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Excitation-Aware Online Identification for Voltage-Constrained DC Motor Speed Tracking: A Simulation Benchmark

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Abstract - *Online identification in motor speed control must balance informative excitation against tracking accuracy and actuator demand. This paper presents a simulation-based comparison of a frozen-model controller, recursive least squares (RLS) without probing, RLS with continuous probing, RLS with triggered probing, and triggered normalized least-mean-squares (NLMS). The archived benchmark comprises 50 paired NumPy/SciPy simulation runs per scenario and includes voltage and slew-rate constraints, held-out model testing, measurement noise, load changes, and plant-parameter changes. In the nominal noise-free case, triggered RLS obtained mean tracking root-mean-square error (RMSE) of 0.00652 rad/s and requested probing effort of 2.202 V^2 s, compared with 0.01118 rad/s and 6.400 V^2 s for continuous RLS probing. However, the triggered estimator had larger held-out model error, and its performance deteriorated substantially under measurement noise (0.08790 rad/s). Thus, reduced excitation demand and improved nominal tracking do not imply better identification or robust adaptation. The result is a simulation benchmark, not a new convergence theorem or hardware demonstration.*

Key Words: DC motor, online system identification, recursive least squares, excitation scheduling, constrained control, simulation benchmark.

1. INTRODUCTION

Discrete-time adaptive control combines a model updated from measured data with a control action computed from that model. Classical work established recursive estimation, parameter excitation and adaptive stabilization as distinct concerns . A small tracking error does not imply that plant parameters are identified accurately; a controller can track a nearly constant command even when the regressor contains little information. Adding a probing input may improve identification but also perturbs the regulated output and raises actuator demand.

The earlier source manuscript studied projection and RLS methods for generic low-order systems. Its external review identified missing repeated experiments, limited novelty, inadequate reporting of actuator effort and no reproducible comparison of tracking and identification . We therefore narrow the scope to a DC motor simulation study and report only numerical evidence available in the saved benchmark. The main contribution is an openly qualified comparison of excitation choices under a common constrained-control protocol. We do not claim a new stability proof, superior robustness, or physical validation.

2. MODEL AND METHODS

2.1 Plant interpretation and discrete identification

A standard armature-controlled DC motor obeys the continuous-time relations

$$L\,(di/dt) = u - R\,i - K_e\,\omega; \quad J\,(d\omega/dt) = K_t\,i - b\,\omega - \tau_L.$$

where u denotes voltage, i armature current, ω shaft speed, and τ_L load torque. These equations provide physical interpretation; the archived numerical summary does not give sufficient motor coefficients or sample timing to independently reconstruct the full implementation from this document alone. We do not supply invented parameter values.

A discrete-time input–output model can be written as

$$\hat{\omega}_k = \varphi_k^T \hat{\theta}_{k-1}, \quad e_k = \omega_k - \hat{\omega}_k.$$

with regressor φ_k comprising available lagged inputs and outputs. Under conventional RLS, for example,

$$g_k = P_{k-1}\,\varphi_k / [\lambda + \varphi_k^T P_{k-1}\,\varphi_k]; \quad \hat{\theta}_k = \hat{\theta}_{k-1} + g_k e_k; \quad P_k = [P_{k-1} - g_k \varphi_k^T P_{k-1}] / \lambda.$$

These are standard algorithm equations , not independently verified exact hyperparameter settings of the saved simulations; forgetting factor, initialization and trigger thresholds must be recovered from source code before archival submission.

2.2 Compared control and probing policies

The archived experiments compare five arms: frozen-model control, RLS without added probing, RLS with continuous probing, RLS with triggered probing, and triggered NLMS. All use the same finite-horizon constant-voltage predictor, an admissible-model repair rule, and input limits of $|u| \le 12$ V and $|u_k - u_{k-1}| \le 1.2$ V per sample. The source describes triggered probing as guided by regressor information but

does not document the full trigger logic in the available results summary. It would be misleading to give a threshold or pseudocode not verified against the underlying implementation.

2.3 Evaluation and reproducibility boundaries

The archived study used a Python NumPy/SciPy implementation with 50 paired trials for each scenario (seeds 2001–2050). Scenarios include nominal noise-free operation, low noise, measurement noise, load step, parameter change, and saturation. A separate equal-RMS excitation study considered DC, one-tone, three-tone and pseudorandom-binary-sequence (PRBS) inputs. A held-out test uses an independently reset plant, an alternative rate-limited multisine input, and frozen estimates. MATLAB/Octave parity was not confirmed. These are numerical simulations, not hardware measurements.

