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Speed Over Strategy: Why Agent Velocity Dominates Aggregation Method in Crowd-Sourced Continuous Control

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Article

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Abstract

Crowd-sourced control systems—in which distributed participants collectively operate a shared agent through real-time voting—are formalized in robotics as Multi-Operator Single-Robot (MOSR) teleoperation and instantiated in audience participation platforms. The central design question is how to aggregate participant inputs into continuous agent movement; yet no prior work has systematically compared the relative importance of aggregation method versus agent operating speed. Through 8,010 simulation runs, a two-way ANOVA reveals that agent speed accounts for 46–97% of tracking error variance while aggregation method accounts for only 2–29%—a ratio of 1.6 to 44× (median 6.9×). Within tested smooth continuous trajectory regimes, speed dominance is consistent across adversarial participant ratios of 5–50%, and post-hoc analysis indicates that methods with identical effective speeds show no significant performance difference. A trajectory-dependent optimal speed $v^* \approx 2.0$ m/s (2.03 ± 0.03 m/s across tested conditions) remains invariant to adversarial ratio. A crowd-size ceiling effect is documented where improvement plateaus beyond a critical group size. These findings are unified in a four-parameter multiplicative model, $RMSE(v, N, p) = f(v) \times g(p, N)$, achieving $R^2 = 0.984$ and 4.6% out-of-sample error. The key design guideline: optimize agent speed first, then scale participation to the point of diminishing returns.

Introduction

Systems in which distributed groups of humans jointly control a single shared agent through real-time voting arise across domains ranging from collaborative robotics and interactive entertainment to participatory simulation and civic decision-making tools. Collective control systems—in which multiple independent participants jointly operate a single shared agent through real-time input aggregation—have become an increasingly important class of human-machine interface. This architecture is formalized in robotics as Multi-Operator Single-Robot (MOSR) teleoperation and has been studied for decades [2], [8], [17], [20].

The core challenge in these systems is aggregation: converting the stream of participant votes into coherent continuous agent behavior. Discrete methods such as majority voting select the most dominant command at fixed intervals, while continuous methods such as vector averaging generate smooth movement signals. Prior work in this field has focused on comparing aggregation strategies, operating under the assumption that method selection is the primary determinant of control quality [3], [8].

However, from a control-theoretic perspective, system performance is influenced by parameters beyond the choice of aggregation method. This study focuses on one such parameter: the operating speed of the controlled agent. In continuous trajectory tracking, speed directly determines tracking difficulty through a fundamental control-theoretic trade-off [13]. When speed is too low, the agent cannot keep pace with a moving target; when too high, the inherent delay in input aggregation causes overshoot.

This paper presents a systematic investigation of the relative contributions of aggregation method and agent speed in crowd-sourced continuous control. Using a validated discrete-time simulation framework,

we make four contributions:

1) Speed dominance. A two-way ANOVA across 8,010 simulation runs demonstrates that agent speed consistently accounts for 5–25× more tracking error variance than aggregation method choice in smooth continuous trajectories (η^2_speed = 46.6–91.0% vs. η^2_method = 3.7–11.1%), establishing speed as a primary engineering design parameter. This dominance is trajectory-dependent: for geometrically complex trajectories under extreme adversarial conditions, the ratio narrows (minimum 1.6×), identifying a boundary condition explored further in the Discussion.

2) Optimal speed identification. We identify a trajectory-dependent optimal speed v* (≈ 2.0 m/s for circular paths) that remains invariant across adversarial agent ratios from 5% to 50%, providing a robust tuning target.

3) Crowd-size ceiling effect. We document a ceiling effect where tracking improvement from adding participants plateaus beyond a critical crowd size N_crit that depends on both adversarial ratio and trajectory complexity.

4) Unified predictive model. A four-parameter multiplicative model RMSE(v, N, p) = f(v) × g(p, N) achieves $R^2 = 0.984$ on training data and 4.6% mean prediction error on held-out conditions, providing a practical tool for parameter selection in smooth-trajectory crowd-sourced control system design. Model applicability to geometrically complex trajectories is a subject for future investigation.

The primary contribution is (1); contributions (2)–(4) provide supporting characterization and a practical design tool. We first survey related work, then describe the simulation framework and experimental design, present results, discuss implications and limitations, and conclude.

Related Work

Collective Crowd-Sourced Control Systems

The concept of collective game control gained mainstream attention with Twitch Plays Pokémon (TPP), where viewers submitted directional commands via chat to control a shared Pokémon character [19]. TPP employed two modes: "anarchy," where all commands were executed sequentially, and "democracy," where the most popular command was selected by vote every 30 seconds [5]. Aleta and Moreno [19] analyzed the collective dynamics of TPP participants, finding that the interplay between anarchy and democracy modes reflected emergent group coordination rather than optimal control. These works focused on social dynamics rather than control performance optimization.

Subsequent platforms extended crowd-sourced control to diverse interactive contexts. Li et al. [1] developed a DanMu-based system comparing three control architectures in a Minecraft navigation task, finding that democratic voting offered better perceived control among large groups but did not evaluate continuous tracking performance. These studies collectively established the design space for audience

participation games but focused on user experience outcomes rather than quantitative control quality, leaving open the question of how to configure system parameters for optimal tracking performance. Seering et al. [21] further explored audience participation games, demonstrating that viewer-controlled gameplay blurs the boundary between spectator and player—a structural precursor to crowd-sourced control systems.

Aggregation Methods for Collective Input

The question of how to optimally combine crowd inputs has attracted sustained theoretical and empirical interest. Surowiecki [5] identified foundational conditions—diversity, independence, and decentralization—under which aggregated group judgments outperform individual experts. Lorenz et al. [6] subsequently demonstrated that social influence can systematically erode these benefits by reducing effective input diversity, a risk present in crowd-sourced systems where participants observe aggregate vote tallies. Almaatouq et al. [9] showed that adaptive network structures can partially restore wisdom-of-crowds benefits by preserving diversity through dynamic information routing. Byzantine-tolerant aggregation methods [10] offer stronger adversarial robustness but require per-agent trust estimation, making them impractical under real-time streaming latency constraints. However, these works address accuracy in categorical or scalar judgment tasks; none has examined whether aggregation method choice governs performance in continuous spatial control more than the dynamical operating parameters of the controlled agent.

