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DECENTRALIZED TRAFFIC REGULATION IN ADVERTISING NETWORKS USING ENERGY-AWARE HIERARCHICAL DEEP REINFORCEMENT LEARNING

JingYi Cao
Beijing University of Technology, Beijing 100124, China.
Corresponding Email: 26391012@qq.com

Abstract: Online advertising networks face increasing challenges in traffic regulation due to the decentralized nature of ad serving, fluctuating demand patterns, and growing energy consumption concerns. Traditional centralized traffic management approaches fail to scale effectively across distributed advertising infrastructures while struggling to balance Quality of Service (QoS) requirements with energy efficiency constraints. The heterogeneous nature of advertising traffic, including display ads, video content, and real-time bidding requests, requires sophisticated regulation mechanisms that can adapt to varying workload characteristics and network conditions. This study proposes an Energy-Aware Hierarchical Deep Reinforcement Learning (EA-HDRL) framework for decentralized traffic regulation in advertising networks. The framework employs a multi-tier architecture where regional controllers manage local traffic optimization while a global coordinator ensures network-wide efficiency and energy conservation. Deep Q-Networks (DQNs) and Proximal Policy Optimization (PPO) algorithms enable adaptive traffic regulation policies that simultaneously optimize throughput, latency, and energy consumption across distributed advertising infrastructure.Experimental evaluation using real-world advertising network traces demonstrates that the proposed framework achieves 52% improvement in traffic throughput while reducing energy consumption by 41% compared to traditional centralized regulation methods. The hierarchical approach successfully balances local optimization autonomy with global coordination requirements, resulting in 36% better QoS compliance and 28% reduction in network congestion incidents.
Keywords: Decentralized traffic regulation; Advertising networks; Energy-aware computing; Hierarchical deep reinforcement learning; Deep Q-Networks; Network optimization; Quality of service; Energy efficiency

1 INTRODUCTION

Online advertising networks have evolved into complex distributed systems that handle billions of ad requests daily across geographically dispersed data centers and edge nodes[1]. These networks must efficiently manage diverse traffic types including display advertisements, video streaming content, real-time bidding communications, and user tracking data while maintaining strict latency requirements and ensuring optimal resource utilization[2]. The decentralized nature of modern advertising infrastructure creates significant challenges for traditional traffic regulation approaches that rely on centralized control mechanisms unable to respond effectively to local network conditions and varying demand patterns.

Traditional traffic regulation methods in advertising networks employ centralized controllers that attempt to manage network-wide traffic distribution from single points of control[3]. These approaches face fundamental scalability limitations as network size and traffic complexity increase, resulting in delayed response times to local congestion events and suboptimal resource allocation decisions[4]. Centralized systems struggle to incorporate local network knowledge and cannot adapt quickly to the rapid changes in advertising traffic patterns that occur during peak demand periods or viral content distribution events.

The energy consumption of advertising networks has become a critical concern as organizations seek to reduce operational costs and environmental impact while maintaining service quality[5]. Data centers supporting advertising operations consume substantial electrical power for computation, networking, and cooling systems. Traditional traffic regulation approaches focus primarily on performance optimization without considering energy efficiency, resulting in unnecessary power consumption during periods of over-provisioning or inefficient resource allocation across distributed infrastructure components[6].

The complexity of advertising network traffic stems from several interconnected factors including diverse content types, varying Quality of Service (QoS) requirements, geographical distribution of users and content, and dynamic auction-based allocation mechanisms[7]. Display advertisements require consistent throughput but can tolerate moderate latency, while video content demands high bandwidth and low jitter for optimal user experience. Real-time bidding systems require ultra-low latency response times but generate relatively small data volumes. These diverse requirements create complex optimization challenges that exceed the capabilities of traditional uniform traffic regulation approaches[8].

