Diffusion Models for Intelligent Transportation Systems: A Survey

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Abstract-Intelligent Transportation Systems (ITS) are vital in modern traffic management and optimization, significantly enhancing traffic efficiency and safety. Recently, diffusion models have emerged as transformative tools for addressing complex challenges within ITS. In this paper, we present a comprehensive survey of diffusion models for ITS, covering both theoretical and practical aspects. First, we introduce the theoretical foundations of diffusion models and their key variants, including conditional diffusion models and latent diffusion models, highlighting their suitability for modeling complex, multi-modal traffic data and enabling controllable generation. Second, we outline the primary challenges in ITS and the corresponding advantages of diffusion models, providing readers with a deeper understanding of the intersection between ITS and diffusion models. Third, we offer a multi-perspective investigation of current applications of diffusion models in ITS domains, including autonomous driving, traffic simulation, trajectory prediction, and traffic safety. Finally, we discuss state-of-the-art diffusion model techniques and highlight key ITS research directions that warrant further investigation. Through this structured overview, we aim to provide researchers with a comprehensive understanding of diffusion models for ITS, thereby advancing their future applications in the transportation

Index Terms—Intelligent Transportation Systems, Diffusion Models, Autonomous Driving, Traffic Simulation, Traffic Forecasting, Traffic Safety.

I. INTRODUCTION

S urbanization accelerates and populations grow, the demand for public transportation services increases alongside a steep rise in vehicle numbers. These trends have gradually revealed several issues in current transportation systems, such as traffic congestion and accidents. With advancements in computer technologies and transportation systems, many cities are increasingly focused on developing intelligent transportation systems (ITS) [1], which leverage cutting-edge technologies and extensive traffic data to enable efficient, high-quality, and safe traffic management. ITS encompasses sev-

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eral domains, including autonomous driving, which enhances traffic safety and efficiency; traffic simulation, which enables modeling, analysis, and testing of various strategies; traffic forecasting, which aims to reduce congestion and optimize services; and traffic safety, which seeks to minimize accidents and improve overall safety.

Traffic data are inherently heterogeneous and multi-modal, including vehicle and pedestrian trajectories, driving images or videos, spatial-temporal graphs derived from GPS positions, and textual data such as traffic rules and accident reports. These data often exhibit complex spatial-temporal dependencies and uncertainties. Additionally, the data may be noisy, incomplete, or difficult to obtain, with privacy concerns particularly affecting personal GPS data collection. Consequently, processing these multi-modal, complex, and often imperfect datasets presents a significant challenge for ITS.

In the past few decades, researchers have employed various approaches to address the challenges of ITS. For example, Recurrent Neural Networks (RNNs) are often used to model temporal relationships, while Convolutional neural networks (CNNs) are commonly utilized to capture spatial structure [2]. And graph-based approaches have demonstrated superior capabilities in extracting spatial correlations within traffic networks [3], [4]. However, these approaches often exhibit limitations when handling noisy or incomplete data. In contrast, generative models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have proven effective for traffic data generation and imputation tasks [5], [6]. However, GANs suffer from unstable training, and VAE has the limitation of low-quality output. Diffusion models, as a powerful class of generative models, offer advantages such as ease of training, enhanced generative performance, controllable generation, and multi-modal capabilities. To date, diffusion models have been applied across a wide range of vision tasks [7], with promising applications such as Sora [8]. Inspired by these developments, an increasing number of researchers in the ITS domain have begun to adopt diffusion models to address various challenges in ITS. Therefore, originating in image processing and computer vision, diffusion models are now being applied across various traffic tasks, from autonomous driving and traffic simulation to traffic forecasting and traffic safety. As illustrated in Fig. 1, diffusion models are suitable for processing various traffic data, and are capable of addressing a wide range of various traffic tasks based on task-specific conditions or unconditional methods.

There have been numerous surveys on ITS [2], [9], as well as specific technologies within the ITS domain [3], [4],

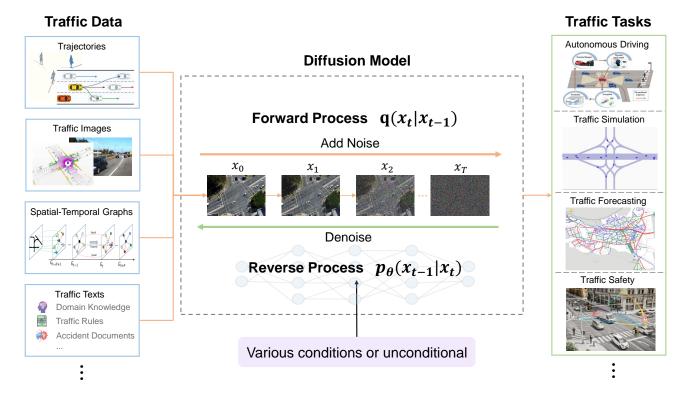


Fig. 1: Overview of applying diffusion models to traffic tasks using various traffic data types, including trajectories, traffic images, spatial-temporal graphs, and traffic-related texts.

[10]. Similarly, several reviews have focused on diffusion models [11], [12], [13] and their applications in areas such as computer vision [7] and medical imaging [14]. However, there is currently no comprehensive review of diffusion models within the ITS domain.

To address this gap, this paper presents a detailed literature review on diffusion models in ITS. First, we outline how diffusion models have emerged as powerful tools for various traffic tasks. Specifically, we introduce the theoretical foundations of diffusion models, along with conditional diffusion models and latent diffusion models, which extend their applicability to more specific tasks within ITS. Second, we examine the key challenges in ITS and the corresponding advantages of diffusion models. Third, we investigate the applications of diffusion models in areas such as autonomous driving, traffic simulation, traffic forecasting, and traffic safety within ITS, as shown in Fig. 6. In particular, we review these applications based on criteria such as task, denoising condition, or model architecture, as illustrated in Table. I. Finally, we provide an outlook on potential future directions for diffusion models in ITS. Our goal is to bridge the gap between the diffusion model and transportation research communities, fostering interdisciplinary collaboration and advancing the application of diffusion models in transportation.

In summary, the main contributions of this paper include:

- To the best of our knowledge, this is the first comprehensive literature review focused on the application of diffusion models in ITS.
- We systematically introduce how diffusion models have

become powerful approaches for various traffic tasks by processing multi-modal and complex traffic data. Additionally, we explore the key challenges in ITS and the corresponding advantages of diffusion models. This analysis offers readers deeper insights into the intersection of ITS and diffusion models.

- We present a comprehensive and up-to-date literature review of diffusion models in the ITS domain, focusing on applications in autonomous driving, traffic simulation, traffic forecasting, and traffic safety. By analyzing these applications through multiple perspectives, we aim to offer researchers from various ITS subfields a clear and efficient overview of the latest advancements in diffusion models.
- We discuss the cutting-edge techniques in diffusion models, and highlight key research directions for diffusion models in ITS that are worthy of further exploration.

The remainder of the paper is organized as follows: Sec. II presents theoretical foundations of diffusion models and their key variants. Sec. III outline the key challenges in ITS and the corresponding advantages of diffusion models. Sec. IV-Sec. VII explores the diverse applications of diffusion models within ITS, including autonomous driving, traffic simulation, traffic forecasting, and traffic safety. Sec. VIII discusses several promising directions for future research. Finally, the conclusions are drawn in Sec. IX.

Diffusion models have emerged as transformative tools in the field of ITS. This section outlines how diffusion models have become powerful and flexible methods for addressing various traffic-related challenges. First, we explore the theoretical foundations of diffusion models, which lies in their ability to learn the underlying data distribution through a process of noise injection and subsequent denoising. This makes them highly effective for modeling complex traffic dynamics. Next, we introduce key variants of diffusion models, particularly conditional diffusion models and latent diffusion models, which extend their applicability to more specific and challenging tasks within ITS. By incorporating domain-specific conditions and leveraging latent spaces, diffusion models can be applied to multi-modal traffic data, offering solutions to a wide range of traffic-related tasks.

A. Foundations of Diffusion Models

Diffusion models are a powerful class of probabilistic generative models that gradually perturb data by adding Guassian noise to data, and then learn to reverse this process to generate new data. During training, the model learns to denoise the data at each step, effectively transforming random noise into coherent and realistic outputs.

