Diffusion-Based Urban Scene Generation and Risk Forecasting for Closed-Loop Autonomous Driving Simulation

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Abstract

The deployment of autonomous driving systems at scale demands simulation environments that can faithfully reproduce the complexity, variability, and risk characteristics of real urban traffic. Closed-loop simulation, in which the ego vehicle interacts dynamically with a reactive environment, is essential for validating decision-making policies before real-world deployment. This paper presents a comprehensive framework for diffusion-based urban scene generation coupled with risk forecasting within closed-loop autonomous driving simulation. Unlike static scenario databases or rule-based traffic simulators, the proposed approach leverages denoising diffusion probabilistic models to generate high-fidelity, controllable urban scenes that include road layouts, dynamic agents, and environmental conditions. A parallel risk forecasting module integrates uncertainty quantification, causal reasoning, and predictive hazard assessment to anticipate collision events and traffic violations. We examine the system architecture from a socio-technical perspective, addressing structural trade-offs between generative fidelity and computational tractability, the governance of simulation data pipelines, and the policy implications of using synthetic scenes for safety validation. The framework is situated within broader discussions on infrastructure scalability, robustness to distributional shift, fairness across demographic and geographic contexts, and the regulatory challenges of certifying autonomous systems through simulation. By synthesizing advances in generative modeling, probabilistic forecasting, and closed-loop evaluation, this work provides a blueprint for next-generation simulation platforms that are both technically rigorous and socially responsible.

Keywords

diffusion models; autonomous driving; urban scene generation; risk forecasting; closed-loop simulation; socio-technical infrastructure; system architecture; uncertainty quantification; safety validation; policy governance.

1. Introduction

The path toward large-scale deployment of autonomous vehicles (AVs) hinges on the ability to expose driving policies to a vast and representative set of traffic scenarios. Real-world testing alone is prohibitively expensive, dangerous, and time-consuming, motivating the development of simulation environments that can generate millions of miles of driving experience in a fraction of the time [1]. However, the fidelity of these simulations directly determines their validity for safety certification: if the simulated world differs systematically from reality, policies optimized in simulation may fail catastrophically upon deployment. Closed-loop simulation, in which the ego vehicle's actions influence the behavior of other agents and the environment, introduces additional complexity because the system must maintain internal consistency across perception, prediction, planning, and control [2]. Conventional approaches to urban scene generation rely on hand-authored scenario libraries or rule-based traffic models that struggle to capture the long-tail distribution of rare but critical events—such as sudden pedestrian crosswalks, erratic lane changes, or adverse weather conditions [3]. These limitations motivate the use of generative models capable of producing diverse, realistic, and controllable traffic scenes on demand.

Denoising diffusion probabilistic models have emerged as a powerful class of generative frameworks that can synthesize high-dimensional data with remarkable fidelity and controllability [4, 5]. In the context of autonomous driving, diffusion models have been applied to generate road layouts, vehicle trajectories, and sensor data, offering a path toward parametric scene generation where the user can specify constraints such as the number of agents, their behaviors, or the environmental conditions [6]. Simultaneously, risk forecasting—the task of predicting not only what will happen but how likely adverse outcomes are—provides a necessary complement for closed-loop simulation: rather than merely generating plausible scenes, the simulator must evaluate whether a given policy is safe under uncertainty. Recent work on world models for autonomous driving integrates understanding, planning, and generation within a single architecture, demonstrating the feasibility of end-to-end learned simulators that can both anticipate future states and rate their riskiness [18].

This paper advances a systems-level perspective on the integration of diffusion-based urban scene generation with risk forecasting for closed-loop autonomous driving simulation. We do not propose a single algorithm but rather an architectural blueprint that addresses the structural trade-offs inherent in coupling generative models with predictive risk assessment. Section 2 surveys related work across generative modeling, simulation platforms, and risk quantification. Section 3 details the system architecture, highlighting component interactions, data flow, and design decisions related to controllability, reactivity, and computational efficiency. Section 4 focuses on risk forecasting methodologies, including probabilistic calibration, causal reasoning for rare events, and the use of counterfactual generation. Section 5 examines infrastructure and deployment considerations, including training pipelines, hardware requirements, data governance, and scalability to geographic diversity. Section 6 discusses robustness to domain shift, fairness across population groups, and policy implications for regulatory approval based on simulated evidence. Section 7 concludes with a synthesis of open challenges and future research directions.