The metrics are tracking RMSE, held-out model RMSE, final coefficient error, requested additive probing effort, and actuator-demand proxies. In particular, the discrete voltage-effort proxy $E_u = T_s \Sigma(u_k)^2$ has units V^2 s and is not physical electrical energy. Requested probing effort is computed before actuator limiting. The values are comparable within this simulation protocol, not measurements of battery energy.

Interpretive validity and comparison controls. The evaluation distinguishes closed-loop tracking, identified input-output dynamics, and actuator commands. These quantities can disagree. A controller without probing may follow a nearly constant command accurately while estimating the dynamic parameters poorly; probing can improve model validation while perturbing speed. The saved study uses a separate held-out input, independent plant reset and frozen parameters during validation.

The simulation protocol reports 50 paired seeds, but the saved summary does not contain the underlying paired records needed for independent confidence intervals. Accordingly this manuscript reports descriptive differences rather than statistical significance. The voltage limits are ±12 V and 1.2 V per sample. Since the archived summary omits sample timing, these cannot be interpreted as V/s. The voltage-effort proxy has units V^2 s, not joules.

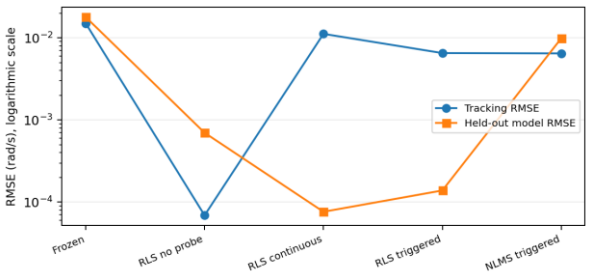
3. RESULTS

3.1 Nominal performance and trade-offs

Table 1 reports the archived nominal means. Triggered RLS has 41.63% lower tracking RMSE than continuous RLS (0.0065237 versus 0.011176 rad/s), alongside 65.60% lower requested probing effort (2.202 versus 6.400 V^2 s). However, held-out model RMSE is worse (0.00013883 versus 0.000076409 rad/s), and coefficient error rises from 0.1228% to 0.2581%. A no-probe controller tracks the constant command nearly perfectly but shows higher coefficient error; tracking and parameter recovery must be evaluated separately.

Nominal tracking and identification RMSE (archived means).

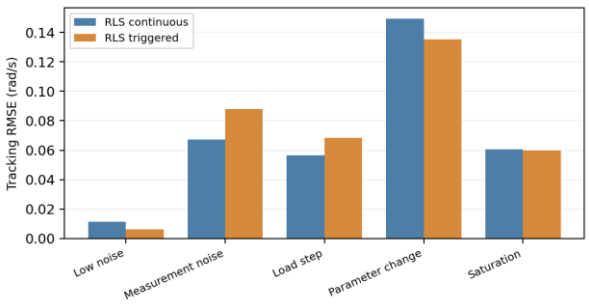
Method	Track RMSE	Held-out RMSE
	rad/s	rad/s
Frozen	0.01504	0.017895
RLS no probe	0.0000691	0.0006994
RLS continuous	0.011176	0.0000764
RLS triggered	0.006524	0.0001388
NLMS triggered	0.006465	0.0098652



Nominal tracking and held-out identification RMSE; axes and values are computed from the archived results table (no new trial execution).

3.2 Noise, disturbances and actuator demand

Figure 2 contrasts triggered and continuous RLS under five reported cases. Under measurement noise, triggered RLS deteriorates to 0.087903 rad/s, versus 0.067301 rad/s with continuous RLS. Under a load step, the corresponding values are 0.068204 and 0.056589 rad/s. Triggered RLS is lower under the low-noise case (0.0062815 vs. 0.011191 rad/s), but both strategies perform considerably worse than the triggered NLMS arm in the measurement-noise test (0.0026592 rad/s). This is empirical evidence against a universal performance ranking.



Tracking RMSE under non-nominal scenarios; figures reconstructed only from reported summary values.

The saved actuator summary reports nominal voltage-effort proxies of 2118.5 and 2114.4 V^2 s for continuous and triggered RLS, respectively, and slew-effort proxies of 63.126 and 26.564 V^2. All simulated runs respected the 12 V magnitude limit and 1.2 V per-sample change limit. A catastrophic failure was defined by a nonfinite speed, speed magnitude above 2 rad/s, or current magnitude above 30 A; none occurred in these runs. This does not prove good tracking or closed-loop stability.

3.3 Separate excitation-quality study

At equal stated perturbation RMS (0.3266 V around a 4 V bias), noise-free final coefficient errors were 1.857% (DC), 1.865% (one tone), 0.1589% (three tones) and 0.1223% (PRBS). With speed-noise standard deviation 0.003, these errors became 35.04%, 43.94%, 36.41% and 29.99%, respectively. The last-window regressor rank, evaluated with

threshold 10^{-9}, is a limited numerical diagnostic: sensor noise may inflate apparent rank without improving unbiased identification. Neither frequency count nor numerical rank alone establishes usable persistent excitation .