This section provides an overview of three predominant formulations in diffusion models: Denoising Diffusion Probabilistic Models (DDPMs), which utilize discrete steps to incrementally add and remove noise; Noise Conditioned Score Networks (NCSNs), which estimate the gradient of the log-density of the data distribution to guide sample generation; and Stochastic Differential Equations (SDEs), which offer a continuous-time perspective that unifies and generalizes both DDPMs and NCSNs under a common mathematical framework.

1) Denoising Diffusion Probabilistic Models (DDPMs):

DDPMs [15], [16] utilize two Markov chains: a forward (diffusion) process that gradually adds Gaussian noise to data, transforming it into pure noise over multiple steps, and a reverse (denoising) process, learned through neural networks—typically based on a U-Net architecture [17]—that progressively removes the noise to reconstruct the original data.

Forward (Diffusion) Process. The forward (diffusion) process incrementally corrupts the data by adding Gaussian noise in a series of T steps. Given a data distribution $x_0 \sim q(x_0)$, the forward process starts with the original data x_0 and generates a sequence of latent variables x_1, x_2, \ldots, x_T through different diffusion steps. The process is defined by a Markov chain where each state x_t depends only on the previous state x_{t-1} :

$$q(x_t|x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t \mathbf{I}), \forall t \in \{1, \dots, T\}$$
(1)

where $\beta_t \in (0,1)$ is a hyperparameter representing the noise variance schedule that controls the amount of noise added at each step. I denotes the identity matrix, and $\mathcal{N}(x; \mu, \sigma)$

represents a normal distribution with mean μ and covariance σ .

The entire forward process can be expressed directly in terms of the original data x_0 using the reparameterization trick:

$$x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, \quad \epsilon \sim \mathcal{N}(0, \mathbf{I})$$
 (2)

3

where $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{s=1}^t \alpha_s$.

Reverse (Denoising) Process. The goal of DDPMs is to learn the reverse of this diffusion process, where the model starts with Gaussian noise and progressively removes the noise to generate new data. The reverse process is also modeled as a Markov chain, but it is parameterized by a neural network $p_{\theta}(x_{t-1}|x_t)$ that generates $p_{\theta}(x_0)$ in a step-by-step manner:

$$p_{\theta}(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \mu_{\theta}(x_t, t), \sigma^2 \mathbf{I})$$
(3)

In the DDPM [16], the covariance σ^2 is fixed to a constant value, and the mean $\mu_{\theta}(x_t, t)$ is reformulated as:

$$\mu_{\theta}(x_t, t) = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{\beta_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_{\theta}(x_t, t) \right) \tag{4}$$

where $\epsilon_{\theta}(x_t, t)$ represents the neural network's prediction of the noise component at step t.

The objective of training a DDPM is to minimize the variational bound on the negative log-likelihood, which can be simplified to a mean squared error loss between the predicted noise and the actual noise [16]:

$$\mathcal{L}(\theta) = \mathbb{E}_{t,x_0,\epsilon} \left[\|\epsilon - \epsilon_{\theta}(x_t, t)\|^2 \right]$$
 (5)

where $\epsilon \sim \mathcal{N}(0, \mathbf{I})$ is the Gaussian noise, and x_t is the noisy data generated during the forward process.

2) Noise Conditioned Score Networks (NCSNs):

NCSNs [18] are a class of score-based generative models that focus on estimating the score function of the data distribution. Instead of explicitly modeling the reverse diffusion process, NCSNs learn the gradient of the log-density of the data distribution at various noise levels via score matching [19], and subsequently generate samples via Langevin dynamics [20], [21].

Score Matching. Given an unknown data distribution $p_{data}(x)$, the score function of the data density $p_(x)$ is defined as $\nabla_x \log p(x)$. The score network \mathbf{s}_θ , a neural network parameterized by θ , is trained to estimate the score function $\nabla_x \log p(x)$. When the data distribution is unknown, score estimation can be performed using sliced score matching [22] or denoising score matching [23]. In NCSNs [18], denoising score matching is adopted, wherein data are perturbed with multiple levels of Gaussian noise. Specifically, the noise distribution is pre-specified as $q_\sigma(\tilde{x}|x) = \mathcal{N}(\tilde{x}|x,\sigma^2\mathbf{I})$, and the gradient of the log-likelihood with respect to the noisy data is given by $\nabla_{\tilde{x}} \log q_\sigma(\tilde{x}|x) = -(\tilde{x}-x)/\sigma^2$. Given a sequence noise scales $\sigma_1 < \sigma_2 < ... < \sigma_L$, the denoising score matching objective for all $\sigma \in \{\sigma_i\}_{i=1}^L$ is defined as:

$$\mathcal{L} = \frac{1}{L} \sum_{i=1}^{L} \lambda(\sigma_i) \mathbb{E}_{p(x)} \mathbb{E}_{\tilde{x} \sim q_{\sigma_i}(\tilde{x}|x)} \left[\left\| \mathbf{s}_{\theta}(\tilde{x}, \sigma_i) + \frac{\tilde{x} - x}{\sigma_i^2} \right\|_2^2 \right]$$
(6)

where \tilde{x} is a noised version of x, and $\lambda(\sigma_i)$ is a weighting function depending on σ_i .

Langevin Dynamics. To generate samples, NCSNs employ annealed Langevin dynamics, starting with large noise levels and gradually annealing down to lower noise levels. At each noise level, Langevin dynamics is iteratively applied using the learned score function to recover the original data distribution progressively. The update rule for Langevin dynamics is given by:

$$\tilde{x}_t = \tilde{x}_{t-1} + \frac{\alpha_i}{2} \mathbf{s}_{\theta}(\tilde{x}_{t-1}, \sigma_i) + \sqrt{\alpha_i} \mathcal{N}(0, \mathbf{I})$$
 (7)

where $\alpha_i = \epsilon \cdot \sigma_i^2/\sigma_L^2$, and $t \in [1,T]$. When $\alpha_i \to 0$ and $T \to \infty$, the final generated sample converges to the original data distribution $p_{data}(x)$.

3) Stochastic Differential Equations (SDEs):

SDEs [24] provide a continuous-time framework that unifies the concepts of DDPMs and NCSNs. Specifically, both the forward and reverse processes in these models are formulated as solutions to stochastic differential equations, with the reverse process requiring the estimation of score functions for noisy data distributions.

Forward Process. In the SDEs [24], the forward process can be represented as the solution to an Itô SDE [25]:

$$dx = \mathbf{f}(x,t)dt + g(t)d\mathbf{w}$$
 (8)

where $\mathbf{f}(\cdot,t)$ denotes the drift coefficient of x(t), $g(\cdot)$ represents the diffusion coefficient of x(t), and \mathbf{w} is a Brownian motion.

The forward processes in DDPMs and NCSNs can be regarded as discretizations of two different SDEs [24]. For DDPMs, the corresponding SDE is:

$$dx = -\frac{1}{2}\beta(t)xdt + \sqrt{\beta t}d\mathbf{w}$$
 (9)

whereas for NCSNs, the corresponding SDE is expressed as:

$$dx = \sqrt{\frac{d[\sigma^2(t)]}{dt}} d\mathbf{w}$$
 (10)

Reverse Process. To generate samples, starting from samples of the standard Gaussian distribution x(T) and reversing the process, the reverse-time SDE is solved [26]:

$$dx = [\mathbf{f}(x,t) - g(t)^2 \nabla_x \log p_t(x)] dt + g(t) d\bar{\mathbf{w}}$$
 (11)

where $\bar{\mathbf{w}}$ is a Brownian motion with time flows backwards from T to 0, and dt is an infinitesimal negative timestep.

Similar to NCSNs, to estimate the score function $\nabla_x \log p_t(x)$, we train a time-dependent score model $\mathbf{s}_{\theta}(x_t,t)$ by generalizing the score matching objective to continuous time. The objective function is given by:

$$\mathcal{L} = \mathbb{E}_{t} \left\{ \lambda(t) \mathbb{E}_{x(0)} \mathbb{E}_{x(t)|x(0)} \left[\left\| \mathbf{s}_{\theta}(x(t), t) - \nabla_{x(t)} \log p(x(t) \, | \, x(0)) \right\|_{2}^{2} \right] \right\}$$
(12)

where t is uniformly sampled over the interval [0,T], and $\lambda(t)$ is a positive weighting function.