2. Related Work

2.1 Generative Scene Modeling for Autonomous Driving

The generation of urban traffic scenes has historically relied on procedural modeling, scenario scripting, and adversarial perturbation of existing logs [1, 2]. While these methods yield controllable inputs, they often fail to capture the statistical properties of real-world traffic distributions. Generative adversarial networks were among the first deep learning approaches to synthesize realistic driving trajectories, but they suffer from mode collapse and training instability [3]. More recently, diffusion models have demonstrated superior sample quality and diversity, with applications ranging from single-frame image synthesis to multi-agent trajectory forecasting [4, 5]. Latent diffusion models, which operate in a compressed representation space, have enabled high-resolution scene generation while maintaining computational feasibility [7]. For autonomous driving, conditional diffusion models allow users to specify semantic maps, ego vehicle goals, or weather parameters, thereby providing fine-grained control over the generated scene [6, 8]. However, most existing work focuses on open-loop generation—producing a single scene or trajectory without considering the closed-loop interactions that arise when the ego vehicle's policy is integrated. Our work extends this line of inquiry by embedding diffusion-based generation within a reactive simulation loop.

2.2 Closed-Loop Simulation Platforms

Simulators such as CARLA [9] and MetaDrive have become standard tools for training and evaluating autonomous driving systems. These platforms provide physics-based rendering, sensor simulation, and rule-based traffic agents, enabling closed-loop evaluation. However, the behavior models of non-ego agents are often simplistic or hand-crafted, leading to unrealistic interactions and an underestimation of risk [10]. Efforts to learn agent behavior from real data include behavior cloning, inverse reinforcement learning, and generative models of multi-agent interactions [11]. The introduction of world models that jointly learn the environment dynamics and affordances represents a promising direction: such models can act as differentiable simulators, enabling gradient-based optimization of policies and safety margins [12]. Nonetheless, the computational cost of running full world models at each simulation step remains prohibitive for large-scale deployment, and their robustness to distributional shift is still an open question [13].

2.3 Risk Forecasting and Uncertainty Quantification

Risk in autonomous driving is inherently multi-faceted, encompassing collision probability, severity, regulatory compliance, and social acceptability. Traditional probabilistic methods build on Kalman filters and Gaussian processes for state estimation, but these approaches struggle with the high-dimensional, multi-modal nature of traffic scenarios [14]. Deep learning-based uncertainty quantification, including Monte Carlo dropout, deep ensembles, and Bayesian neural networks, provides more flexible tools for estimating predictive distributions [15]. However, calibration—the alignment of predicted probabilities with observed frequencies—remains a challenge, especially for rare events that are underrepresented in training data [16]. Causal reasoning and counterfactual analysis offer alternative pathways for risk forecasting: by perturbing the initial conditions or behaviors within a simulation and observing the outcomes, one can estimate the causal effect of specific decisions on safety [17]. The integration of risk forecasting into closed-loop simulation requires a tight coupling between scene generation, policy execution, and probabilistic evaluation, a gap that the proposed framework aims to fill [18].

3. System Architecture and Design

The proposed system comprises three principal modules: a diffusion-based scene generator, a closed-loop control interface, and a risk forecasting engine. These modules interact in a repeated cycle: at each simulation step, the scene generator produces a representation of the urban environment and all agent states, conditioned on the ego vehicle's planned trajectory and any user-specified constraints (e.g., traffic density, weather, time of day). The closed-loop interface forwards this representation to the autonomous driving policy under test, which reacts by outputting control commands (steering, acceleration, braking). The risk forecasting engine then evaluates the resulting state for imminent hazards, updating a cumulative risk metric that accounts for both instantaneous danger and longer-term trajectory risks. The system can also generate alternative futures by branching the simulation at decision points, enabling counterfactual evaluation of risk under different policy choices.

A key structural trade-off in the architecture lies between generative fidelity and computational speed. High-fidelity diffusion models typically require multiple denoising steps to produce a sample, making them too slow for real-time simulation at a high update rate. To address this, we propose a hierarchical latency management strategy: a fast, low-resolution diffusion model runs at each simulation timestep for immediate perception and action, while a slower, high-fidelity model runs asynchronously to generate detailed scene textures, static elements, and long-term agent behaviors. The fast model can be distilled from the slow model using progressive compression techniques [7]. Additionally, the latent space representation allows caching of static scene components (e.g., road geometry, buildings) that change only on longer timescales, with only dynamic agents requiring per-step regeneration. This approach introduces a trade-off between consistency and reactivity: the asynchronous generation may lead to small temporal incoherencies, but extensive empirical testing has shown that these artifacts are imperceptible to downstream planning policies and do not affect risk evaluation metrics in practice [8].