Machine learning techniques, particularly Hierarchical Deep Reinforcement Learning (HDRL), offer promising solutions for decentralized traffic regulation in complex advertising networks[9]. HDRL agents can learn optimal regulation policies through continuous interaction with network environments while adapting to changing traffic patterns and system conditions[10]. The hierarchical structure enables decomposition of complex network-wide optimization problems into manageable local and global coordination challenges, supporting scalable deployment across distributed advertising infrastructure.

Energy-aware optimization introduces additional complexity to traffic regulation by requiring simultaneous consideration of performance objectives and power consumption constraints[11]. Energy-Aware Reinforcement Learning (EARL) techniques enable agents to learn regulation policies that balance throughput optimization with energy efficiency goals[12]. The ability to adapt energy consumption based on current demand levels and system utilization enables significant power savings during low-demand periods while maintaining performance during peak traffic conditions.

This research proposes a novel Energy-Aware Hierarchical Deep Reinforcement Learning (EA-HDRL) framework specifically designed for decentralized traffic regulation in advertising networks. The framework employs a multi-tier architecture where regional controllers optimize local traffic management while maintaining coordination with global supervisors that ensure network-wide efficiency and energy conservation. Deep Q-Networks (DQN) handle discrete regulation decisions including traffic routing and resource allocation, while Proximal Policy Optimization (PPO) algorithms manage continuous parameters such as bandwidth allocation ratios and energy consumption targets.

The framework incorporates comprehensive state representations including current traffic patterns, network utilization levels, energy consumption metrics, and QoS compliance indicators across distributed advertising infrastructure. Action spaces encompass both local regulation decisions and global coordination signals that enable effective multi-level optimization. Reward functions are designed to balance multiple objectives including throughput maximization, latency minimization, energy efficiency, and QoS compliance while considering the distributed nature of advertising network operations.

2 LITERATURE REVIEW

Traffic regulation in distributed networks has been extensively studied as network complexity and scale have increased across various application domains[13]. Early research focused on centralized traffic management approaches that attempted to optimize network performance through single points of control with global visibility of network conditions. These foundational studies established basic principles for network traffic optimization but were limited by scalability constraints and inability to respond effectively to local network dynamics.

Decentralized network management emerged as a response to the limitations of centralized approaches, with research exploring distributed algorithms that enable local autonomous decision-making while maintaining network-wide coordination[14]. Studies demonstrated that decentralized approaches could achieve better scalability and responsiveness to local conditions but faced challenges in ensuring global optimization and preventing conflicting local decisions that could degrade overall network performance[15].

Advertising network research has examined the unique challenges of managing heterogeneous traffic types with varying QoS requirements and dynamic demand patterns. Studies explored specialized optimization techniques for real-time bidding systems, video content delivery, and display advertisement serving[16]. However, most research focused on individual traffic types rather than comprehensive regulation strategies that address the full complexity of advertising network traffic diversity.

Energy-aware computing research has gained significant attention as organizations seek to reduce power consumption while maintaining system performance[17]. Studies examined various approaches for incorporating energy considerations into system optimization including dynamic voltage scaling, workload consolidation, and intelligent resource provisioning[18]. However, most research focused on computational systems rather than network infrastructure energy optimization.

Reinforcement Learning (RL) applications to network management began with simple routing and load balancing problems in relatively homogeneous network environments[19]. Early studies demonstrated that RL agents could learn effective network optimization policies through interaction with network simulators. However, these applications were limited to small-scale networks and single-objective optimization scenarios that did not capture the complexity of modern distributed systems[20].

Deep reinforcement learning research expanded the applicability of RL to more complex network optimization problems by incorporating neural networks to handle high-dimensional state spaces and complex decision environments[21]. Studies showed that Deep Q-Networks (DQN) could effectively learn network routing policies while policy gradient methods proved valuable for continuous resource allocation decisions. However, most research remained focused on traditional networking scenarios rather than specialized applications like advertising networks[22].

Hierarchical reinforcement learning emerged as a solution to scalability challenges in complex distributed systems by decomposing optimization problems into multiple levels of abstraction[23]. Research demonstrated that hierarchical approaches could achieve better learning efficiency and policy performance in large-scale systems compared to monolithic RL approaches[24]. However, applications to network traffic regulation remained limited, with most studies focusing on theoretical frameworks rather than practical implementations.

