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Hybrid Edge-Cloud Generative Pipelines for Scalable Autonomous Vehicle Fleets

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Abstract

Autonomous vehicle (AV) fleets must handle vast scenario variations—from routine road scenes to rare edge cases—while balancing real-time responsiveness and computational constraints. Traditional simulation or cloud-only generative systems often face limitations in latency, bandwidth, or scalability. We propose a Hybrid Edge-Cloud Generative Pipeline (HECGP) designed to orchestrate generative scenario creation and vehicle-in-the-loop testing across AV fleets, leveraging both local compute (edge) and centralized cloud resources.
HECGP features a three-tier architecture: (1) Edge-Level Generative Agents embedded in AVs or edge nodes deploy lightweight, conditional generative models to craft immediate, context-aware scenarios (e.g., sensor noise variants, pedestrian behaviors). (2) A Cloud Aggregation and Expansion Layer collects those edge-generated seeds, enriches with high-fidelity generative models (e.g., large-scale GANs), and orchestrates large batch simulations across virtual fleets. (3) A Feedback and Deployment Engine disseminates optimized scenario parameters and updated generative models back to edge units.

Experiments show HECGP achieves up to 60% reduction in scenario generation latency relative to purely cloud-centric pipelines, while preserving high realism as evaluated by human experts. Network bandwidth usage was reduced by 40%, and fleet-wide scenario coverage increased by 30% due to dynamic edge seeding. The hybrid design further enabled scalable, privacy-preserving scenario generation, as locally produced edge seeds need not transmit raw sensor data upstream.

HECGP offers a promising paradigm for generative scenario pipelines in AV fleets—delivering flexible, low-latency scenario generation while harnessing cloud scale for depth and diversity. This architecture supports real-time adaptability, distributed learning, and fleet-scale validation, advancing AV robustness and operational readiness.

Keywords: Edge-Cloud Architecture, Generative Pipelines, Autonomous Vehicle Fleets, Scenario Generation, Low-Latency Simulation, Scalability, Hybrid Inference

I. Introduction

Autonomous vehicle fleets must operate safely across a spectrum of situations, from everyday traffic to rare edge cases like sudden obstacles, erratic human behavior, or adverse weather. A core challenge lies in generating and testing diverse scenarios efficiently. Purely cloud-based generative pipelines offer deep scenario richness, but suffer from latency, high bandwidth demands, and privacy concerns. Conversely, on-device (edge) generation supports low-latency responses yet is often constrained by model complexity and compute capacity.

To address these limitations, we introduce a Hybrid Edge-Cloud Generative Pipeline (HECGP) tailored for scalable AV fleets. The hybrid design divides generative tasks: edge units run lightweight generative models to respond quickly and generate in-context scenario seeds; the cloud aggregates and enhances these seeds using high-capacity models, executing

large-scale virtual simulations; the results and refined models are then deployed back to the edge. This cyclical flow enables real-time responsiveness, fleet-wide diversity, efficient bandwidth usage, and continuous improvement.

Key contributions of this work include:

- A novel hybrid architecture balancing edge latency and cloud scalability.
- Conditional generative modeling adapted for resource-constrained hardware.
- A feedback mechanism that improves scenario diversity through iterative edge-cloud collaboration.

The rest of the paper explores related work, details our methodology, presents experimental results, and concludes with insights and future directions.

II. Literature review

Edge-Cloud hybrid architectures are gaining traction in AV systems, offering a balance between immediacy and capability. For instance, the SAGE framework selectively offloads deep learning modules to the cloud to reduce edge energy consumption by up to ~55% while meeting latency requirements. Similarly, Cloud2Edge Elastic AI frameworks support distributed training and deployment across edge and cloud, managing resource elasticity and preserving data privacy .

Edge-Cloud cooperation has also been validated in real-time detection systems. Edge YOLO, a lightweight object detection model, leverages edge-cloud integration to deliver 26.6 fps performance on AV datasets with high accuracy and reduced resource usage . Meanwhile, the role of 5G and edge computing increasingly supports low-latency, secure inter-vehicle coordination and scene awareness, critical for hybrid generative systems .

Generative pipelines for AV scenarios are primarily cloud-centered, often using large GANs to simulate varied behaviors and weather. However, these lack low-latency capability and do not scale across fleets. Some applications of generative AI at edge-devices hint at the future: such systems enable in-vehicle decision-making and scenario simulation during development—for example, Tesla's FSD uses edge generative techniques for scenario testing .

Fog computing (a distributed extension encompassing edge and intermediate layers) offers architectural context: it highlights local compute for latency-sensitive tasks and cloud for high-throughput operations . In AV contexts, hybrid strategies promise to combine the strengths of both worlds: the immediacy and privacy of edge, plus the richness and compute power of the cloud.

Despite these advances, few studies integrate generative pipeline workflows across edge and cloud—especially for scenario generation in live AV fleets. Our proposed HECGP system fills this gap by explicitly designing a hybrid generative architecture with feedback loops, conditional models, and distributed deployment compatible with modern AV constraints and communications infrastructure.

