn-on ( $r_{\text{turn}} \downarrow$ )

### TEST Phase ( $n = 34$ , Blind Evaluation)

**Config 003 on TEST:** - **Pass@20%:** 58.8% (20/34) ← **EXACT TIE with frozen Solver** - **Pass@10%:** 8.8% (3/34) - **RMS median:** 17.1%

**Statistical outcome:** Zero-percentage-point improvement over the frozen Solver configuration.

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## A.4 Interpretation

### A.4.1 Why Did the Grid Search Tie?

Three plausible explanations:

1. **Local Optimum:** The frozen Solver parameters lie near a flat maximum in shape parameter space. Perturbations of  $\pm 10\text{-}15\%$  do not significantly improve generalization to unseen data.
2. **BIC Selection Noise:** With  $n = 65$  TRAIN galaxies, BIC can select configurations that differ by  $<1$  percentage point on TEST due to sampling variance. The tied result suggests both configurations are effectively equivalent.
3. **Physics Dominance:** The acceleration-gating mechanism ( $G(g_b)$ ) drives predictive performance. Shape parameters ( $\alpha, p, r_{\text{turn}}$ ) provide second-order refinement but do not fundamentally alter the zero-tuning baseline.

### A.4.2 Validation of Frozen Parameters

The tie between Config 003 and the frozen Solver **validates** the original parameter selection. Had the grid found a configuration with 65% pass@20%, it would suggest the frozen baseline was poorly chosen. Instead, the null result confirms that the Solver's frozen parameters are near-optimal within the explored parameter space.

### A.4.3 Robustness to Shape Variations

Config 003 differs from the frozen Solver in three parameters yet achieves identical TEST performance. This demonstrates that the 58.8% result is **not knife-edge sensitive** to specific parameter values—a desirable property for a physical model intended for predictive use.

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## A.5 Parameter Sensitivity (TRAIN Results)

Analysis of the 81-configuration grid reveals which parameters most influenced TRAIN fits:

1.  $p$  (**onset smoothness**): Lower values ( $p = 1.5$ ) dominated the top 10 BIC rankings
2.  $r_{\text{turn}}$  (**onset radius**): Earlier turn-on ( $r_{\text{turn}} = 1.7$  kpc) consistently improved TRAIN BIC
3.  $\alpha$  (**radial decay**): Weak sensitivity;  $\alpha \in \{0.5, 0.6\}$  performed equally well
4.  $A_0$  (**amplitude**): Negligible effect; variations of  $\pm 10\%$  had minimal impact

**Implication:** Onset shape ( $p, r_{\text{turn}}$ ) optimizes TRAIN fit quality, but this preference does not generalize to TEST (as evidenced by the tie). This is consistent with the interpretation that the acceleration gate—not onset details—drives predictive accuracy.

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## A.6 Methodological Rigor

### A.6.1 Pre-Registration Adherence

- ☒ Grid locked before execution (committed in pre-registration document)
- ☒ BIC selection rule followed without deviation
- ☒ Blind TEST evaluation (no peeking, no post-selection adjustments)
- ☒ Stop rule enforced (reported winner without further tuning)

**Verdict:** Protocol followed exactly as pre-registered.

### A.6.2 Overfitting Risk

**Concern:** Did selecting from 81 configurations overfit the TRAIN set?

**Mitigation:** BIC inherently penalizes model complexity. Moreover, the TEST result (58.8%) matched the frozen baseline—indicating no overfitting penalty accrued from the selection process.

**Power analysis:** With 81 configurations and  $n = 34$  TEST galaxies, random chance could produce  $\pm 1$  galaxy fluctuation ( $\sim 3\text{pp}$ ). We observed 0pp change, consistent with a null effect.

### A.6.3 Multiple Comparisons

**Concern:** Does testing 81 configurations constitute a multiple testing problem?

**Answer:** No. We selected **one** configuration (Config 003) based on TRAIN BIC and evaluated it **once** on TEST. This is a single hypothesis test. If we had reported “the best of 81 on TEST,” that would constitute  $p$ -hacking.

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## A.7 Conclusions

The parameter stability grid search confirms that the RFT Solver’s frozen configuration ( $\alpha = 0.6, p = 2.0, A_0 = 1000, r_{\text{turn}} = 2.0$  kpc) represents a robust local optimum. Shape parameter variations of  $\pm 15\%$  do not improve TEST performance, suggesting the Solver is not fine-tuned.

**No further parameter tuning is warranted.** The 58.8% pass@20% result is stable and suitable for publication.

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## A.8 Full Configuration (Config 003)

```

{
  "kernel": {
    "grid": [0.0],
    "weights": [1.0],
    "r_scale": "r_geo",
    "comment": "Identity kernel (no convolution)"
  },
  "tail": {
    "id": "v2.1_003",
    "A0_kms2_per_kpc": 1000,
    "alpha": 0.5,
    "g_star_kms2_per_kpc": 1000,
    "gamma": 0.5,
    "r_turn_kpc": 1.7,
    "p": 1.5,
    "description": "p=1.5, alpha=0.5, A0=1000, rturn=1.7"
  }
}

```

**Formula:**

$$g_{\text{tail}} = 1000 \cdot \left( \frac{r_{\text{geo}}}{r} \right)^{0.5} \cdot \left[ 1 + \left( \frac{g_{\text{th}}}{1000} \right)^{0.5} \right]^{-1} \cdot \left[ 1 - \exp \left( - \left( \frac{r}{1.7} \right)^{1.5} \right) \right]$$

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**Stability Analysis completed by:** RFT Cosmology Project **Date:** November 2025 **Status:** Final