B. Variants of Diffusion Models

In this section, we introduce key variants of diffusion models, including conditional diffusion models and latent diffusion models (LDMs), which have significantly advanced the field of intelligent transportation systems. These models not only enhance the ability to generate realistic traffic data but also offer flexibility and controllability in modeling complex traffic environments. By incorporating domainspecific information, such as historical data, traffic layouts, or external semantic features, conditional diffusion models enable the generation of more accurate and diverse traffic scenarios that reflect real-world conditions. Meanwhile, LDMs operate in a lower-dimensional latent space, facilitating faster training and inference times while maintaining the fidelity of generated outputs. Additionally, LDMs allows multi-modal conditions within the latent space. These capabilities make LDMs particularly useful for image-based, video-based, or text-involved traffic tasks. Collectively, these advanced models demonstrate the potential of diffusion models to revolutionize intelligent transportation systems, providing powerful tools for traffic simulating, forecasting, and optimization in increasingly dynamic urban environments.

1) Conditional Diffusion Models:

The three types of standard diffusion models introduced above are unconditional, where the inputs are limited to the perturbed data x_t and the diffusion step t. Conditional diffusion models, on the other hand, incorporate conditional information as an extra input, allowing for control over the generation process according to specific requirements. This capability makes them highly adaptable for various applications in intelligent transportation systems. Below, we focus on four primary conditioning mechanisms: concatenation-based, crossattention-based, classifier-based, and classifier-free-based approaches. Concatenation-based methods are simple to implement but may struggle to capture complex relationships between the data and conditions. Cross-attention-based methods excel at modeling long-range dependencies and complex interactions, and enable multi-modal conditioning, but they do not offer control over the strength of the conditions. Classifierbased approaches provide adjustable guidance through external classifiers but can be limited by the accuracy and generalization capability of the classifier. Classifier-free-based methods are flexible and do not require additional classifiers, but they often come with increased training costs. The visualization of these four conditioning mechanisms is shown in Fig. 2.

Concatenation-based. In concatenation-based mechanisms, the conditioning information is directly concatenated with the perturbed data x_t or the diffusion step t, and then fed into the model for sample generation. This method is simple and effective, allowing the model to leverage the conditioning information throughout the denoising process. For example, in the field of intelligent transportation systems, conditioning on historical data [27], [28], [29] or map feature [30] has been employed for generating traffic trajectories. Similarly, image features [31], [32] or traffic layout [33] have been directly concatenated with the noise data vector for generating traffic scenarios. Additionally, conditioning on trip regions [34], road

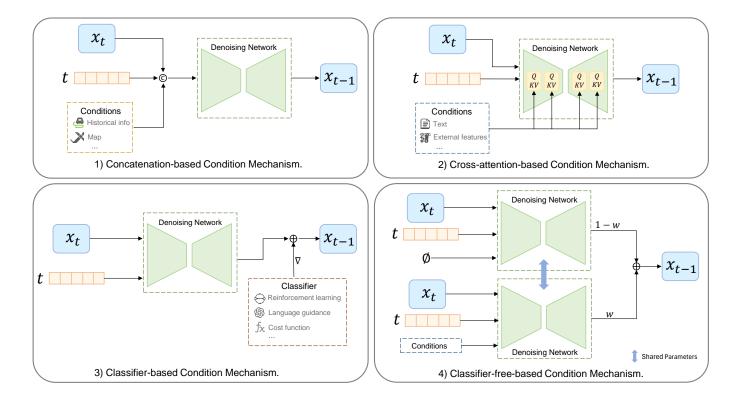


Fig. 2: Different condition mechanisms for diffusion models. (1) Concatenation-based mechanism incorporates conditions such as historical data and maps directly into the input. (2) Cross-attention-based mechanism integrates conditions like text and external features through cross-attention layers. (3) Classifier-based mechanism uses an external classifier to guide denoising based on conditions such as reinforcement learning or cost functions. (4) Classifier-free mechanism combines conditional and unconditional denoising models, balancing both with a weight parameter.

network [35], or graph structure [36] has been applied in traffic flow generation. These examples emphasize the effectiveness of concatenation-based mechanisms in diverse transportation applications.

Cross-attention-based. Cross-attention-based conditional diffusion models integrate the cross-attention layers [37] into the denoising networks, enabling effective fusion of conditioning information during the denoising process and guiding the network to generate outputs aligned with the conditions. The cross-attention mechanism plays an important role in facilitating the interaction between the conditioning information and the noisy data, especially in scenarios where their relationship is complex or involves different modalities, such as text and images. Stable Diffusion [38] introduced a general-purpose conditioning mechanism based on cross-attention, enabling multi-modal conditional inputs, making diffusion models into powerful and flexible generators. Building on this foundational work, numerous studies have applied this cross-attention-based conditioning mechanism in the field of intelligent transportation systems. For example, conditioning on text [39], [40], [32], [33], [41], [42], drive actions [30], external features and semantic features [43], origin-destination-departure time (ODT) feature [44], or bounding boxes [42] has been used for various traffic-related tasks.

Classifier-based. The classifier-based mechanism incorporates conditions by using a task-related classifier to guide the

diffusion sampling process, enabling controllable generation. Dhariwal and Nicho [45] proposed a classifier-guidance approach, where an additional classifier $p_{\phi}(y|x_t,t)$ is trained on noisy data x_t and the diffusion step t. The gradients of the guidance $\nabla_{x_t} \log p_{\phi}(y|x_t,t)$ are then used to guide the diffusion sampling process towards a specified class label y. Given a pre-trained diffusion model $p_{\theta}(x_t,t)$ and a pre-trained classifier $p_{\phi}(y|x_t,t)$, the diffusion sampling process is as follows:

$$x_{t-1} = \mathcal{N}(\mu_{\theta}(x_t, t) + w\nabla_{x_t} \log p_{\phi}(y|x_t, t), \sigma^2 \mathbf{I})$$
 (13)

where w is a hyperparameter controlling the strength of the guidance; as w increases, the generated samples more closely adhere to the specified conditions.

Following this work, many studies related to traffic trajectory generation and motion planning have designed various classifiers to controllably generate traffic scenarios that comply with traffic rules and ensure trajectory smoothness. For example, the cumulative rewards learned through reinforcement learning [46], motion planning cost function [47], STL formulas based on traffic rules [48], language-based loss function [49], and driving behavior classes [50] have been designed as classifier to generate task-conditioned samples.

Classifier-free-based. The classifier-free mechanism combines unconditional and conditional diffusion models, achieving a balance between fidelity and diversity without the need

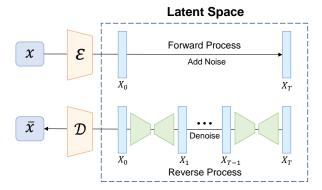


Fig. 3: Illustration of latent diffusion models. Compared to standard diffusion models, they incorporate a pre-trained encoder \mathcal{E} and decoder \mathcal{D} , with the diffusion and denoising processes operating in latent space rather than pixel or data space.

to train a separate classifier. Additionally, it should be noted that the conditional diffusion model can employ either a concatenation mechanism or a cross-attention mechanism. In classifier-free diffusion guidance [51], the authors jointly train a conditional and an unconditional diffusion model, setting the condition \mathbf{c} to \varnothing for the unconditional model. Then, a weighted average of the conditional and unconditional scores is used to estimate the score function:

$$\tilde{\epsilon}_t = w \, \epsilon_{\theta}(x_t, t, \mathbf{c}) + (1 - w) \, \epsilon_{\theta}(x_t, t, \varnothing)$$
 (14)

where w is also a guidance scale.

For many traffic-related generation tasks, researchers have employed the classifier-free guidance mechanism to regulate the diversity of the generated outputs [52], [50], [53], [54], [55], [34]. This approach prevents the outputs from following the conditional guidance too closely or being constrained too tightly.

2) Latent Diffusion Models:

The latent diffusion models (LDMs) [38] incorporate pretrained perceptual compression models, VQGAN [56], which consist of an encoder \mathcal{E} and a decoder \mathcal{D} , as illustrated in the Fig. 3. This approach enables diffusion models to leverage a lower-dimensional latent space, thereby reducing the computational burden during training and speeding up inference while maintaining high fidelity in generated outputs. Following this work, Blattmann et al. [57] extended LDM to the video latent diffusion model (VLDM) by introducing temporal layers and finetuning the autoencoder of pre-trained LDM using video data.