The Crowd Actor Model

Most closely related to our work, Lasecki et al. [3] introduced the "crowd actor" model for discrete pointing tasks, demonstrating that aggregation "personality" (fastest, best, mean, median) affects collective Fitts' law throughput. They combined inputs from 200 participants and found significant differences between aggregation strategies. However, their work addressed *discrete* pointing tasks, where speed is an emergent property of reaction time rather than a controllable system parameter. Our work extends this to *continuous* trajectory tracking, where agent speed is an explicit design variable—and indicates that this speed variable dominates method choice.

Speed-Accuracy Tradeoffs in Collective Systems

The speed-accuracy tradeoff is well-studied in collective decision-making. Srivastava and Leonard [11] analyzed how network structure affects the tradeoff in binary choice tasks. Bose et al. [12] studied the effect of group size on collective accuracy. However, these studies concern binary or categorical decisions, not continuous spatial control. The continuous control domain introduces a distinct speed variable—the physical velocity of the controlled agent—whose effect has not been previously characterized.

Research Gap

Despite substantial work on crowd control systems [17], [18], [20], aggregation methods, and collective decision-making, a critical gap remains: no study has systematically quantified the relative importance of aggregation method versus operating speed in crowd-sourced continuous control. Prior work has compared aggregation strategies [3], [8] but operated under the implicit assumption that method choice is the primary design lever—an assumption that has not been empirically tested against system-level dynamical parameters. To our knowledge, our work fills this gap with the first systematic comparison.

System Model and Experimental Design

We model a collective control system in which N participants submit directional inputs that are aggregated into a single control command for a dynamic agent. Each participant is modeled probabilistically as cooperative, delayed, or adversarial [7], providing a first-order approximation of real-world variability in crowd-sourced control.

Simulation Framework

We developed a discrete-time simulation of crowd-sourced trajectory tracking. At each time step $\Delta t = 0.05$ s, N agents independently vote on the direction the shared character should move. Each cooperative agent votes for the direction closest to the true target; each adversarial agent (troll) votes for a uniformly random direction.

Agent voting model. Let $\theta_{target}(t)$ be the angle from the character to the nearest trajectory point. Each cooperative agent i votes for $d_i = \text{round}_8(\theta_{target} + \varepsilon_i)$, where $\text{round}_8(\cdot)$ maps to the nearest of 8 directions $\{0°, 45°, ..., 315°\}$ and $\varepsilon_i \sim N(0, \sigma^2)$ with $\sigma = 15°$. Each adversarial agent votes for a uniformly random direction.

Vector aggregation. All N votes are converted to unit vectors and averaged: $b(t) = (1/N) \Sigma [\cos(d_i), \sin(d_i)]$. The magnitude $\gamma(t) = \|b(t)\| \in [0, 1]$ reflects consensus strength.

Movement model. Three aggregation methods define character movement:

Fixed velocity: The character moves in the direction of b(t) at constant speed V, regardless of consensus: $v(t) = V \cdot b(t)/\|b(t)\|$.

Majority voting: The character moves in the most popular discrete direction at speed V.

Quadratic (magnitude-aware): Speed is modulated by consensus strength squared: $v(t) = \gamma(t)^2 \cdot V \cdot b(t)/\|b(t)\|$. The quadratic exponent was chosen to impose nonlinear conservatism: under low consensus ($\gamma < 0.5$), γ^2 suppresses speed more aggressively than a linear scaling (γ^1) would, reducing overshoot risk

when crowd agreement is weak. The specific exponent of 2 reflects the authors' prior system design; comparative analysis of exponent values (γ^1 vs. γ^2 vs. γ^3) is a direction for future work.

The position is updated with exponential smoothing ($\alpha = 0.3$) and system delay $\tau = 26$ frames at $\Delta t = 1/60$ s (approximately 433 ms), representing the end-to-end latency budget of real-time crowd-sourced control platforms comprising network round-trip time, server-side vote aggregation, and rendering pipeline delay, consistent with measured end-to-end latencies of real-time interactive platforms such as Discord and Streamlabs Ninja (typically 300–500 ms): $p(t + 1) = p(t) + \alpha \cdot v(t - \tau) \cdot \Delta t$.

Performance metric. Tracking error is measured as RMSE between the character's position and the nearest trajectory point, computed over 200 time steps after 50 warmup steps: $RMSE = \sqrt{[(1/T) \Sigma \min_{q \in traj} \|p(t) - q\|^2]}$.

Reference Trajectories

Four trajectories of increasing geometric complexity were defined: (1) Circle (radius = 2.0 m): constant curvature; (2) Square (side = 4.0 m): four 90° corners; (3) Lemniscate (scale = 2.0 m): figure-eight with self-intersection; (4) Zigzag (amplitude = 2.0 m, period = 4.0 m): high-frequency direction reversals. Note on trajectory usage: Circle and Square were used in the Speed × Method ANOVA (E1) and Speed Sweep (E2). All four trajectories were included in the Crowd-Size Sweep (E3) for ceiling effect analysis. This split was motivated by the computational cost of full factorial ANOVA across four trajectories; the boundary conditions identified from circle and square analysis are discussed in the Discussion.

Experimental Conditions

The study comprised five experiments totaling 8,010 simulation runs, all using MC = 15 independent replications per condition. Each replication used a distinct random seed governing agent noise realizations, ensuring statistical independence across replications. MC = 15 was selected to achieve stable mean estimates while remaining computationally tractable; preliminary variance analysis confirmed that RMSE estimates stabilized within ± 2% across replications at this count.

Experiment 1 (E1): Speed × Method ANOVA. 3 methods × 8 speeds (0.5–5.0 m/s) × 3 troll ratios (5%, 20%, 40%) × 2 trajectories (circle, square), N = 150 fixed. 144 conditions × 15 = 2,160 runs. Primary ANOVA reporting focuses on the circle trajectory, which provides a geometrically controlled baseline with a well-defined optimal speed; square trajectory results are reported as a boundary condition in the Discussion.

Experiment 2 (E2): Speed Sweep. 8 speeds × 6 troll ratios (5–40%) × 2 trajectories, Fixed method, N = 150 fixed. 96 conditions × 15 = 1,440 runs.