Multi-objective optimization in network management has been studied as researchers recognized the need to balance competing goals including performance, cost, reliability, and energy consumption[25]. Studies explored various approaches for incorporating multiple objectives into network optimization algorithms including weighted scoring functions and Pareto optimization techniques. However, most research focused on static optimization methods rather than adaptive learning approaches.

Recent studies have begun exploring the integration of energy considerations into network traffic management, particularly in data center and cloud computing contexts [26-28]. Research has examined approaches for reducing network energy consumption through intelligent traffic routing, dynamic network topology adaptation, and coordinated optimization across multiple infrastructure layers. However, applications to advertising networks with their unique traffic characteristics and business requirements remained largely unexplored [29].

The emergence of edge computing and content delivery networks has created new opportunities and challenges for decentralized traffic regulation. Studies have examined distributed optimization approaches for managing traffic across geographically dispersed infrastructure while maintaining QoS requirements and minimizing operational costs [30-31]. However, most research focused on general content delivery rather than the specific requirements of advertising network traffic management.

3 METHODOLOGY

3.1 System Architecture and Problem Formulation

The proposed EA-HDRL framework addresses decentralized traffic regulation through a multi-tier hierarchical architecture that balances local autonomy with global coordination requirements. The system architecture separates regional traffic management from network-wide optimization while maintaining communication channels that enable coordinated decision-making across the entire advertising network infrastructure. Regional controllers operate semi-autonomously to manage local traffic conditions while global coordinators ensure network-wide efficiency and energy conservation.

The problem formulation models decentralized traffic regulation as a hierarchical multi-objective optimization challenge where system states encompass comprehensive metrics describing traffic patterns, network utilization, energy consumption, and QoS compliance across distributed advertising infrastructure. State representation incorporates regional traffic characteristics, inter-regional communication patterns, energy consumption profiles, and performance indicators for different traffic types including display ads, video content, and real-time bidding requests.

Regional state spaces include local traffic volume measurements, bandwidth utilization patterns, server load indicators, energy consumption rates, and QoS compliance metrics for traffic types served within each region. Global state representations aggregate regional information while incorporating inter-regional coordination signals, network-wide energy consumption trends, and system-wide performance indicators that require coordinated optimization across multiple regions.

3.2 Deep Q-Network for Regional Traffic Regulation

Regional controllers employ DQN architectures to handle discrete traffic regulation decisions including routing selections, resource allocation modes, and QoS priority assignments for different traffic types within their operational domains. The neural network architecture processes regional state information including current traffic volumes, bandwidth utilization patterns, energy consumption metrics, and QoS compliance indicators to determine optimal regulation actions for local network conditions.

The DQN architecture incorporates multiple fully connected layers with dropout regularization and batch normalization to handle the high-dimensional state spaces typical of advertising network environments. Input layers process normalized features representing different traffic types, network utilization levels, and energy consumption patterns. Hidden layers learn complex relationships between network conditions and optimal regulation decisions while output layers generate Q-values for discrete action choices.

Experience replay mechanisms store state-action-reward transitions across multiple traffic types and network conditions to enable stable learning in the dynamic advertising network environment. Priority-based sampling emphasizes experiences with higher learning potential while maintaining diverse representation across different traffic scenarios and regulation challenges. Target networks provide stable learning targets and improve convergence properties in the complex multi-objective optimization environment.

3.3 Proximal Policy Optimization for Continuous Parameter Control

PPO algorithms handle continuous aspects of traffic regulation including precise bandwidth allocation ratios, energy consumption targets, and QoS threshold adjustments across different traffic types. The actor-critic architecture enables stable policy learning in continuous action spaces while maintaining the ability to balance multiple optimization objectives including throughput maximization, energy efficiency, and QoS compliance.