LDMs have gained attention in intelligent transportation systems due to their ability to model complex traffic patterns and generate realistic traffic scenarios. This approach has proven particularly useful in simulating traffic flows [41], predicting vehicle trajectories [28], [58], [59], [30], and enhancing autonomous driving systems through the generation of diverse and realistic traffic scenario data [60], [61], [62], [32], [63], [64].



Fig. 4: The challenges in intelligent transportation systems.

III. CHALLENGES AND TECHNIQUES

This section discusses key challenges in ITS and highlights why diffusion models, as a state-of-the-art generative approach, offer innovative solutions to these challenges. The complexity of traffic systems, combined with the inherent uncertainty and variability in traffic data, presents significant challenges for the development of robust models. These challenges are further compounded by issues such as poor data quality, privacy concerns, and the need for scalable solutions that generalize effectively across different regions and traffic conditions. While various techniques have been developed to address these challenges, diffusion models have emerged as a promising approach due to their advantages: high-fidelity generation, controllable generation, strong flexibility, probabilistic modeling, and multi-modal capabilities. These strengths enhance the accuracy and robustness of ITS models, improving their applicability across diverse scenarios within the ITS field. As illustrated in Fig. 4 and Fig. 5, the key challenges in ITS and the corresponding advantages of diffusion models are highlighted.

A. Challenges in Intelligent Transportation Systems

ITS is a sophisticated system that integrates advanced technologies and data analytics into transportation infrastructure and management to enhance the efficiency and safety of transportation networks [2], [9]. ITS encompasses a broad range of applications, including traffic prediction, autonomous driving, traffic simulation, and so on, all aimed at improving transportation services by using large-scale traffic data and automated systems. However, several challenges affect the effectiveness and implementation of ITS:

- Absence of Quality Data. High-quality data are crucial
 for training reliable models, particularly in supervised
 learning approaches. However, real-world traffic data
 collected from traffic sensors, vehicle sensors, or GPS
 devices are often noisy, incomplete, or insufficient, limiting the ability to accurately predict and simulate traffic
 conditions.
- Privacy Issues. The collection of real-world traffic data from various sources, such as vehicle sensors, GPS devices, and surveillance cameras, raises significant privacy concerns. In particular, obtaining GPS data for traffic flow-related tasks is often challenging due to the need to protect personal and location information.



Fig. 5: The advantages of diffusion models.

- Lack of Rare Events. Rare but critical events, such as accidents, sudden weather changes, or unexpected road blockages, are difficult to model due to their infrequency. This scarcity of data on such events makes it challenging to develop systems that can effectively handle and respond to these situations.
- Difficult to Model Complex Traffic Dynamics. Traffic systems are inherently complex, involving spatial and temporal dynamics at various scales, along with various external factors such as holidays, weathers conditions, and local events. Accurately modeling these dynamics and capturing the intricate relationships between different elements in the transportation network remains a challenge.
- Weak Scalability and Generalization. Many ITS solutions struggle to scale effectively or generalize across different regions and traffic conditions. Solutions that work well in one location may not perform as effectively in another due to variations in traffic patterns, and other local factors.
- Lack of User-friendly Interaction. Many current ITS interfaces and tools are difficult for users to navigate and use effectively. Improving user-friendly interaction is essential to ensure that users can easily understand and utilize the benefits of ITS technologies.

B. Advantages of Diffusion Models

In ITS, various deep learning methods have been employed to address key challenges in various traffic tasks. For example, RNNs [65], [66] have proven effective in modeling temporal relationships in traffic data, and Transformers [37] are widely employed for multi-timestep traffic forecasting. Additionally, graph-based techniques such as Graph Neural Networks (GNNs) [67] and Graph Convolutional Networks (GCNs) [68] have emerged as powerful tools for modeling traffic as graph structures, effectively capturing spatial interactions in transportation networks. However, these approaches often require large amounts of labeled data and tend to perform poorly with noise or incomplete data.

In contrast, generative models serve as flexible frameworks that can not only incorporate architectures such as CNNs, RNNs, and GNNs, enhancing their representational capacity, but are also effective at traffic data generation and imputation. However, generative models such as GANs [69], [70] often suffer from issues like mode collapse and unstable training, while another type of generative models, VAEs [71], [72], frequently produces lower-quality outputs and exhibits limited expressiveness in their latent spaces.

Recently, diffusion models have emerged as a promising class of generative models, offering several unique advantages that make them particularly well-suited for ITS applications:

- **High-fidelity Generation.** Diffusion models have demonstrated the ability to generate high-quality and diverse outputs in traffic-related tasks. Compared to GANs and VAEs, diffusion models exhibit greater ease of training and superior generative capabilities. [45].
- Controllable Generation. By incorporating task-related conditions, such as traffic layout, external factors, or taskrequirements text, conditional diffusion models enable controllable outputs. This capability is particularly useful for a wide range of traffic-related applications, such as generating accident data for safety-critical testing or training accident detection models.
- Strong Flexibility. Diffusion models can be flexibly combined with other methods, including GNNs, reinforcement learning, and even other generative models such as GANs and VAEs. This adaptability allows them to handle complex spatial-temporal dependency in traffic data, improve overall model performance, or improve sampling efficiency.
- Probabilistic Modeling. The inherent probabilistic nature
 of diffusion models provides a robust framework for
 handling uncertainties and variations in traffic data, which
 is essential for predicting real-world, variable traffic situations.
- Multi-modal Capabilities. Traffic data is inherently
 multi-modal, including trajectories, images, spatialtemporal graphs, and textual information. LDMs enable
 multi-modal input training, making them highly suitable
 for various traffic tasks. Moreover, LDMs conditioned on
 user-specific text can provide a user-friendly, languagebased interface.

In the following sections, we will explore specific applications of diffusion models in the field of intelligent transportation systems, including autonomous driving, traffic simulation, traffic forecasting, and traffic safety. These applications will demonstrate how the advantages of diffusion models support their practical implementation in real-world traffic scenarios.

IV. DIFFUSION MODELS FOR AUTONOMOUS DRIVING

Autonomous driving represents one of the most transformative aspects of ITS. The integration of autonomous vehicles (AVs) into ITS can drastically reduce traffic congestion, enhance safety, and improve the overall efficiency of transportation networks. However, achieving full autonomy in driving poses significant challenges due to the complex and

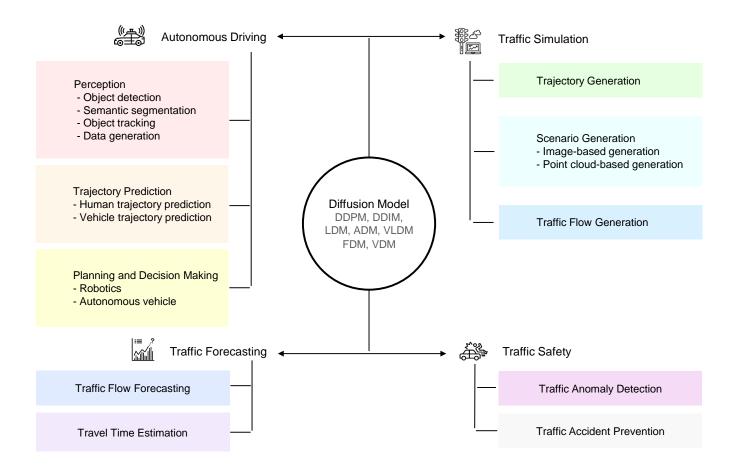


Fig. 6: Overview of the application of diffusion models in various domains of intelligent transportation systems.

dynamic nature of real-world driving environments, which are characterized by unpredictable events, diverse road conditions, and varying traffic behaviors [130], [131], [132]. Addressing these challenges requires advanced models capable of handling uncertainty, learning from vast amounts of data, and making real-time decisions in a safe and reliable manner. Diffusion models, with their ability to model complex distributions, refine data, and generate high-quality predictions, play a crucial role in advancing the capabilities of autonomous driving. However, their computational inefficiency poses challenges. Thus, many research works focus on accelerating these models to meet real-time requirements.

This section explores the application of diffusion models to various aspects of autonomous driving, including perception, trajectory prediction, and planning. By leveraging the strengths of diffusion models, researchers aim to improve the overall performance and safety of AVs, making them more adept at navigating the complexities of modern roadways.