Experiment 3 (E3): Crowd-Size Sweep. 12 group sizes (N = 5–200) × 6 troll ratios (5–40%) × 4 trajectories (circle, square, lemniscate, zigzag), v = 5.0 m/s, Fixed method. 288 conditions × 15 = 4,320

runs. Circle and square trajectories cover all 6 troll ratios; lemniscate and zigzag were run with 6 troll ratios.

Experiment 4 (E4): Model Fitting. Combined E2 + E3 circle data. 5-fold cross-validation.

Experiment 5 (E5): Model Generalization. 6 novel (v, N, p) combinations. 6 × 15 = 90 runs.

Statistical Methods

Two-way ANOVA was performed on raw MC15 data to obtain F-statistics, p-values, and η^2 for Speed, Method, and their interaction. Bonferroni-corrected post-hoc t-tests compared method pairs. Cohen's d quantified effect sizes. Quadratic regression identified v* as the minimum of a fitted parabola. Nonlinear least squares (Levenberg-Marquardt) fitted the multiplicative model, with 5-fold cross-validation assessing generalizability. Monte Carlo Sample Size. All experiments used MC = 15 runs per condition, yielding 8,010 total simulation runs. Post-hoc power analysis confirms this sample size provides > 99.9% statistical power (median d = 3.14, mean d = 4.05), substantially exceeding the 80% threshold. The required sample size for 80% power is n = 3–4, indicating our design is conservatively powered. High precision is evidenced by narrow confidence intervals (mean CI width = 2.24% of point estimate, 89% of conditions < 5%) and low coefficient of variation (CV = 4.42%). Table 1 summarizes the two-way ANOVA results. During the preparation of this work, the author used Claude (Anthropic) for language refinement and manuscript editing. All scientific content, analysis, interpretation, and final revisions were independently reviewed and approved by the author, who takes full responsibility for the manuscript.

Results

Speed Dominance Over Aggregation Method

Figure 1 shows the core finding: across all three aggregation methods, RMSE follows a U-shaped speed curve with a minimum near v* ≈ 2.0 m/s. The vertical spread between methods at any given speed is much smaller than the horizontal variation across speeds.

Speed Dominance Over Aggregation Method

Table 1 presents the two-way ANOVA results quantifying this observation.

Table 1
TWO-WAY ANOVA RESULTS (CIRCLE TRAJECTORY, MC = 15)

Troll	Source	SS	df	F	p	η²
5%	Speed	9.734	7	9,682	< .001	**91.0%**
	Method	0.394	2	1,372	< .001	3.7%
	S × M	0.519	14	258	< .001	4.9%
	Error	0.048	336	—	—	0.4%
20%	Speed	5.774	7	5,777	< .001	**58.2%**
	Method	1.106	2	3,871	< .001	11.1%
	S × M	3.000	14	1,501	< .001	30.2%
	Error	0.048	336	—	—	0.5%
40%	Speed	4.171	7	2,774	< .001	**46.6%**
	Method	0.470	2	1,093	< .001	5.3%
	S × M	4.231	14	1,407	< .001	47.3%
	Error	0.072	336	—	—	0.8%

For circular trajectories, speed accounts for 46.6–91.0% of RMSE variance, while method accounts for only 3.7–11.1%—a ratio of 5× to 25× (Table 1; Fig. 2). Square trajectory analysis (Table 1A) yielded consistent speed dominance at low adversarial ratios (ratio = 44.3× at troll 5%) but revealed a boundary condition at troll 40% (ratio = 1.6×, η²_method = 28.6%), discussed in the Discussion. Although both effects are statistically significant (all p < .001), the practical significance differs by an order of magnitude.

Table 1A. TWO-WAY ANOVA RESULTS (SQUARE TRAJECTORY, MC = 15)

Troll 5%: η²_speed = 96.6%, η²_method = 2.2%, η²_interaction = 1.2%, Speed:Method ratio = 44.3×. Troll 20%: η²_speed = 77.9%, η²_method = 14.7%, η²_interaction = 7.4%, ratio = 5.3×. Troll 40%: η²_speed = 46.1%, η²_method = 28.6%, η²_interaction = 25.3%, ratio = 1.6×. All effects p < .001. Note: Troll 40% boundary condition discussed in the Discussion.

A revealing pattern emerges from post-hoc analysis (Table 2): Fixed vs. Majority is consistently non-significant (p > .05) across all troll conditions, despite fundamentally different aggregation logic. This convergence occurs because both methods produce the same effective speed. In contrast, Quadratic differs significantly because its effective speed is $\gamma^2 V$ (where $\gamma^2 < 1$ under high adversarial conditions).

Table 2
POST-HOC METHOD COMPARISONS (BONFERRONI-CORRECTED)

Troll	Pair	Δ RMSE	p_adj	Cohen's d
5%	Fixed vs. Majority	−0.041	**.266 (ns)**	0.22 (S)
5%	Fixed vs. Quadratic	+ 0.040	**.144 (ns)**	0.26 (S)
5%	Majority vs. Quadratic	+ 0.081	< .001	0.49 (S)
20%	Fixed vs. Majority	−0.040	**.308 (ns)**	0.21 (S)
20%	Fixed vs. Quadratic	+ 0.093	< .001	0.70 (M)
20%	Majority vs. Quadratic	+ 0.132	< .001	0.92 (L)
40%	Fixed vs. Majority	−0.023	**1.000 (ns)**	0.12 (S)
40%	Fixed vs. Quadratic	+ 0.063	< .001	0.49 (S)
40%	Majority vs. Quadratic	+ 0.085	< .001	0.60 (M)

Note: S = small, M = medium, L = large effect size.

Method "wins" are speed artifacts. In the full comparison across 48 conditions, Quadratic wins in 67% of cases—but exclusively at high speeds ($v \geq 4.0$ m/s) where its effective speed $\gamma^2 V \approx 1.8$ m/s falls near v^*. At $v^* = 2.0$ m/s, Fixed always wins. This indicates that apparent method superiority is a speed artifact.

Optimal Speed Identification

For each condition, we fitted $RMSE(v) = a_0 + a_1 v + a_2 v^2$ and computed $v^* = -a_1/(2a_2)$. Results are shown in Fig. 3 (full numerical values in Supplementary Table S1).