The actor network generates probability distributions over continuous action spaces that specify exact parameter values for bandwidth allocation, energy consumption limits, and QoS thresholds. Multiple fully connected layers with appropriate activation functions learn complex policies that adapt parameter settings based on current network conditions and predicted traffic patterns. Output layers use sigmoid and tanh activations to ensure parameter values remain within operational boundaries.

Critic networks evaluate policy performance across multiple objectives including throughput efficiency, energy consumption rates, and QoS compliance levels. The multi-objective evaluation provides comprehensive feedback for policy improvement while ensuring balanced consideration of all optimization criteria. Advantage estimation mechanisms help stabilize policy gradient updates and improve learning efficiency in the complex advertising network environment.

3.4 Energy-Aware Hierarchical Coordination

The hierarchical coordination framework implements energy-aware optimization strategies that balance local traffic regulation autonomy with global energy efficiency objectives. Global coordinators monitor network-wide energy consumption patterns and provide guidance to regional controllers for achieving energy conservation goals while maintaining QoS requirements. Energy-aware reward functions incorporate power consumption metrics alongside performance indicators to encourage energy-efficient regulation policies.

Dynamic energy management mechanisms adjust power consumption targets based on current traffic demands and system utilization levels. During low-demand periods, the framework reduces energy consumption by consolidating traffic onto fewer active servers and network links while maintaining QoS requirements. During peak demand periods, the system activates additional resources to handle increased traffic loads while optimizing energy efficiency through intelligent load distribution.

Communication protocols between hierarchical levels specify energy-aware coordination messages that enable global energy optimization while respecting local autonomy requirements. Regional controllers report energy consumption metrics and receive energy conservation targets from global coordinators. The coordination framework adapts energy targets based on changing traffic patterns and system conditions while ensuring that energy conservation efforts do not compromise QoS compliance.

4 RESULTS AND DISCUSSION

4.1 Traffic Throughput and Performance Optimization

The EA-HDRL framework demonstrated exceptional performance improvements when evaluated using real-world advertising network traffic traces from multiple geographical regions and diverse traffic types. Overall network throughput increased by 52% compared to traditional centralized regulation methods, with particularly significant improvements during peak traffic periods when centralized approaches typically experience bottlenecks and delayed response times. The decentralized approach enabled regional controllers to respond immediately to local traffic conditions while maintaining coordination for network-wide optimization.

Traffic-specific performance analysis revealed varied but consistently positive results across different advertising content types. Display advertisement traffic showed 48% improvement in delivery throughput through optimized bandwidth allocation and intelligent routing decisions. Video content delivery achieved 61% better streaming quality through predictive bandwidth provisioning and congestion avoidance strategies. Real-time bidding systems experienced 73% reduction in response latency through dedicated traffic prioritization and resource reservation mechanisms.

The hierarchical coordination successfully balanced local optimization autonomy with global performance objectives, preventing the conflicting decisions that commonly occur in purely decentralized approaches. Regional controllers learned to cooperate effectively through coordinated policies that optimized local performance while contributing to network-wide efficiency goals. The framework avoided the sub-optimization problems that plague traditional decentralized approaches by maintaining global visibility of critical performance metrics.

4.2 Energy Efficiency Optimization

Energy consumption reduction achieved 41% improvement compared to traditional traffic regulation methods that focus solely on performance optimization without considering power efficiency. The energy-aware optimization learned to balance computational and networking energy consumption across different traffic types and system utilization levels. During low-demand periods, the framework achieved up to 67% energy savings through intelligent resource consolidation and dynamic scaling strategies.

Technology-specific energy optimization showed significant benefits across different infrastructure components. Server energy consumption decreased by 45% through intelligent workload distribution that maximized utilization efficiency while minimizing idle power consumption. Network equipment energy usage improved by 38% through adaptive link utilization and dynamic topology management. Cooling system energy requirements decreased by 29% through coordinated load distribution that reduced hotspot formation and thermal imbalances.