A. Perception

Perception in autonomous driving systems refers to the technologies that enable self-driving vehicles to sense and understand their environment [133]. However, sensor data are often affected by intemperate weather, light conditions, and

other factors, which introduce noises and pose challenges for perception [134]. With the rapid development of diffusion models in the field of computer vision [7], [38], [135], many researchers are now focusing on their applications in autonomous driving perception. The increasing interest in diffusion models is attributed to their ability to enhance the clarity and quality of sensor data under diverse conditions [83], [136], [137], as well as their proficiency in modeling uncertainty in perception [138], [31]. By leveraging these strengths, researchers aim to enhance perception tasks such as object detection, semantic segmentation, and object tracking, thereby contributing to safer and more reliable autonomous vehicles. In the following part, we present a review of the current advancements in the application of diffusion models for these perception tasks.

1) Object Detection:

Object detection involves locating and sizing objects within an image[134]. Specifically, it entails determining the presence of objects and their positions by drawing bounding boxes around them. Recent advancements have introduced diffusion models to enhance detection accuracy. For example, Chen et al. [79] first redefined 2D object detection as a denoising diffusion process conditioned on the corresponding image, transforming noisy bounding boxes into precise object boxes. Notably, their model demonstrates superior flexibility, enabling

TABLE I: Applications of diffusion models in intelligent transportation systems. To classify existing models, three key criteria are considered: the task, the denoising condition, and the architecture. Additionally, the datasets and open source are provided. The following abbreviations are used to denote the architectures: DDPM (Denoising Diffusion Probabilistic Model) [16], DDIM (Denoising Diffusion Implicit Model) [73], ADM (Ablated Diffusion Model) [45], LDM (Latent Diffusion Model) [38], LED (LEapfrog Diffusion Model) [74], VLDM (Video Latent Diffusion Model) [57], EDM (Elucidating Diffusion Model) [75], FDM (Flexible Diffusion Model) [76], D3PM (Discrete Denoising Diffusion Probabilistic Model) [77], CARD (Classification and Regression Diffusion Model) [78].

Paper	Task	Denoising Condition	Architecture	Datasets	Year	Open Source
DiffusionDet [79]	2D object detection	conditioned on image feature	DDIM	CrowdHuman [80] COCO [81]	2023 ICCV	DiffusionDet
DetDiffusion [82]	2D object detection	conditioned on perception- aware attributes	LDM	COCO [81]	2024 CVPR	
DiffBEV [83]	BEV semantic segmentation 3D object detection	conditioned on BEV feature	DDPM	nuScenes [84]	2024 AAAI	DiffBEV
DDP [31]	BEV map segmentation semantic segmentation depth estimation	conditioned on image feature	DDIM	ADE20K [85] NYU-DepthV2 [86] KITTI [87] et al.	2023 ICCV	DDP
VPD [88]	semantic segmentation image segmentation depth estimation	conditioned on text	LDM	ADE20K [85] RefCOCO [89] NYU-DepthV2 [86]	2023 ICCV	VPD
Chen et al. [90]	multi-object tracking	conditioned on text	LDM	MOT20 [91] et al.	2024 CVPR	LtD-MOT
Luo et al. [92]	multi-object tracking	conditioned on two adjacent raw images	DDPM	MOT20 [91] et al.	2024 AAAI	DiffusionTrack
Xie et al. [93]	object tracking	unconditional	DDIM	GOT-10k [94] LaSOT [95]	2024 CVPR	DiffusionTrack
Luo et al. [96]	3D point cloud generation	conditioned on shape latent [97]	DDPM	ShapeNet	2021 CVPR	DPC
DiffuMask [39]	semantic segmentation perception data augmentation	conditioned on text	LDM	VOC [98] ADE20K [85] Cityscapes [99]	2023 ICCV	DiffuMask
DatasetDM [40]	perception data augmentation	conditioned on text	LDM	COCO [81] et al.	2023 NIPS	DatasetDM
MID [27]	human trajectory prediction	conditioned on observed tra- jectories	DDPM	SDD [100] ETH [101] UCY [102]	2022 CVPR	MID
LED [74]	human trajectory prediction speed up	conditioned on observed tra- jectories	LED	SDD [100] et al.	2023 CVPR	LED
SingularTrajectory [103]	human trajectory prediction speed up	conditioned on observed scene	DDIM	ETH [101] et al.	2024 CVPR	SingularTrajectory
IDM [104]	human trajectory prediction speed up	conditioned on observed tra- jectories conditioned on endpoint	DDPM	SDD [100] et al.	2024 arxiv	
LADM [105]	human trajectory prediction speed up	conditioned on coarse future trajectory	VAE DDPM	ETH [101] et al.	2024 TIM	
BCDiff [106]	human trajectory prediction instantaneous trajectory pre- diction	conditioned on gate	DDPM	SDD [100] et al.	2024 NIPS	
MotionDiffuser [28]	multi-agent prediction	conditioned on observed scene , constraints classifier guidance	LDM	WOMD [107]	2023 CVPR	
SceneDiffusion [58]	multi-agent prediction	conditioned on observed scene, interval time unconditional	LDM	Argoverse [108]	2023 ITSC	
Equidiff [29]	vehicle trajectory prediction	conditioned on observed tra- jectories, interactions	DDPM	NGSIM [109]	2023 ITSC	
Yao et al. [110]	vehicle trajectory prediction	conditioned on observed tra- jectories, map	DDPM	Argoverse2 [111]	2023 CSIS-IAC	
Diffuser [46]	behavior planning	unconditional classifier guidance	ADM	D4RL [112]	2022 ICML	diffuser
Decision Diffuser [52]	decision making behavior planning	conditioned on rewards, constraints, skills classifier-free guidance	ADM	D4RL [112]	2023 ICLR	

MPD [47]	motion planning	unconditional classifier guidance	DDPM	PointMass2D	2023 IROS	mpd
Diffusion-ES [113]	motion planning	unconditional	truncated DDPM	nuPlan [114]	2024 CVPR	diffusion-es
Drive-WM [60]	motion planning multiview video generation	conditioned on adjacent views	VLDM	nuScenes [84]	2024 CVPR	Drive-WM
GenAD [61]	motion planning multiview video generation	conditioned on past frame, text	VLDM	WOMD [107] et al.	2024 CVPR	DriveAGI
CTG [48]	vehicle trajectory generation	conditioned on observed scene STL-based guidance	ADM	nuScenes [84]	2023 ICRA	CTG
CTG++ [49]	multi-agent trajectory generation	conditioned on observed scene language-based guidance	ADM	nuScenes [84]	2023 CoRL	CTG++
Dragtraffic [59]	multi-agent trajectory generation	conditioned on initial scene, text	LED	WOMD [107]	2024 IROS	Dragtraffic
DJINN [50]	multi-agent trajectory generation	conditioned on arbitrary state classifier-free guidance behavior classes guidance	EDM	Argoverse [108] INTERACTION [115]	2024 NIPS	
Pronovost et al. [30]	multi-agent trajectory generation	conditioned on map, tokens	EDM LDM	Argoverse2 [111]	2023 NIPS	
Rempe et al. [53]	human trajectory generation	conditioned on observed scene classifier-free guidance	ADM	ETH [101] et al. nuScenes [84]	2023 CVPR	trace pacer
FDM [76]	image-based driving scenario generation	conditioned on previously sampled frames	FDM	Carla [116]	2022 NIPS	
GAIA-1 [54]	image-based driving scenario generation	conditioned on past image, text, action tokens classifier-free guidance	VDM FDM	real-world dataset	2023 arxiv	
DriveDreamer [62]	image-based driving scenario generation	conditioned on image, road structure, text	LDM VLDM	nuScenes	2023 arxiv	DriveDreamer
DriveDreamer-2 [117]	image-based driving scenario generation	conditioned on structured info by LLMs, text	EDM	nuScenes [84]	2024 arxiv	DriveDreamer2
Panacea [32]	image-based driving scenario generation	conditioned on image, text, BEV sequence	LDM DDIM	nuScenes [84]	2024 CVPR	panacea
DrivingDiffusion [33]	image-based driving scenario generation	conditioned on key-frame, optical flow prior, text, 3D layout	VDM LDM	nuScenes [84]	2023 arxiv	DrivingDiffusion
WoVoGen [63]	image-based driving scenario generation	conditioned on past world volumes, actions, text, 2D image feature	LDM	nuScenes [84]	2023 arxiv	WoVoGen
LiDMs [64]	point cloud-based driving sce- nario generation	unconditional conditioned on arbitrary data	LDM	nuScenes [84] KITTI-360 [118]	2024 CVPR	LiDAR-Diffusion
Copilot4D [55]	point cloud-based driving sce- nario generation	conditioned on past observa- tions, actions classifier-free guidance	D3PM ADM	nuScenes [84] et al.	2024 ICLR	
KSTDiff [119]	traffic flow generation	conditioned on urban knowledge graph, region feature, volume estimator	CARD	real-world dataset	2023 SIGSPA- TIAL	KSTDiff
DiffTraj [34]	GPS trajectory generation	conditioned on trip region, departure time et al. classifier-free guidance	DDIM, ADM	real-world dataset	2023 NIPS	DiffTraj
Diff-RNTraj [35]	GPS trajectory generation	conditioned on road network	DDPM	real-world dataset	2024 arxiv	
ChatTraffic [41]	traffic flow generation	conditioned on text	LDM		2024 arxiv	ChatTraffic
Rong et al. [120]	origin-destination flow generation	conditioned on node feature, edge feature	DDPM, ADM	real-world dataset	2023 arxiv	
DiffSTG [36]	traffic flow forecasting	Conditioned on past graph signals, graph structure	DDIM	PEMS [121] et al.	2023 GIS	DiffSTG
SpecSTG [122]	traffic flow forecasting traffic speed forecasting	conditioned on past graph sig- nals feature, adjacency matrix	DDPM	PEMS [121] et al.	2024 arxiv	SpecSTG
DiffUFlow [43]	traffic flow forecasting	conditioned on pass feature map, coarse-grained flow map, semantic features	DDPM	real-world dataset	2023 CIKM	