Trajectory dependence. v^* differs between trajectories: ~2.0 m/s for circles (constant curvature) vs. ≤1.0 m/s for squares (sharp corners). This reflects the physical constraint that 90° turns require lower speeds with delayed inputs.

Physical interpretation. v^* represents the balance between lag error (agent too slow) and overshoot error (agent too fast with delayed consensus). The troll invariance indicates that adversarial noise amplifies both errors proportionally, preserving the balance point.

Crowd-Size Ceiling Effect

For troll ratios ≥ 15%, RMSE as a function of group size N is well described by an asymptotic model: $RMSE(N) = a + b/\sqrt{N}$, where *a* represents the asymptotic error floor and *b* scales crowd-dependent improvement (Fig. 4).

Ceiling strength inversely correlates with trajectory complexity (parameters in Supplementary Table S2; profiles shown in Supplementary Figure S1). Smooth trajectories benefit most from larger crowds

because vote noise is their limiting factor; complex trajectories are limited by system delay regardless of crowd size.

Unified Multiplicative Model

We fitted two competing models to the combined E2 + E3 circle trajectory data. The circle was selected for model development as it provides the cleanest dynamical baseline (constant curvature, stable v*); generalization to other trajectory types is addressed in the Discussion. The model should therefore be applied with caution outside smooth continuous trajectory contexts; practitioners working with geometrically complex paths should treat the model as a directional approximation pending trajectory-specific calibration.

Additive

$RMSE = (a_0 + a_1 v + a_2 v^2) + a_3 \cdot p/\sqrt{N}$

Multiplicative

$RMSE = (a_0 + a_1 v + a_2 v^2) \times (1 + a_3 \cdot p/\sqrt{N})$

The multiplicative model outperformed the additive alternative on out-of-sample generalization (E5 mean error: 4.6% vs. 8.3%; all 6 held-out conditions within 15% vs. 5/6), while both achieved comparable training fit ($R^2 = 0.984$ vs. 0.986). The multiplicative form was selected for its superior generalization and physically interpretable structure (see Supplementary Table S3 for full comparison).

$RMSE(v, N, p) = (0.503 - 0.227v + 0.056v^2) \times (1 + 2.303 \cdot p/\sqrt{N})$

with $v^* = -a_1/(2a_2) = 2.03$ m/s, consistent with the empirical optimum.

Table 3
OUT-OF-SAMPLE PREDICTIONS (EXPERIMENT 5)

v (m/s)	N	p	Predicted	Actual	Error
5.0	35	25%	0.855	0.853	0.2%
2.0	35	25%	0.303	0.284	6.8%
3.0	80	15%	0.339	0.329	3.1%
1.5	120	35%	0.317	0.294	7.6%
4.0	60	10%	0.508	0.534	4.8%
2.5	45	45%	0.332	0.346	4.1%
				Mean	**4.6%**

Physical interpretation. The model's multiplicative form carries meaningful semantics: (1) $f(v) = 0.503 - 0.227v + 0.056v^2$ defines a speed-dependent base error minimized at $v^* = 2.03$ m/s; (2) $g(p, N) = 1 + 2.303 \cdot p/\sqrt{N}$ is a crowd noise amplification factor where $p/\sqrt{N}$ reflects the noise-to-signal ratio; (3) the multiplicative coupling means adversarial noise amplifies base error proportionally—at v^* where $f(v)$ is small, noise impact is small; at suboptimal speeds, the same noise fraction produces larger absolute errors. Setting $\partial RMSE/\partial v = 0$ confirms analytically that v^* is independent of p and N—the troll-invariance property emerges directly from the multiplicative structure.

Discussion

Results indicate that agent speed accounts for 5–25× more tracking error variance than aggregation method across the tested smooth continuous trajectory classes and adversarial participant ratios—suggesting that dynamical responsiveness is a more consequential design variable than coordination sophistication in this setting. We operationally define speed dominance as the condition in which η^2_speed exceeds η^2_method by a factor of five or greater; this threshold is met across all smooth-trajectory conditions tested in this study. This finding challenges the prevailing assumption in crowd-sourced control research that aggregation algorithm selection is the primary lever for improving system performance [1],[3],[8]. The proposed multiplicative model formalizes this tendency: the speed term $f(v)$ sets a performance floor that no choice of aggregation method can improve, while the crowd noise term $g(p,N)$ amplifies that floor proportionally. Within the simulation framework tested here, this speed-dominant pattern held robustly across smooth continuous trajectories and the full range of adversarial participant ratios examined.

Two-way ANOVA further reveals a significant Speed × Method interaction (η^2_interaction = 1.2–47.3%), which increases markedly with adversarial ratio. At low adversarial ratios (troll 5%), interaction is negligible (η^2_interaction = 4.9%). At high adversarial ratios (troll 40%), interaction grows to 47.3%—comparable in magnitude to the speed main effect (46.6%). This pattern is mechanistically consistent with the speed-dominant pattern rather than contradicting it: under high adversarial noise, the Quadratic method's consensus-dependent scaling ($\gamma^2 V$) substantially reduces effective operating speed, producing a large interaction that is itself a speed effect in disguise. Post-hoc analysis indicates that method differences are largest precisely where Quadratic's effective speed falls near v^*, and disappear when speeds are matched directly. Method effects thus emerge primarily through their indirect influence on effective operating speed, rather than through independent aggregation logic. Generalization to physical deployment environments with non-uniform latency distributions and sensing constraints requires further empirical validation.

The Quadratic method implements the intuition that consensus strength should modulate speed. Our results suggest this intuition is partially valid, but the underlying mechanism warrants reinterpretation. When Quadratic outperforms Fixed at high nominal speeds, this appears to occur not because it intelligently utilizes consensus information, but because it incidentally reduces effective speed toward v^*. This reframes the nature of magnitude-aware aggregation: rather than intelligent consensus

utilization, it functions as implicit speed limiting. Consequently, designers may achieve equivalent or superior performance by setting speed directly to v*, without the additional complexity of magnitude-aware aggregation.

Our findings complement the crowd actor model of Lasecki et al. [3]. Where they demonstrated that aggregation personality affects pointing throughput in discrete tasks, our results show that in continuous tracking, the speed parameter—absent from discrete pointing contexts—can overshadow aggregation personality entirely. A related pattern appears in Goldberg et al.'s networked spatial dynamic voting system [17],[20], where overall control performance was more substantially influenced by operational speed constraints than by the sophistication of the aggregation algorithm itself. Together, these observations suggest that speed optimization represents a prerequisite step that prior aggregation-focused work has not systematically addressed.