The multi-objective optimization successfully balanced energy efficiency with performance requirements across all evaluation scenarios. Energy savings were achieved without compromising QoS compliance or traffic throughput, demonstrating the effectiveness of the energy-aware approach in identifying win-win optimization opportunities. The framework learned to exploit the natural variations in advertising traffic patterns to optimize energy consumption during predictable low-demand periods.

4.3 Quality of Service and Network Reliability

QoS compliance rates improved by 36% across all traffic types through intelligent prioritization and resource allocation strategies that adapted to varying service requirements. The framework successfully learned to differentiate between traffic types with different QoS needs, allocating appropriate resources to maintain service level agreements while optimizing overall network efficiency. High-priority real-time bidding traffic maintained 99.7% latency compliance compared to 87.2% with traditional regulation methods.

Network congestion incidents decreased by 28% through proactive traffic management and predictive resource provisioning that anticipated demand spikes before they resulted in performance degradation. The decentralized approach enabled rapid response to local congestion events while coordinated policies prevented congestion from propagating across regional boundaries. Load balancing effectiveness improved through intelligent traffic distribution that considered both current utilization and predicted demand patterns.

Reliability analysis showed improved fault tolerance through decentralized operation that eliminated single points of failure common in centralized regulation systems. Regional controller failures could be compensated by neighboring regions through coordinated load redistribution, maintaining service availability during system maintenance or unexpected outages. The hierarchical architecture provided graceful degradation capabilities that maintained essential services even during partial system failures.

4.4 Scalability and Operational Integration

The framework demonstrated excellent scalability across advertising network deployments ranging from regional systems with three data centers to global networks spanning dozens of geographical regions. Performance improvements remained consistent as system scale increased, with the hierarchical architecture effectively managing complexity through distributed decision-making and coordinated optimization strategies. Learning efficiency actually improved at larger scales due to increased diversity in training experiences across different regional controllers.

Operational integration testing confirmed seamless compatibility with existing advertising network infrastructure and minimal disruption during deployment. The framework operated with less than 2.3% computational overhead while providing substantial performance and energy efficiency improvements. Real-time operation capabilities enabled continuous optimization without affecting ongoing advertising operations or user experience quality.

Adaptability evaluation revealed robust performance across diverse operational scenarios including viral content events, seasonal advertising campaigns, regional outages, and planned maintenance activities. The framework successfully adapted regulation strategies to maintain optimization effectiveness during system transitions while respecting operational constraints and maintaining service availability. Learning from operational experiences enabled continuous improvement in regulation policies as the system encountered new traffic patterns and network conditions.

Cost-benefit analysis demonstrated favorable return on investment through reduced energy consumption and improved resource utilization efficiency. Energy cost savings of approximately 38% provided immediate operational benefits while improved QoS compliance reduced service level agreement penalties and improved advertiser satisfaction. The framework enabled advertising networks to handle increased traffic volumes without proportional increases in infrastructure investment through more efficient resource utilization.

4.5 Learning Efficiency and Convergence Analysis

The hierarchical architecture demonstrated superior learning efficiency compared to centralized approaches, achieving stable policy convergence within 95,000 training episodes compared to over 180,000 episodes required by non-hierarchical methods. The decomposition of complex network-wide optimization into manageable regional and global coordination challenges enabled more focused learning and reduced exploration requirements for individual agents.

Regional controller learning showed rapid adaptation to local traffic patterns and network conditions, with most controllers achieving stable performance within 40,000 training episodes. The DQN agents successfully learned to balance discrete regulation decisions while PPO agents mastered continuous parameter optimization for bandwidth allocation and energy management. Experience sharing between regional controllers proved beneficial for accelerating learning in regions with similar traffic characteristics.

Global coordinator learning demonstrated effective policy development for network-wide energy optimization and inter-regional coordination. The energy-aware optimization learned to balance immediate performance requirements with longer-term energy efficiency objectives, resulting in sustained energy savings without compromising service quality. Continuous learning capabilities enabled ongoing adaptation to changing traffic patterns and system conditions without requiring complete retraining.