Xu et al. [123]	traffic flow forecasting	unconditional	DDPM	real-world dataset	2023 ICASSP	
ST-SSPD [124]	traffic flow forecasting	conditioned on past data points, temporal encoding, node identifier	DDPM	METR-LA [125] et al.	2023 MobiArch	
Difforecast [126]	traffic flow forecasting image generation	conditioned on past S-T image	DDPM	real-world dataset	2023 BigData	
Lin et al. [44]	origin-destination travel time estimation	conditioned on origin, destination, departure time	DDPM	real-world dataset	2023 MOD	_
DiffTAD [127]	trajectory anomaly detection	unconditional	DDIM	NGSIM [109]	2024 KBS	
VAD [128]	video anomaly detection	unconditional conditioned on original features	LDM, DDIM	CUHK Avenue [129] et al.	2023 ICCV	
AdVersa-SD [42]	accident video understanding accident preventing	conditioned on text, bounding boxes	LDM	MM-AU [42]	2024 CVPR	MM-AU

a dynamic number of boxes and iterative evaluation during inference. Additionally, Wang et al. [82] presented a pioneering framework that integrates diffusion models and perceptive models to enhance data generation quality and perception capabilities. The framework leverages perception-aware attributes as conditions and employs perception-aware loss as a form of supervision during the image generation process. This conditional approach enables the generation of images tailored to specific perceptual criteria, thereby improving the performance of downstream tasks such as object detection.

2) Semantic Segmentation:

Semantic segmentation involves classifying each pixel in an image into a predefined category [134]. Bird's Eye View (BEV) perception holds significant importance in the domain of autonomous driving perception, especially for semantic segmentation. Recent works have utilized the diffusion model to enhance BEV perception [83], [138], [136]. Notably, Zhou et al. [83] first applied conditional diffusion models to denoise and refine BEV features, addressing noise and distortions from camera parameters and LiDAR scans, significantly improving BEV semantic segmentation and 3D object detection. In detail, three BEV features serve as conditions for the diffusion model, enabling progressive denoising and enhancing fine-granularity details such as object boundaries and shapes.

Beyond BEV feature conditioning [83], image features [31] and text [88] have also been employed as conditions in semantic segmentation tasks. Ji et al. [31] introduced DDP, a noise-to-map method that progressively removes noise from a Gaussian distribution, guided by image features, to produce visual perception. DDP stands out for its dynamic inference capabilities, and natural awareness of the perception uncertainty. Additionally, DDP is easy to generalize to most dense visual perception tasks without needing task-specific designs. Motivated by the compelling generative semantic of a text-to-image diffusion model [38], Zhao et al. [88] proposed VPD, a framework utilizing pre-trained text-to-image diffusion models for visual perception tasks. By prompting the denoising decoder with textual inputs and refining text features with an adapter, VPD aligns visual content with text prompts and leverages cross-attention maps for guidance. This work suggests that pre-trained text-to-image diffusion models can efficiently adapt to downstream visual perception tasks, bridging generative models and visual perception.

3) Object Tracking:

Object tracking involves locating an object or multiple objects in a video, maintaining their identities, and tracking their trajectories over time [139]. Chen et al. [90] addressed the challenge of trajectory length imbalance in multiple object tracking (MOT) datasets by proposing Stationary and Dynamic Camera View Data Augmentation (SVA and DVA) and a Group Softmax module. Specifically, the DVA employs a conditional diffusion model to alter scene backgrounds, helping the network focus more on pedestrian features. This approach effectively alleviate the impact of long-tail distribution, enhancing tracking system effectiveness. Additionally, Luo et al. [92] proposed a noise-to-tracking framework, which formulates object detection and association jointly as a consistent denoising diffusion process from paired noise boxes to paired ground-truth boxes, enabling consistency between detection and tracking. In contrast, Xie et al. [93] introduced a novel noise-to-target tracking paradigm, employing a point set-based denoising diffusion process for dynamic and precise target localization, offering superior self-correction and appearance variation handling capabilities. This method also simplifies the post-processing, enabling real-time tracking capabilities.

4) Perception Data Generation:

Recent advancements [39], [40] have highlighted the efficacy of diffusion models in synthesizing images and their corresponding annotations. Specifically, Wu et al. [39] have concentrated on semantic segmentation, utilizing a text-guided pre-trained diffusion model to generate synthetic images with pixel-level semantic mask annotations. Building upon this work, Wu et al. [40] presented a dataset generation model that also leverages the knowledge learned by pre-trained diffusion models to produce diverse perception annotations. It emphasizes a unified perception decoder, which can be trained with minimal human-labeled data, to generate extensive high-fidelity images paired with various perception annotations including depth, segmentation, and human pose estimation.

3D point cloud data, another form of perception data, has also seen significant progress in generative modeling. Several studies have applied diffusion models for the generation of 3D point clouds. Luo et al. [96] introduced a novel generative model by treating 3D point cloud generation as a reverse diffusion process. The model conditions on a shape latent, and demonstrates flexibility and robustness in generating high-

quality, realistic 3D point clouds. Following this work, Sun et al. [140] addressed the vulnerability of 3D point cloud recognition models to adversarial attacks by leveraging the diffusion model designed in [96] as the base model for the adversarial point cloud purification.

B. Trajectory Prediction

Trajectory prediction in autonomous driving systems involves using past states of traffic participants in a given scene to forecast their future states [141]. The primary challenges include the uncertainty and multi-modality of future behavior, the complex interactions between traffic participants, and environmental influences like road geometry [141], [142]. In recent years, diffusion models have emerged as a promising approach for trajectory prediction due to their ability to capture the inherent uncertainty and multi-modality of human behavior and driving behavior. Additionally, diffusion models can flexibly integrate map information, constraints, and other relevant factors.

