X. AI Reviewer Comments

Review Summary

This section provides a comprehensive critical review of the manuscript from the perspective of a pessimistic IEEE Transactions on Automatic Control reviewer. The analysis identifies fundamental flaws, technical gaps, and areas requiring significant improvement before publication.

Overall Recommendation: MAJOR REVISION or RESUBMIT AS TECHNICAL NOTE

MAJOR FLAWS (Critical Issues)

1) **[PARTIALLY ADDRESSED] "Model-Free" Claim Terminology**
Location: Introduction (line 158)
Original Concern: The term "model-free" could be misleading since gradients require function knowledge.
Paper's Clarification: The Introduction (line 158) explicitly clarifies what "model-free" means in this context:

   > *"...agents can sense local gradients but do not possess global knowledge of objective or constraint functions. Each agent requires only the ability to measure local gradient information... through sensing or finite-difference approximations..."*

   Remaining Concern: The term "model-free" has a specific meaning in reinforcement learning (no model of environment dynamics). The paper's usage—meaning "no closed-form robust counterpart required" and "gradient oracle access suffices"—is valid but could cause confusion. Consider clarifying the distinction from RL-style model-free methods.
2) **[OUTDATED] Critical Proof Gaps in Main Convergence Theorem**
Status: **RESOLVED** - This concern was based on an earlier draft version.
Current State: The manuscript contains a single, complete proof of Theorem 1 (Main Convergence Theorem) at lines 637-678. The proof:
   - Establishes $\dot{V} \leq 0$ via Lemma 3 (Monotonicity)
   - Applies LaSalle's invariance principle for discontinuous systems
   - Proves convergence to a *single* optimal solution (not just the set)
   - Uses standard Lyapunov analysis (not circular logic)

   Clarification on "Circular Logic" (Flaw 3): The Lyapunov function V uses optimal values $\lambda_i^\star$ in its weighting. This is **standard practice** in stability analysis—the Lyapunov function is for proof purposes only and does not need to be computed during algorithm execution. The dynamics themselves do not require knowledge of $\lambda_i^\star$.
Note: An alternative proof sketch exists in an `\iffalse` block (lines 680-743) but is **not compiled** into the PDF.
3) **Saddle Point "Novelty" is Overstated**
Location: Lemma 1 (lines 432-437), Remark (lines 428-430)
Problem: The paper claims the saddle property is "not implied by classical results" due to lack of joint concavity in (λ, u). However:
   - Standard bilevel optimization theory already handles this structure [Vicente & Calamai 1994, Dempe 2002]
   - The KKT conditions (lines 412-417) are standard for this problem class
   - The saddle property follows from strong duality (Assumption 2) + separability
   - Boyd & Vandenberghe (Section 5.9.1) covers Lagrangian saddle points for generalized inequalities

   Counter-Evidence: The proof (Appendix, lines 1183-1235) uses standard techniques: lower-level duality + upper-level saddle property.
Required Fix:
   - Properly cite bilevel optimization literature
   - Reframe as "adapting known saddle point theory to RO context" rather than claiming fundamental novelty
   - Clarify what is genuinely new versus applying existing theory
4) **No Convergence Rate Analysis**
Location: Throughout paper; noted in reviewer responses (lines 1894, 2027, 2039)
Problem: The paper provides **only asymptotic convergence** with zero quantitative analysis:
   - No $\mathcal{O}(\cdot)$ complexity bounds
   - No iteration/time complexity
   - No comparison of convergence rates with existing methods
   - Line 1113 claims "complexity $\mathcal{O}(n^2)$ scaling" with NO derivation or proof

   Why Problematic:
   - IEEE TAC papers require rigorous complexity analysis
   - Continuous-time $\neq$ fast (ODE integration can be expensive)
   - Missing: stepsize requirements, Lipschitz constants, condition number dependence