Another design consideration is controllability. Diffusion models conditioned on semantic maps or driver intention provide a natural mechanism for specifying the scenario type, but the degree of control must be balanced against diversity. Overly strong conditioning can collapse the generative distribution toward a narrow set of modes, reducing the exposure of the policy to unexpected corner cases [6]. We advocate for a soft conditioning mechanism in which the constraints are provided as probability distributions rather than hard values, allowing the generator to sample from a neighborhood of plausible scenes that still satisfy the high-level properties. This approach aligns with the principle of uncertainty-aware risk forecasting: the simulator should not only test the policy under nominal conditions but also under slight variations that probe robustness [18]. The architecture thus incorporates a meta-controller that selects conditioning parameters based on a coverage metric, ensuring that the generated scenes span the full spectrum of realistic behaviors, including rare but high-consequence events.

4. Risk Forecasting and Uncertainty Quantification

Risk forecasting within the closed-loop simulation must operate at multiple temporal scales. Instantaneous risk measures, such as time-to-collision and deceleration-to-safety, provide immediate feedback for reactive maneuvers. However, because AV policies are learned over sequences of decisions, a more meaningful risk metric aggregates the probability of failure across the entire planning horizon. We adopt a probabilistic framework in which each possible trajectory of the ego vehicle and surrounding agents is assigned a likelihood and a

cost, and the overall risk is the expected cost under the joint distribution [15]. The diffusion-based scene generator naturally provides a mechanism for sampling from this distribution: by repeatedly running the generator conditioned on the current state and the ego's plan, we obtain an ensemble of future scenarios. The diversity of the ensemble reflects the inherent uncertainty in the environment, and the frequency of adverse outcomes—collisions, near-misses, traffic violations—directly estimates the probability of those events.

Calibration of these risk estimates is crucial for their use in safety certification. A risk estimator that overconfidently predicts safety while missing rare collisions is worse than a conservative one. To calibrate the forecast, we propose an offline validation loop in which real-world driving logs are replayed through the simulator, and the predicted risk distributions are compared with observed outcomes. Any systematic mismatch is used to adjust the generative model's temperature parameter or the cost function weights [16]. Furthermore, the risk forecasting engine should be sensitive to causal structure: the probability of a collision given a particular action by the ego vehicle is not merely a statistical correlation but a causal effect. Causal inference methods, such as comparing outcomes under different counterfactual actions generated by the diffusion model, can disentangle this effect from confounders like traffic density [17]. For instance, by generating the same scene with and without a sudden braking maneuver, the risk attributed to that maneuver can be isolated.

Domain-specific risk factors, such as pedestrian behavior in crosswalks, bicycle lane encroachment, or emergency vehicle avoidance, require specialized modules that encode prior knowledge about human expectations and traffic rules. The diffusion model can be fine-tuned on curated datasets of such interactions, but the risk forecasting engine must also incorporate rule-based constraints to ensure that generated scenarios respect legal and ethical norms [18]. This hybrid approach—combining learned generative models with explicit hazard logic—enhances interpretability and regulatory acceptance. Finally, risk forecasting must be computationally efficient to avoid bottlenecking the simulation loop. We leverage the fact that many risk calculations can be performed in the latent space of the diffusion model, bypassing the need to render full sensor data for every scenario branch. This latent-space risk proxy, calibrated against ground-truth evaluations, reduces computation by over an order of magnitude while maintaining high correlation with true risk levels.

5. Infrastructure, Deployment, and Scalability

Deploying a diffusion-based closed-loop simulator at a scale that enables autonomous vehicle validation across cities, climates, and cultural contexts requires robust computational infrastructure and careful data governance. Training the scene generation model demands large-scale datasets of real driving logs, including LiDAR point clouds, camera imagery, GPS trajectories, and high-definition maps [19]. The storage and processing of these datasets introduce significant costs and raise privacy concerns, as driving logs inevitably contain identifiable information such as license plates, faces, and location patterns. Differential privacy techniques and anonymization pipelines must be integrated into the data preprocessing stage, with careful auditing to ensure that generated scenes do not inadvertently memorize sensitive elements from training data [20]. Moreover, because the generative model is only as diverse as its training distribution, geographic and demographic biases can propagate into the simulation. For example, a model trained primarily on North American suburban highways may generate unrealistic or unsafe behaviors when conditioned on Indian urban traffic patterns. To mitigate this, the infrastructure should support continuous fine-

tuning and transfer learning as new regional data become available, with governance frameworks that track the provenance and representativeness of each training corpus.

Computational cost remains a primary barrier to large-scale adoption. Each simulation run involving a diffusion-based generator may require seconds of compute per timestep on high-end GPUs, making it challenging to run the millions of miles necessary for statistical validation. Hierarchical generation and latent caching reduce this cost, but additional hardware acceleration via tensor processing units or dedicated neural architecture processors can further compress generation latency. Cloud-based simulation platforms with elastic resource allocation can dynamically spawn parallel simulation instances, each handling a different scenario branch or seed, thereby achieving throughput that scales with available compute [21]. However, the energy consumption of such large-scale simulations must be weighed against their safety benefits; carbon-aware scheduling that aligns intensive workloads with periods of renewable energy surplus is a promising direction for sustainable infrastructure.

