Major Highlights and Significance of the Paper

- Introduces the **first deterministic Double-Sided Walrasian Auction framework** for decentralized resource allocation in collaborative Multi-Access Edge Computing (MEC) environments.
- Addresses the emerging challenge of **"AI-fatigue"** in Ultra-Reliable Low-Latency Communication (URLLC) networks by eliminating the dependency on computationally intensive Deep Reinforcement Learning (DRL) models.
- Replaces black-box neural-network optimization with a **fully explainable, interpretable, and mathematically provable economic optimization framework**.
- Establishes a novel integration of **economic equilibrium theory, game-theoretic market dynamics, and edge computing resource allocation** for next-generation IoT systems.
- Derives exact **Karush-Kuhn-Tucker (KKT) closed-form optimal strategies** for both IoT buyers and edge-server sellers, enabling real-time decentralized decision-making.
- Proposes a robust **gradient-clipped tâtonnement price convergence mechanism** that guarantees stable Walrasian equilibrium even under highly congested and non-stationary network conditions.
- Achieves mathematically guaranteed **Pareto-optimal market clearing**, ensuring efficient utilization of limited edge computational resources without centralized control.
- Demonstrates exceptional scalability in large-scale MEC systems with more than **10,000 concurrent IoT devices**, making the framework suitable for future 6G smart infrastructure.
- Provides up to **1000× faster execution performance** compared to DRL-based frameworks such as MADDPG, enabling real-time deployment in latency-critical applications including autonomous vehicles and industrial IoT.
- Significantly reduces computational overhead, memory requirements, and training complexity by avoiding neural-network training, reward engineering, and state-space explosion.
- Introduces an energy-aware allocation mechanism based on Dynamic Voltage and Frequency Scaling (DVFS), ensuring optimized edge-server energy utilization while maintaining high social welfare.
- Validated using real-world Vehicular Edge Computing (VEC) datasets containing chaotic, heterogeneous, and non-stationary traffic patterns, demonstrating strong practical applicability.
- Demonstrates stable convergence behavior under heavy traffic congestion and extreme resource demand, proving the framework's robustness for real-world deployment.
- Enables intelligent urgency-aware prioritization of latency-sensitive tasks, naturally filtering low-priority traffic during network saturation scenarios.
- Maintains maximum achievable system social welfare without increasing overall energy expenditure, outperforming conventional equal-allocation heuristics.
- Ensures strict compliance with physical hardware capacity constraints of heterogeneous edge servers while maximizing network efficiency.
- Provides a highly scalable and lightweight framework suitable for future applications in:
    - Autonomous transportation systems

    - Smart cities
    - Industrial IoT
    - UAV-assisted MEC
    - 6G wireless networks
    - Real-time edge intelligence systems
- Establishes a strong theoretical foundation for future research on:
    - Blockchain-enabled MEC markets
    - Trust-aware decentralized edge computing
    - Federated and distributed intelligence
    - Multi-hop collaborative edge offloading
    - Economic AI alternatives for resource orchestration
- Offers a transformative paradigm shift from learning-heavy AI resource allocation toward **economically grounded, low-latency, and interpretable decentralized optimization frameworks** for next-generation communication systems.