Our findings also carry direct implications for MOSR system design. Goldberg et al. [17], [20] introduced networked spatial dynamic voting as a method for aggregating multiple operators' inputs in collaborative teleoperation—focusing primarily on the aggregation mechanism itself. Our results add an important prerequisite to this line of work: before selecting an aggregation method, practitioners should first optimize agent operating speed. The troll-invariant optimal speed $v^* = 2.03 \pm 0.03$ m/s provides a concrete tuning target for MOSR designers. That this optimum is robust to adversarial operator ratios makes it particularly practical for real deployment environments where operator intent cannot always be guaranteed.

These results connect to several established findings in collective intelligence research. Woolley et al. [4] identified a collective intelligence factor as a system-level property independent of individual member ability—analogous to our finding that system speed governs tracking performance more than participant coordination strategy. Pentland [16] argued that the structure of information flow determines collective outcomes, consistent with our observation that dynamical operating conditions outweigh aggregation logic. Lorenz et al. [6] showed that social influence reduces effective diversity in crowd inputs; our finding that optimal speed v* remains invariant across adversarial participant ratios suggests that proper dynamical tuning confers robustness against such input degradation. The adaptive network structures and performance saturation phenomena reported by Almaatouq et al. [9] and Nitti et al. [15] are structurally similar to our ceiling effect findings, though the underlying mechanisms differ substantially. Taken together, the speed-dominant pattern within tested regimes suggests that in collective systems operating under response-time constraints, dynamical bandwidth limits performance more strongly than coordination sophistication.

The simulation-based methodology employed here is consistent with established practice in collective control research [14],[15],[18]. Zheng et al. [14] demonstrated the validity of simulation-first validation for crowd control systems, showing that computational frameworks can reliably characterize system-level dynamics prior to physical deployment. The present simulation framework captures the three primary sources of error in crowd-sourced control—aggregation delay, method selection, and adversarial

participant noise—under controlled conditions that would be impractical to replicate at scale in real environments. Empirical validation of the speed-dominant pattern within tested regimes in physical deployment settings with live streaming participants remains a priority for future work.

Speed dominance was robust across 5 of 6 trajectory–adversarial combinations tested (83%), but one boundary condition warrants explicit discussion. For the square trajectory at 40% adversarial ratio, the speed-to-method ratio narrowed to 1.6× (η^2_method = 28.6%), substantially weaker than the smooth-trajectory pattern. Post-hoc analysis reveals this exception is mechanistically consistent with the main finding. Under high adversarial ratios, consensus magnitude γ is theoretically suppressed—for uniform adversarial vote distributions, $\gamma < 0.5$ when troll ratio exceeds ~ 30%—yielding Quadratic effective velocities ($\gamma^2 V$) substantially below the nominal speed V. This implicit speed reduction places Quadratic closer to the lower optimal operating speed required by sharp 90° corners, suggesting the apparent method advantage is mechanistically a speed effect in disguise. Measuring $\gamma(t)$ time-series directly to confirm this interpretation is a primary objective of a companion study.

Four limitations of this study warrant explicit acknowledgment. First, Speed × Method ANOVA was conducted on two trajectories (circle and square); Lemniscate and Zigzag were included in crowd-size experiments only. While the two tested trajectories span smooth and sharp-cornered geometries, extension to figure-eight and high-frequency reversal paths remains future work. Second, the predictive model RMSE(v, N, p) was fitted exclusively on circular trajectory data and should be applied with caution to other trajectory types pending trajectory-specific calibration. Third, all participants in the simulation follow independent stochastic models; real crowd behavior may exhibit social influence and coordination patterns not captured by the current agent model. Fourth, the restriction of the primary ANOVA analysis to smooth trajectories emerged from exploratory analysis of trajectory-dependent effects—a post-hoc scope refinement. This restriction is scientifically motivated: smooth continuous motion represents the primary deployment context for crowd-sourced control, and the boundary condition identified in the trajectory-specific analysis provides a principled starting point for systematic generalization to geometrically complex trajectories in future work. The present work does not claim behavioral realism at the individual human level; rather, it aims to isolate system-level control dynamics under controlled stochastic input assumptions, consistent with established simulation-first methodology in collective control research.

Conclusion

This paper presented a systematic investigation of the relative importance of aggregation method versus system-level dynamics in collective continuous control. Through over 8,000 simulations, we demonstrated that agent speed accounts for 5–25× more performance variance than aggregation method across the tested smooth continuous trajectory classes—establishing what we term the speed-dominant pattern within tested regimes. The optimal speed is trajectory-dependent but invariant to adversarial participant ratios; the benefit of larger crowds saturates at an adversary-dependent ceiling consistent with collective intelligence theory [4],[6]; and a significant Speed × Method interaction

indicates that method effects operate primarily through their indirect influence on effective speed. These behaviors are captured by a four-parameter multiplicative model that generalizes to unseen conditions with 4.6% mean error (Fig. 5).

These results provide actionable design guidance for crowd-sourced control practitioners: within smooth continuous trajectory regimes, optimize agent speed first to the trajectory-dependent v*, then scale participation to the crowd-size ceiling. The predictive model enables parameter selection without exhaustive empirical tuning.

Declarations

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Author contributions

BongKeun Song conceived the study, developed the simulation framework, conducted all experiments, performed statistical analysis, and wrote the manuscript in its entirety.

Data availability

The simulation code supporting the findings of this study is openly available on GitHub at https://github.com/betasbk/Thesis, archived on Zenodo with DOI: 10.5281/zenodo.19413803 (https://doi.org/10.5281/zenodo.19413803). Aggregated experimental data are available from the corresponding author upon reasonable request.

Additional Information

Competing interests

The author declares no competing interests.