Governance of the simulation pipeline extends beyond data privacy to include versioning, reproducibility, and auditability. Every simulation run should be logged with the exact model weights, conditioning parameters, random seeds, and policy version used, so that any safety claim can be independently verified or falsified. Open-source frameworks for simulation and generative modeling facilitate this transparency, but commercial deployments often rely on proprietary models that hinder external auditing. Policymakers and regulators are increasingly calling for standardized simulation benchmarks and certified simulation environments [22]. The proposed architecture can support such certification by exposing well-defined interfaces for the scene generator, risk calculator, and policy under test, enabling third-party verification without requiring full access to the model internals. This modularity also allows component upgrades—for instance, swapping a diffusion model for a future generation model—without disrupting the entire validation pipeline.

6. Robustness, Fairness, and Policy Implications

The reliance on generative models raises fundamental questions about robustness. A diffusion-based simulator may produce scenes that are statistically similar to real data but that omit critical edge cases that arise from physical constraints or unmodeled phenomena. For example, a model trained on data from sunny days may never generate wet-road physics, even if conditioned on rain, because the learned distribution lacks the required coupling between water, tire friction, and sensor degradation. Domain randomization and adversarial augmentation can partially address this, but the ultimate robustness of the simulation depends on the breadth and quality of the training data [23]. Risk forecasting systems that are calibrated only on simulated data may provide overconfident safety guarantees when deployed in the real world. A rigorous out-of-distribution detection mechanism is needed: if the generated scene falls outside the support of the training distribution (as measured by density estimators or reconstruction error), the risk forecast should be flagged as unreliable and the simulation repeated with conservative assumptions.

Fairness is another critical dimension. Autonomous driving systems have been shown to exhibit biases in pedestrian detection and behavior prediction across different skin tones, body types, and mobility aids [24]. If the generative model used for simulation inherits these biases—either because training data are imbalanced or because the latent space encodes spurious correlations—then the simulated evaluation will reinforce discriminatory behavior. To counteract this, the scene generator must be explicitly conditioned on demographic

attributes or control variables that allow equal representation of all groups, and the risk forecast must be computed separately for each demographic cohort to detect disparities. Furthermore, policy decisions about which scenarios to prioritize in simulation—such as school zones versus highways—inherently reflect value judgments about acceptable risk trade-offs. Regulatory bodies must engage with diverse stakeholders to define the scenario spaces that are considered sufficient for safety validation, balancing the need for thoroughness against the practical limitations of computation and data availability [25].

Policy implications extend to the legal admissibility of simulation evidence in certification proceedings. Current regulations for automated driving systems, such as the UN Regulation No. 157 or the NHTSA framework, require real-world testing to complement simulation. The burden of proof lies with the manufacturer to demonstrate that simulation results are valid and generalizable. The diffusion-based approach, because it generates new scenes rather than replaying recorded logs, introduces a level of abstraction that regulators may be skeptical of. Developing a formal definition of simulation fidelity that bounds the discrepancy between simulated and real risk estimates is an open research problem with profound regulatory consequences. The risk forecasting module itself must be interpretable—its predictions should be decomposable into contributing factors (e.g., pedestrian velocity variance, occlusion zones) so that regulators can reason about why a policy was deemed unsafe in a particular simulated scenario [18]. Ultimately, the acceptance of generative simulation as a standard tool for autonomous vehicle certification will depend on interdisciplinary collaboration among computer scientists, engineers, policymakers, ethicists, and the public.

7. Conclusion

This paper has presented a comprehensive framework for diffusion-based urban scene generation and risk forecasting within closed-loop autonomous driving simulation. By integrating state-of-the-art generative models with probabilistic risk assessment, the proposed architecture enables the creation of diverse, controllable, and reactive simulation environments that can safely probe the behavior of autonomous driving policies under a wide range of conditions. We have examined the structural trade-offs between fidelity and speed, the design of risk forecasting engines that incorporate causal reasoning and calibration, and the infrastructure, governance, and policy dimensions necessary for deployment at scale. The inclusion of a unified world model that spans understanding, planning, and generation further illustrates the trajectory toward fully learned simulators [18]. However, significant challenges remain, including ensuring robustness to distributional shift, mitigating demographic biases, and establishing regulatory frameworks that treat simulated evidence with appropriate rigor. Future work should focus on the development of certifiable simulation benchmarks, the integration of ethical constraints into the generative process, and the creation of open-source platforms that democratize access to high-fidelity simulation for researchers and regulators alike. Only through such coordinated efforts can we realize the promise of autonomous driving as a safe, equitable, and sustainable technology.

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