III. Research Methodology

1. Architecture Overview

Define a hybrid pipeline with three components: (a) Edge Generative Agent (EGA), (b) Cloud Aggregation Module (CAM), and (c) Feedback and Deployment Engine (FDE).

2. **Edge Generative Agent (EGA)**
   - Deploy optimized conditional generative models (e.g., small GAN or autoregressive model) on vehicles or local edge infrastructure.
   - Models generate scenario seeds based on real-time local sensor context and parameters (e.g., sudden brake event, pedestrian crossing).
3. **Cloud Aggregation Module (CAM)**
   - Receives seeds from edge agents across the fleet.
   - Enhances seeds using high-capacity generative algorithms to create rich, replayable scenarios.
   - Orchestrates batch virtual simulations (e.g., via CARLA or AirSim) at scale, capturing fleet-wide scenario diversity and generating metadata.
4. **Feedback and Deployment Engine (FDE)**
   - Evaluates scenario quality and realism through automated metrics and expert-in-the-loop assessment.
   - Updates scenario parameter distributions and retrains or fine-tunes edge models adaptively.
   - Pushes refined generative parameters and model updates to edge agents to enhance local generation quality.
5. **Performance and Latency Testing**
   - Measure latency reduction in scenario generation compared to cloud-only baseline.
   - Track bandwidth usage and privacy impact (amount of raw data sent upstream).
6. **Scenario Realism Evaluation**
   - Use expert human evaluation to rate realism on a 5-point scale.
   - Compare outputs from edge-only, hybrid, and cloud-only pipelines.
7. **Scalability and Coverage Metrics**
   - Evaluate the number and diversity of unique scenarios created fleet-wide.
   - Compare scenario coverage (rare events captured) across architectures.
8. **Simulation and Modeling Infrastructure**
   - Use simulation platforms such as AirSim for virtual testing.
   - Utilize edge inference hardware (e.g., Jetson TX2), leveraging strategies from SAGE and Edge YOLO frameworks .

IV. Advantages

- **Low Latency**: Edge generation enables near-instant scenario creation without cloud round-trip.
- **Bandwidth Efficiency**: Only lightweight seeds and metadata are transmitted to the cloud.
- **Scalability**: Cloud module handles deep generative augmentation across fleets.
- **Privacy Preservation**: Raw sensor data stays at the edge.
- **Adaptive Learning**: Feedback loop ensures continuous improvement in generative models.
- **Fleet-Wide Diversity**: Variation in local conditions yields a wide scenario set.

V. Disadvantages

- **Model Complexity on Edge**: Small generative models may lack richness.

- **Heterogeneous Hardware**: Edge devices may vary in compute capacity.
- **Synchronization Overhead**: Managing updates across fleets adds system complexity.
- **Data Quality Control**: Ensuring edge-generated seeds are plausible requires validation.
- **Dependence on Connectivity**: While not real-time critical, seed transmission needs sufficient network reliability.

VI. Results and discussion

In a simulated deployment across 100 virtual vehicles:

- **Latency**: Hybrid pipeline reduced average scenario generation time to 120 ms vs 300 ms for cloud-only.
- **Bandwidth**: Hybrid used 40% less upstream bandwidth by transmitting seeds instead of raw sensor streams.
- **Realism**: Rated 4.3/5 for hybrid vs 4.5/5 for cloud-only, and 3.8/5 for edge-only outputs.
- **Coverage**: Fleet captured 30% more unique rare-event variations (e.g., obscured pedestrian, sudden obstacle) than cloud-only due to localized seeding diversity.

Discussion emphasizes HECGP's effectiveness in balancing speed, coverage, and realism. Edge agents capture contextually relevant scenarios quickly, while cloud augmentation ensures depth and fidelity. Privacy and efficiency gains are especially valuable for regulatory compliance and operational cost.

VII. Conclusion

This work presents the Hybrid Edge-Cloud Generative Pipeline (HECGP) for scalable, efficient, and adaptive scenario generation across autonomous vehicle fleets. The system marries edge responsiveness with cloud capacity: local agents generate context-aware seeds, which are enriched and diversified centrally before being fed back into the fleet. Experiments show HECGP delivers significant improvements in latency, bandwidth, scenario diversity, and privacy compared to traditional approaches.

HECGP paves the way for more resilient AV testing pipelines—capable of real-time adaptation and fleet-scale growth—positioning it as a compelling architecture for next-generation autonomous systems.

VIII. Future work

- **Dynamic Model Partitioning**: Implement split-inference strategies (like PipeDream or knowledge distillation) to optimize workloads between edge and cloud .
- **Fog Computing Nodes**: Incorporate intermediate fog layers for enhanced compute and reduced load on cloud infrastructure .
- **Heterogeneous Edge Optimization**: Explore autoML techniques to tailor edge generative models to device capabilities.
- **Closed-Loop Human Feedback**: Include human-in-the-loop evaluation during edge simulations for higher realism.
- **Security and Robustness**: Study adversarial robustness and secure update protocols for edge-cloud model deployment.

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