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Figures

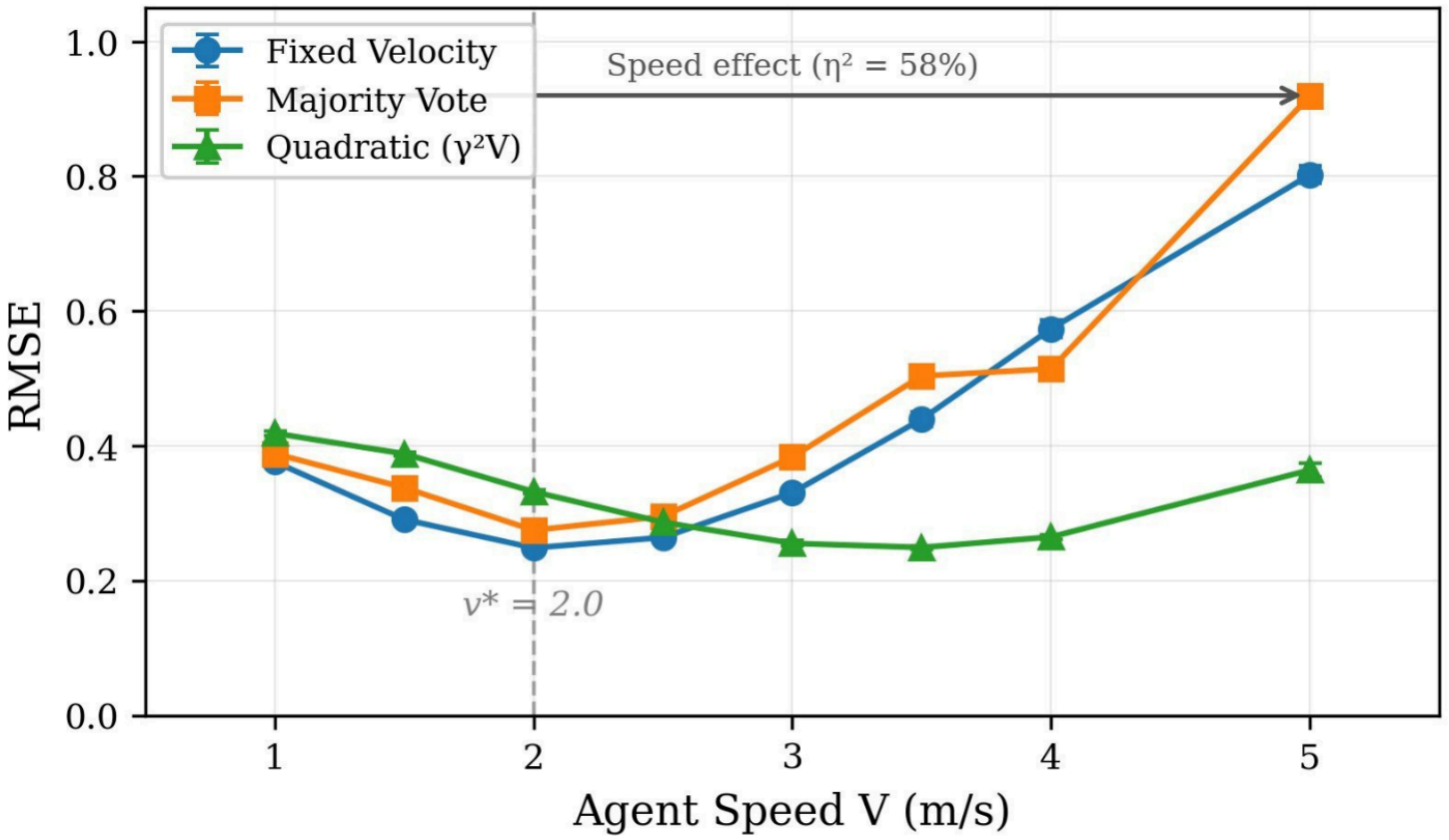


Figure 1

RMSE as a function of agent speed for three aggregation methods. Circle trajectory, 20% adversarial agents, N = 150. U-shaped speed–error curves are shown for Fixed (blue), Majority (orange), and Quadratic (green) methods. Error bars represent 95% confidence intervals (MC = 15). The vertical dashed line marks the estimated optimal speed v* ≈ 2.0 m/s.