1) Human Trajectory Prediction:

To address the challenges of unstable training and unnatural trajectories in human trajectory prediction, Gu et al. [27] proposed Motion Indeterminacy Diffusion (MID). This method first leverages a diffusion model to transform trajectory prediction into a reverse diffusion process, achieving a balance between prediction diversity and determinacy by adjusting the length of a parameterized Markov chain. However, despite its promising performance, MID's 17-second runtime for 100 diffusion steps is impractical for real-time applications in autonomous driving systems. Following this pioneering work, many subsequent studies have focused on the application of diffusion models in trajectory prediction [74], [103], [104], [105], [143], [144]. Notably, to address the time-consuming problem, Mao et al. [74] introduced a trainable leapfrog initializer to bypass multiple denoising steps, enabling real-time prediction. Specifically, they employed a two-stage training strategy: the first stage trains a denoising module similar to MID [27], while the second stage optimizes the leapfrog initializer using the frozen denoising module. During inference, the leapfrog initializer allows denoising to start directly from the last few steps, significantly reducing computational time. Later, Bae et al. [103] proposed a unified model, Singular-Trajectory, introducing an adaptive anchor mechanism and leveraging a diffusion-based predictor to enhance prototype paths through a cascaded denoising process. Moreover, the adaptive anchor functions as a good initializer similar to [74], to speed up the denoising process. Additionally, Liu et al. [104] decoupled trajectory prediction uncertainty into intention uncertainty and action uncertainties through two diffusion processes. They also introduced a PriorNet module for estimating prior noise distribution, reducing diffusion steps and consequently cutting inference time by two-thirds. Another study is LADM [105], which integrates the VAEs with diffusion models. This combination enables the diffusion models to refine future trajectories generated by the VAE in a low-dimensional space, enhancing prediction accuracy and supporting real-time inference.

Instantaneous trajectory prediction presents another challenge in human trajectory prediction due to the need for accurate predictions based on very limited observational data [145]. Li et al. [106] addressed this challenge by utilizing bidirectional diffusion models to generate unobserved historical trajectories and future trajectories step-by-step, effectively leveraging complementary information between them. Furthermore, they proposed a gate mechanism to balance the contributions between the observed and future trajectories.

2) Vehicle Trajectory Prediction:

Vehicle trajectories are often governed by physical rules and constraints. Several works have incorporated these constraints as classifiers [28] or conditions [58] into diffusion models, thereby enabling physically feasible trajectory predictions. Jiang et al. [28] utilized a compressed trajectory representation using PCA-base latent diffusion models for multi-agent joint motion prediction. Additionally, they introduced constrained sampling, enabling controlled predictions based on differentiable cost functions as a classifier. Similarly, Westny et al. [146] integrated differential motion constraints into the diffusion model output, generating realistic future trajectories. Another work by Balasubramanian et al. [58] employed conditional latent diffusion models with temporal constraints to predict the motion of vehicles in a traffic scenario, while also providing an unconditional mode as a scene initializer.

In addition to these advancements, other works have combined diffusion models with other network architectures. For example, Chen et al. [29] noticed that previous works did not fully exploit the geometric properties of trajectory. They combined the diffusion models and equivariant transformer as an SO(2)-equivariant diffusion model for vehicle trajectory prediction, thereby fully utilizing the geometric properties of location coordinates. Moreover, they utilized Recurrent Neural Networks and Graph Attention Networks to capture social interactions among vehicles. Additionally, Yao et al. [110] extended the MID model [27] for vehicle trajectory prediction by using Graph Neural Networks to capture interactions between agents and road elements.

C. Planning and Decision-making

In autonomous driving systems, planning and decisionmaking are crucial components. Planning entails generating a safe and comfortable trajectory based on the vehicle's current state, and environmental information [132]. Decision-making involves selecting the optimal high-level action by considering the final goal, the environment, traffic rules, and ensuring safety [147]. Diffusion models have shown promise potential in enhancing these components, particularly in improving generalization and flexibly integrating with other algorithms. Diffusion models exhibit robust generalization to new environments with unseen obstacles [47], [60], which is essential for dynamic environments. Additionally, diffusion models can flexibly integrate with other algorithms, enhancing their effectiveness. Since the autonomous vehicle is a specialized form of robotics, we examine the topic within both the robotics and autonomous driving fields.

1) Planning and Decision-making in Robotics:

Diffusion models can flexibly combine with motionplanning approaches, such as reinforcement learning (RL) [46] or trajectory optimization algorithms [47]. Specifically, Janner et al. [46] proposed the Diffuser model, which combines RL with classifier-guided diffusion models [45] to improve planning and decision-making processes. The Diffuser iteratively denoises trajectories to generate plans, with the sampling process guided by gradients of the cumulative rewards learned through RL. In contrast, the follow-up work, Decision Diffuser [52], employed classifier-free diffusion guidance [51] to generate a sequence of future states, conditioning on rewards, various constraints, and behavior skills. This approach doesn't require a separately trained classifier but learns both a conditional and an unconditional model for the noise. While the Decision Diffuser [52] demonstrates that classifier-free guidance performs better than classifier guidance in practice, the Diffuser [46] enables planning for new rewards without retraining. A different approach was presented by Carvalho et al. [47], who utilized learned diffusion priors to initialize an optimization-based motion planner. This method not only improves and accelerates the planning process but also fosters greater diversity in trajectory planning.

2) Planning and Decision-making in AVs:

Diffusion models have been employed to optimize the planning process in autonomous driving. Yang et al. [113] first combined gradient-free evolutionary search with diffusion models to enhance planning for autonomous driving. Unlike conventional methods that use naive Gaussian perturbations, this approach leverages a truncated diffusion-denoising process to mutate trajectories in the evolutionary search process, ensuring that the resulting mutations remain within the data manifold.

Additionally, several studies have leveraged diffusion models to generate out-of-distribution driving scenarios, thereby improving planning performance. For example, Wang et al. [60] leveraged diffusion models to generate multi-view future state videos, enabling the prediction of future events and risk assessment through these videos, thereby enhancing the safety of end-to-end planning. Furthermore, evaluations on counterfactual events demonstrate that their model improves generalization capabilities in out-of-distribution scenarios. Another video generative model for motion planning is GenAD [61], which has the ability to generalize across diverse and unseen driving datasets in a zero-shot manner. Moreover, GenAD can be adapted for various tasks, including language-conditioned prediction, action-conditioned prediction, and motion planning.

RL has seen widespread application in planning and decision-making for autonomous driving [148], [149]. Recent advancements have incorporated diffusion models to improve the performance and sampling efficiency of RL algorithms [150]. For example, Wang et al. [151] introduced Diffusion-QL, which integrates a conditional diffusion model as the policy and combines it with Q-learning. Subsequently, Liu et al. [152] employed conditional diffusion models as the actor in an Actor-Critic decision-making framework, facilitating policy exploration and learning.

V. DIFFUSION MODELS FOR TRAFFIC SIMULATION

Traffic simulation is a critical tool for developing and testing intelligent transportation systems, allowing researchers and engineers to model, analyze, and simulate the behavior, interactions or movement of traffic participants within a transportation network [153], [10]. Universal methods, such as rule-based or data-driven models often struggle to capture the complexity and variability of real-world traffic dynamics [154]. These methods also lack the controllability to generate diverse and customizable scenarios, which are essential for safety-critical testing [155]. Furthermore, traffic data are often unavailable or suffer from privacy concerns, posing additional challenges for data-driven traffic simulations.

Diffusion models, a type of generative model, have recently emerged as a promising solution for overcoming these challenges in traffic simulation. They are particularly effective at learning the distributions of traffic patterns, enabling the generation of high-fidelity simulations that closely mimic real-world situations. Moreover, diffusion models offer significant advantages in terms of controllability, allowing users to customize generated traffic scenarios, trajectories, and flows according to specific conditions or guidance.

This section explores the applications of diffusion models in traffic simulation, with a focus on their roles in traffic trajectory generation, traffic scenario generation, and traffic flow generation. We also examine recent advancements in this field and discuss how diffusion models are being integrated with other technologies to enhance their effectiveness and applicability in intelligent transportation systems.

A. Traffic Trajectory Generation

Traffic trajectory generation, which focuses on creating realistic and compliant paths for vehicles and pedestrians in traffic simulations, is essential for the development and testing of intelligent transportation systems. Traditional heuristicbased models [156] enable vehicles to adhere to specific trajectories and traffic rules, but they often struggle to capture the complexity of real-world driving behaviors. In contrast, data-driven approaches can produce more realistic and humanlike behaviors [154], but they often lack the controllability to generate user-defined trajectories. Diffusion models stand out for their ability to model real-world traffic data effectively by capturing the complexity and variability of traffic patterns. Additionally, guidance-based diffusion models enhance controllability and flexibility during the inference stage. These strengths of diffusion models make them highly suitable for generating both realistic and controllable trajectories. Recent research has increasingly utilized these advanced diffusion models to improve the realism and controllability of agent trajectory generation, offering significant advancements in traffic simulation.