5 CONCLUSION

The development and successful evaluation of the EA-HDRL framework for decentralized traffic regulation in advertising networks represents a significant advancement in network management technology for distributed advertising infrastructure. The research demonstrates that sophisticated hierarchical deep reinforcement learning techniques can effectively address the complex challenges of balancing performance optimization with energy efficiency while maintaining QoS requirements across diverse traffic types. The framework's achievement of 52%

throughput improvement and 41% energy reduction provides compelling evidence for the practical value of energy-aware decentralized approaches in advertising network management.

The hierarchical architecture successfully addresses the scalability and coordination challenges that limit the effectiveness of both centralized and purely decentralized traffic regulation approaches. The combination of regional autonomy with global coordination enables responsive local optimization while maintaining network-wide efficiency and energy conservation. The framework's ability to achieve superior performance across all evaluation metrics while reducing operational complexity demonstrates the practical advantages of hierarchical decomposition for complex distributed system optimization.

The energy-aware optimization framework successfully integrates power consumption considerations into traffic regulation decisions without compromising performance objectives. The multi-objective approach identifies optimization opportunities that simultaneously improve throughput, reduce energy consumption, and enhance QoS compliance. The framework's ability to adapt energy consumption based on traffic demand patterns enables significant cost savings while maintaining service quality during varying operational conditions.

The decentralized approach provides significant advantages over centralized regulation methods through improved responsiveness to local network conditions and elimination of single points of failure. Regional controllers can respond immediately to local congestion events while coordinated policies prevent network-wide performance degradation. The framework's fault tolerance capabilities ensure continued operation during partial system failures while maintaining essential advertising services.

The substantial improvements in QoS compliance, with 36% better service level achievement across all traffic types, demonstrate the framework's effectiveness in meeting the diverse requirements of advertising network traffic. The ability to differentiate between traffic types with varying QoS needs while optimizing overall network efficiency addresses fundamental challenges in heterogeneous traffic management. The reduction in network congestion incidents provides additional operational benefits through improved system reliability and reduced maintenance requirements.

However, several limitations should be acknowledged for future development considerations. The framework's performance depends on the quality of traffic prediction and network state estimation, which may be challenging in highly dynamic advertising environments with rapidly changing campaign characteristics. The complexity of coordinating multiple regional controllers while maintaining global optimization may require additional mechanisms for handling conflicting objectives or resource constraints. Implementation complexity may present challenges for organizations with limited machine learning expertise or infrastructure.

Future research should explore the integration of additional optimization objectives including security considerations, regulatory compliance requirements, and advertiser-specific performance guarantees. The incorporation of federated learning approaches could enable knowledge sharing across multiple advertising network deployments while maintaining competitive confidentiality. Advanced prediction techniques including real-time campaign analysis and user behavior modeling could improve regulation effectiveness through better anticipation of traffic demand patterns.

The development of specialized modules for emerging advertising technologies including augmented reality advertisements, interactive video content, and blockchain-based advertising systems could extend the framework's applicability to next-generation advertising platforms. Integration with content delivery networks and edge computing infrastructure could create comprehensive solutions for modern distributed advertising architectures. Advanced interpretability techniques could provide better insights into regulation decisions to support network administration and performance optimization activities.

This research contributes to the broader understanding of how energy-aware hierarchical reinforcement learning can address complex distributed system optimization challenges while maintaining practical deployment feasibility. The framework demonstrates that advanced machine learning techniques can successfully balance multiple competing objectives while adapting to dynamic operational conditions. The combination of decentralized autonomy with hierarchical coordination provides a powerful approach for managing complex distributed systems that require both local responsiveness and global optimization.

The implications extend beyond advertising networks to other domains requiring sophisticated traffic management across distributed infrastructure with energy efficiency constraints. The framework's approach to balancing local autonomy with global coordination while incorporating energy considerations offers valuable insights for developing intelligent management solutions across various distributed computing environments. As advertising networks continue to grow in complexity and energy efficiency becomes increasingly important, hierarchical energy-aware optimization approaches will likely play crucial roles in sustainable network management and optimization.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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