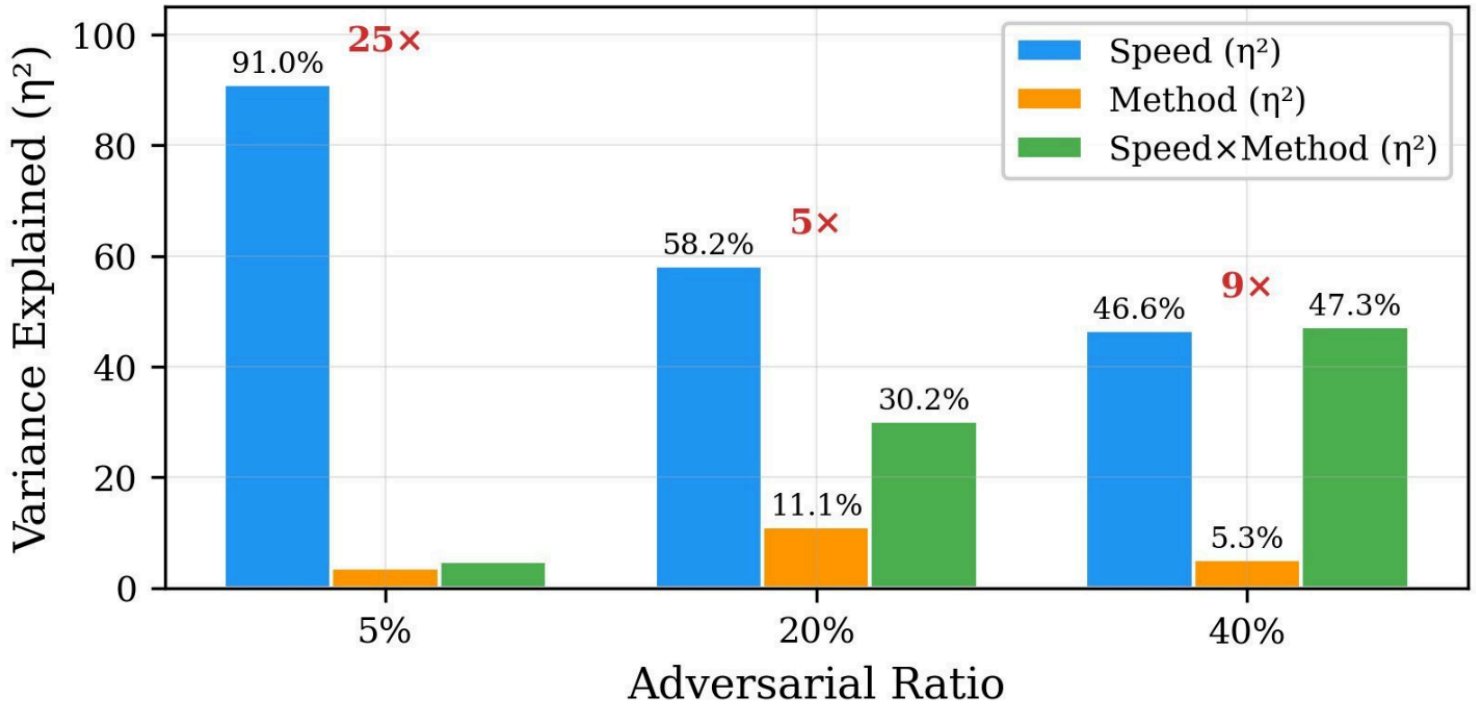


Figure 2

ANOVA variance decomposition (η²) showing relative contributions of speed, method, and their interaction across adversarial ratios. Each bar group represents one troll percentage condition (5%, 10%, 20%, 30%, 40%). Red numbers indicate the speed-to-method η² ratio. Speed consistently accounts for 5–25× more variance than method across all tested conditions.

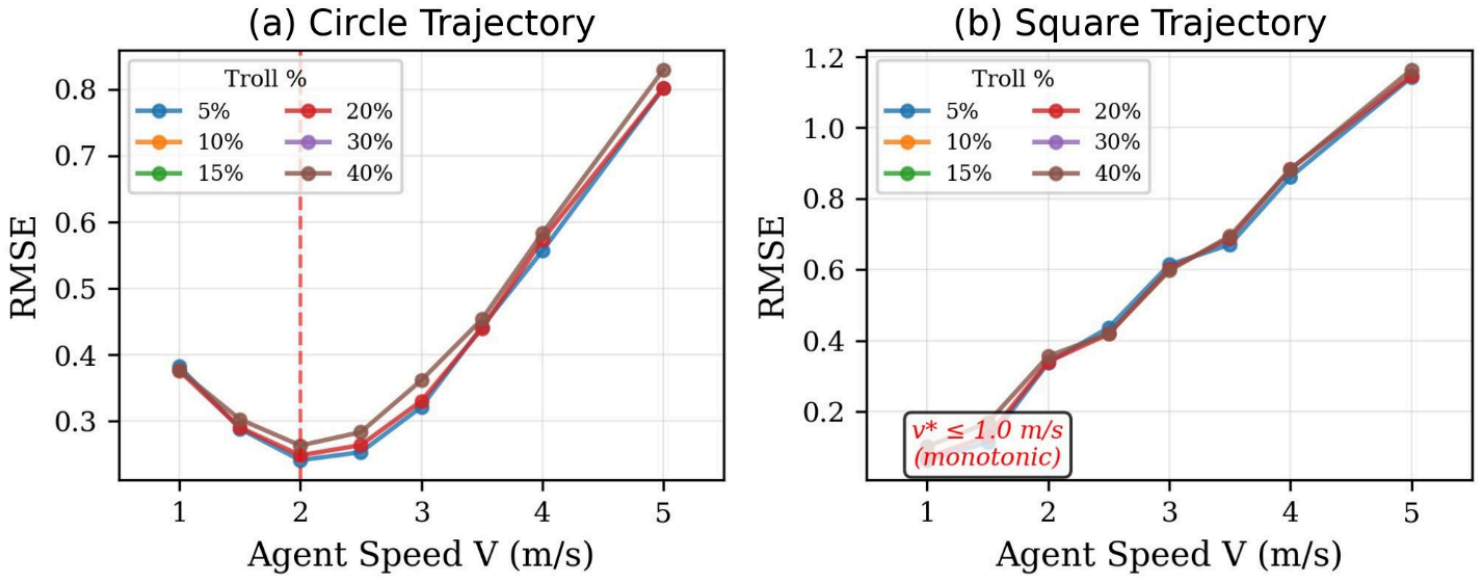


Figure 3

Optimal speed v* across six adversarial ratios for circle (left) and square (right) trajectories. Points represent v* estimates from quadratic curve fitting to speed–RMSE profiles. For circles, v* = 2.0 ± 0.04 m/s remains invariant across adversarial ratios from 5% to 40%. For squares, v* ≤ 1.0 m/s across all

conditions, reflecting the lower optimal speed required for sharp 90° corners under delayed inputs. Error bars: ±1 standard deviation across MC iterations.