3.4 Cross-scenario comparison and failure analysis

Table 2 compares two RLS policies across reported scenarios. The accompanying discussion also reports the separate triggered NLMS outcomes. The values are limited to the archived simulation setting.

Selected scenario tracking RMSE (rad/s; paired simulations).

Scenario	RLS cont.	RLS trig.
Low noise	0.011191	0.006282
Measurement noise	0.067301	0.087903
Load step	0.056589	0.068204
Parameter change	0.149360	0.135440
Saturation	0.060424	0.059812

For the reported measurement-noise scenario, the held-out model errors of continuous and triggered RLS were 0.15425 and 0.15497 rad/s, respectively, compared with 0.010445 rad/s for triggered NLMS. The summary explicitly warns that equation-error RLS with delayed noisy outputs can be biased, and that the regressor Gram-matrix eigenvalue may grow because of noise rather than genuinely informative excitation. These observations motivate direct model validation on an independent sequence instead of declaring adaptation successful from the training residual or a rank threshold alone.

3.5 Distinguishing power, effort and safety constraints

Requested probing effort measures the additive identification perturbation requested before actuator limiting. The voltage-effort proxy $E_u = T_s \Sigma(u_k)^2$ has units V^2 s; it is not electrical energy in joules. Sum-of-squared voltage changes has units V^2 and is a slew-effort proxy, distinct from the hard 1.2 V/sample limit. In the nominal simulations, requested probe effort fell from 6.400 to 2.202 V^2 s with triggered RLS, whereas total voltage effort changed only from 2118.5 to 2114.4 V^2 s. These metrics reflect different kinds of actuator demand and do not establish battery-energy savings.

The absence of catastrophic threshold violations in a finite simulation is weaker than a proof of boundedness. In particular, the archived definition of a catastrophic event uses speed and current thresholds. The controller also includes model repair, but the available summary does not show the repair rule or a formal Lyapunov argument for the actual constrained and noise-corrupted closed loop. The benchmark therefore supports an engineering comparison under specified limits, not a general stability guarantee.

Interpreting numerical contrasts. Continuous probing obtained a better nominal held-out model error, whereas triggered probing obtained a lower nominal tracking error. The reported 65.60% reduction in requested probe effort does not represent equivalent battery-energy savings: the total voltage-effort proxy fell only from 2118.5 to 2114.4 V^2 s (about 0.19%). These estimates are descriptive comparisons of the saved simulation outputs, not statistical proofs of controller superiority.

Under measurement noise, the RLS-based strategies deteriorated and triggered NLMS outperformed them in the saved tests. Plant changes, load disturbances and saturation also produced different rankings. Evaluating tracking, held-out identification, and actuator requirements together is essential. This study provides a bounded simulation benchmark and does not establish a new stable adaptive-control theorem or hardware validation.

4. DISCUSSION AND LIMITATIONS

The comparison supports three restricted conclusions. First, continuous identification probing can trade tracking performance for more informative data. Second, triggered excitation lowers requested probe effort in the nominal setting but can sacrifice held-out model accuracy. Third, noisy measurements and plant changes reveal failure modes of plain equation-error RLS and a simple triggering rule. We make no claim that the trigger is mathematically novel or that the benchmark establishes robust adaptive control.

The most important methodological limitation is that the archived RESULTS.md contains aggregate outputs but not the complete plant parameterization, detailed update schedule, filter settings, trigger thresholds, sample period or executable scripts. The manuscript therefore describes standard RLS equations for context and does not pretend that those equations prove the implementation's stability. Full

reproducibility requires the original source, seed scripts, per-trial CSVs, plant parameters and verified MATLAB/Python numerical parity. The numerical curves here are created directly from the saved tabulated values and should not be mistaken for re-run simulations.

A stronger follow-up should supply all algorithm settings, confirm implementation equivalence, report paired uncertainty intervals, include actuator voltage and current trajectories, compare against modern adaptive-control baselines and test the resulting controller on independently instrumented hardware. An analytical treatment of stability with saturation and corrupted regressors would also be required for stronger guarantees. The present work is an application benchmark based on available evidence, not a proof of superiority.

5. CONCLUSION

A constrained DC motor simulation benchmark shows that excitation scheduling changes the balance between tracking, identification and commanded actuator demand. In the available 50-trial nominal case, triggered RLS reduced tracking RMSE and requested probe effort relative to continuous probing, while providing less accurate held-out identification. Under measurement noise and load changes, the ranking reversed. These limitations are an essential part of the result. The manuscript provides a defensible comparison of recorded simulations and identifies the implementation and validation gaps that must be closed before strong generalization.

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