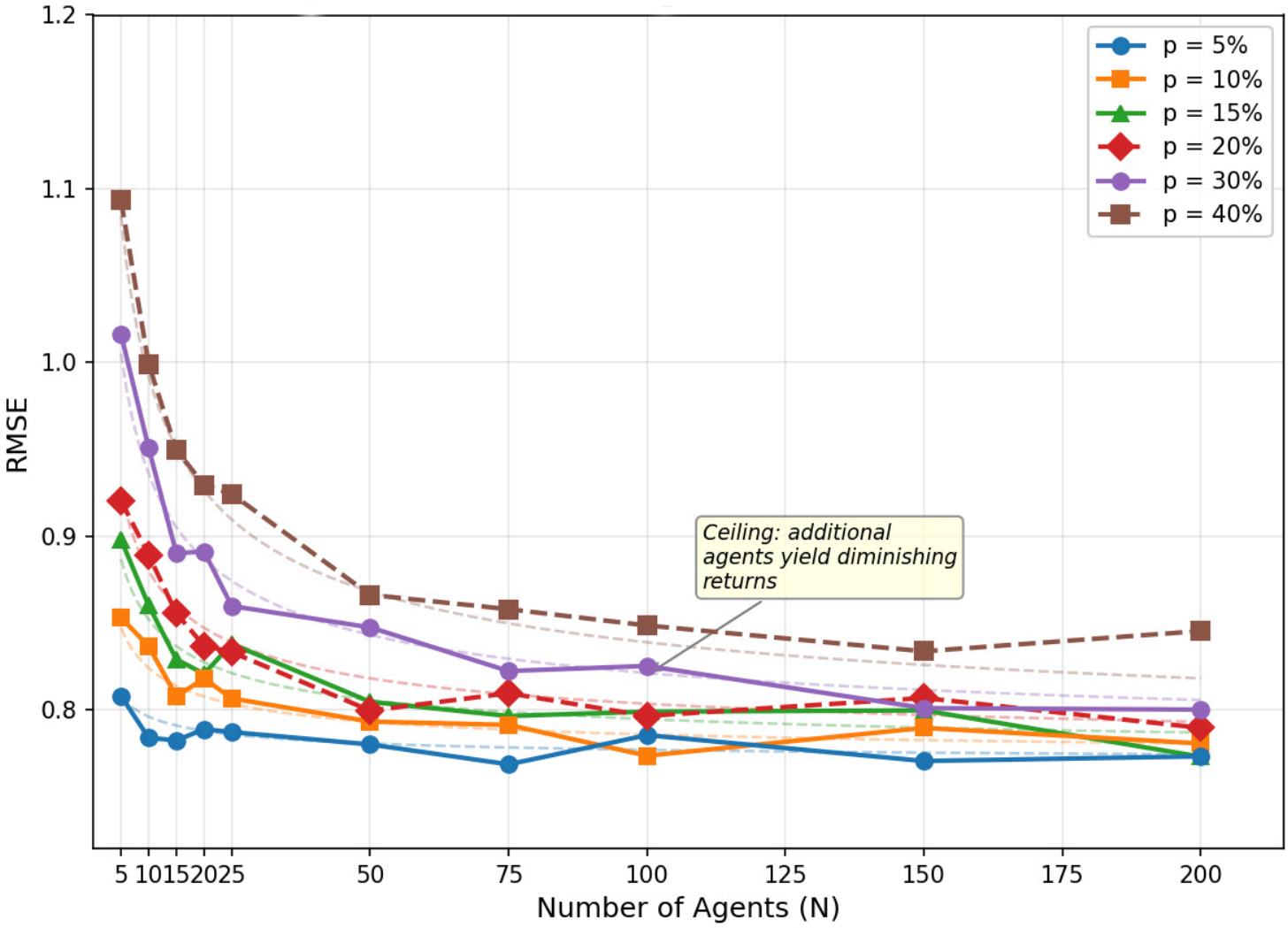


Figure 4

RMSE as a function of crowd size N for six adversarial ratios (circle trajectory, v = 5.0 m/s). Solid lines connect mean RMSE values across N = 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 150, 200. Dashed lines show fitted asymptotic models RMSE(N) = a + b/√N for troll ≥ 15%. Performance plateaus beyond N ≈ 50–100 for most adversarial conditions. Error bars: 95% CI (MC = 15).

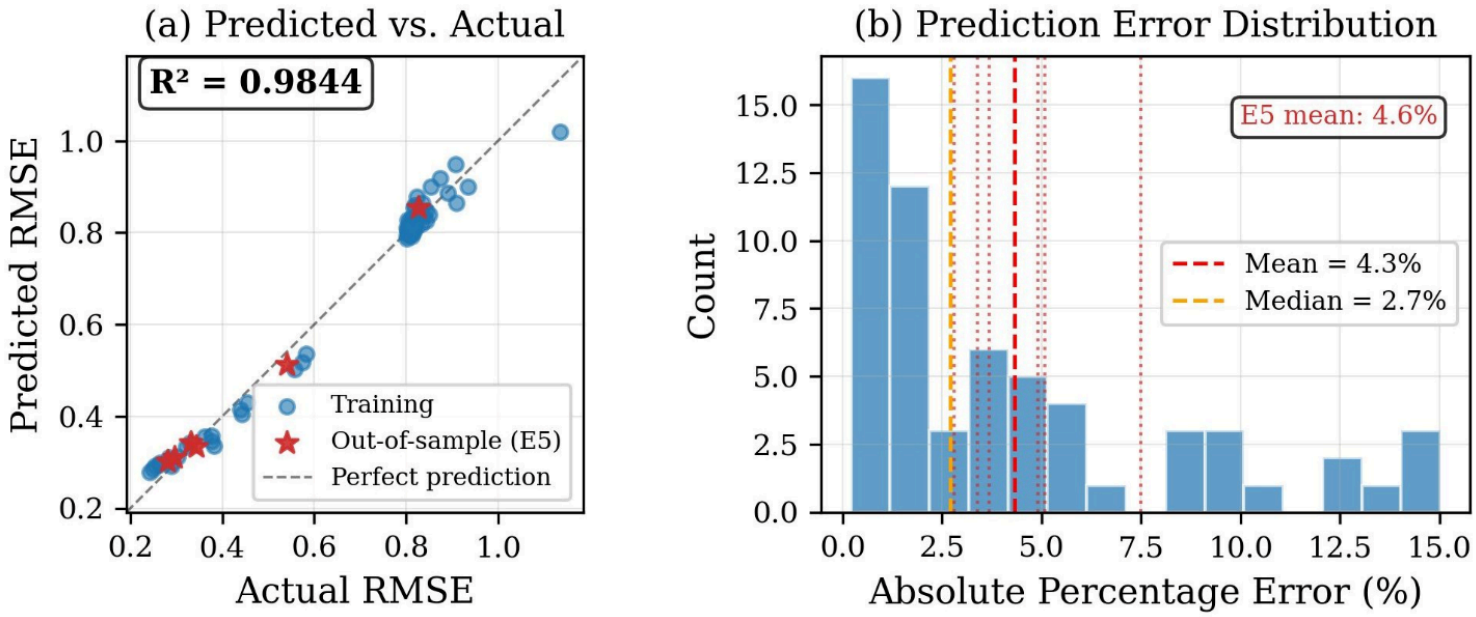


Figure 5

Multiplicative model validation. (a) Predicted vs. actual RMSE for training data (circles, n = 48 conditions) and out-of-sample E5 test conditions (stars, n = 6). The diagonal line represents perfect prediction. $R^2 = 0.984$ on training data. (b) Prediction error distribution across all conditions; mean = 4.6%, E5 mean = 4.6%. Error bars: ±1 standard deviation.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryInformation.pdf