Several studies have utilized classifiers to enhance controllability during sampling, such as using Signal Temporal Logic (STL) rules classifiers [48] or language-based classifiers [49]. Zhong et al. [48] proposed a classifier-guided conditional diffusion model to produce realism and controllable driving trajectories. Unlike the approach of training a reward function

as guidance [46], they utilized STL [157] to guide sampling to generate trajectories that are both physically feasible and compliant with rules. Building on this, Zhong et al. [49] further advanced their model by incorporating language instructions to guide the trajectory sampling process, thereby enhancing user-friendliness. Specifically, they employed a large language model (LLM) to convert user language instructions into a guidance loss, replacing the STL-based guidance loss used in their earlier work [48]. In contrast, wang et al. [59] enhanced user-friendliness and controllability by introducing user-defined context through the cross-attention mechanism. Additionally, they utilized a regression model for initial scene creation to enhance realism.

Meanwhile, recent research has increasingly focused on multi-agent joint trajectories generation, aiming to generate more interactive trajectories [48], [59], [50], [30], [158], [159]. Notably, Niedoba et al. [50] employed both classifier guidance and classifier-free guidance diffusion models to generate joint trajectories for all agents in a traffic scene. They trained a behavior classifier as guidance for conditional sampling, and controlled the strength of conditioning through classifier-free guidance, thereby enabling the flexible sampling of diverse behavior modes. Additionally, Pronovost et al. [30] integrated latent diffusion with object detection and trajectory regression to simultaneously generate poses and trajectories for all agents, conditioned on a map and scenario tokens.

Some research has focused on human trajectory simulation. For example, Rempe et al. [53] introduced a controllable pedestrian simulation system that integrates a trajectory diffusion model (TRACE) for generating pedestrian paths and a physics-based humanoid controller (PACER) to establish a closed-loop system. Furthermore, the guided TRACE model allows users to constrain trajectories based on target waypoints, desired speeds, specified social groups, and other factors.

B. Traffic Scenario Generation

Traffic scenario generation involves creating a temporal sequence of traffic scene elements that simulate the actions, interactions, and events of the participating agents within a driving environment [160], [155]. It plays a significant role in enhancing the efficiency and safety of intelligent transportation systems, as it enables the creation of diverse and safety-critical scenarios. However, traffic scenario generation faces two critical challenges: Consistency and Controllability [161], [32]. Consistency ensures that the generated scenarios are temporally and multi-view coherent, maintaining logical relationships across time and from different viewpoints within the scene. Controllability refers to the ability to guide the generated scenarios to align with specific annotations, conditions, or objectives. Diffusion models have emerged as a powerful tool to address these challenges. Fundamentally, they can effectively model complex data distributions, achieving high levels of realism. Additionally, diffusion models can be flexibly combined with various approaches, such as cross-view and cross-frame attention mechanisms, post-processing techniques, and multi-stage generation processes, to ensure both temporal and multi-view consistency. Moreover, controllable diffusion models, like ControlNet [162], can incorporate multimodal conditioning controls, including layout, text, segmentation, and other inputs, to fine-tune large diffusion models like Stable Diffusion [38], thereby enhancing the controllability of driving scenario generation.

With the rapid development of diffusion models in image [38] generation, video generation [57], [163], [164], and world models [165], [161], diffusion models offer a powerful framework for generating high-quality, consistent, and controllable traffic scenarios. In the following part, we will explore the current advancements in traffic scenario generation from two different perspectives: image-based and point cloud-based approaches.

1) Image-based Driving Scenario Generation:

Recent advancements in diffusion models have led to significant progress in generating realistic and controllable imagebased driving scenarios. For example, Harvey et al. [76] proposed a Flexible Diffusion Model (FDM), that enables the model to sample any arbitrary subset of video frames conditioned on others, thereby optimizing frame sampling schedules and effectively handling long-range temporal dependencies. Building on this foundational work in temporal sequence modeling, Hu et al. [54] integrated a video diffusion decoder with a world model to create high-fidelity and longterm driving scenarios. The world model [165] facilitates the understanding of the environment and the prediction of reasonable object interactions, while the diffusion decoder translates latent representations into high-quality videos with realistic detail. Additionally, it offers fine-grained control over the simulation environment through action and language conditioning. Similarly, DriveDreamer [62] focused on generating highquality, controllable driving videos and policies that align with real-world traffic structures. Building upon the DriveDreamer foundation, Zhao et al. [117] proposed the DriveDreamer-2 framework, which leverages the power of finetuned-LLMs [166], [167] to translate user descriptions into agent trajectories. Additionally, it employs an HDMap generator to produce high-definition (HD) maps. These trajectories and HD maps are then used as structured conditions to ultimately generate multi-view driving scenes.

Next, we discuss the multi-view driving video generation. Wen et al. [32] integrated a pre-trained diffusion model and a decomposed 4D attention mechanism within a two-stage generation pipeline to generate multi-view driving scenario videos with temporal consistency. The first stage trains a multiview image generator, while the second stage expands these images along the temporal axis to create video sequences. Li et al. [33] proposed Driving Diffusion for generating spatially and temporally consistent multi-view videos of complex urban driving scenes. Another important work is WoVoGen [63], which leverages 4D world volumes as foundational elements for multi-camera street-view video generation, addressing key challenges in ensuring intra-world consistency and inter-sensor coherence. Furthermore, these approaches [32], [33], [63] employed the ControlNet [162] framework to achieve Finegrained control, conditioned on the BEV sequences or 3D layout or world volume-aware 2D image feature.

2) Point Cloud-based Driving Scenario Generation:

Meanwhile, the generation of realistic driving scenarios from point cloud data has gained significant attention due to its importance in traffic simulation [64], [55], [168]. Notably, Ran et al. [64] concentrated on generating realistic LiDAR driving scenes from a latent space that incorporates geometric priors to capture realism, enhancing pattern realism, geometry realism, and object realism. Furthermore, their approach leverages a pre-trained model, CLIP [169], to enable controllability under arbitrary conditions, including text prompts, semantic maps, and camera views. Zhang et al. [55] proposed Copilot4D for building unsupervised world models. This approach leverages VQVAE [170] to tokenize point cloud observations, and combines MaskGIT [171] with discrete diffusion models [77] to efficiently decode and denoise tokens in parallel, enhancing point cloud-based driving scene forecasting.

C. Traffic Flow Generation

Traffic flow generation involves creating synthetic data that models the movement of vehicles or pedestrians across specific regions within a transportation network [10]. These synthetic data are crucial for macroscopic simulations [153], as modeling real-world human mobility trajectories often suffers from privacy concerns. However, traffic flow generation presents several challenges. Firstly, the non-independent and identically distributed nature of trajectories between different areas and the inherent stochasticity of human behavior make traffic pattern modeling complicated. Secondly, traffic flow influenced by external factors such as traffic conditions, departure times, and local events, adds further complexity. Diffusion models are adept at handling stochasticity and uncertainty, making them particularly well-suited for traffic flow generation. Furthermore, diffusion models can be flexibly combined with various approaches, such as GCNs, RNNs, and attention mechanisms, to model the spatiotemporal dependencies of traffic data. Additionally, diffusion models enable conditional generation based on text, road networks, external factors, and other inputs, allowing for the generation of customized traffic flow patterns. To explore how diffusion models have been applied in traffic flow generation, we review several notable advancements in the field.

Effectively capturing spatiotemporal dependencies is crucial in traffic flow generation, given that traffic flow data typically involves spatiotemporal information. Recently, DiffSTG [36] and ChatTraffic [41] introduced a GCN-based architecture to effectively model spatiotemporal dependencies, while TimeGrad [172] employs an RNN, and both CSDI [173] and STPP [174] utilize attention mechanisms for this purpose. In contrast, Zhou et al. [119] proposed the KSTDiff model, which leverages an urban knowledge graph (UKG) to capture the spatiotemporal dependencies of urban flow. Additionally, they developed a volume estimator that integrates region-specific features to guide the diffusion model's sampling process, enabling the accurate generation of urban flow across different regions. Notably, ChatTraffic [41] also presented the first textto-traffic generation framework. This approach incorporates BERT [175], a pre-trained text encoder, to extract text embedding, which serves as conditions to guide the generation of traffic flow.

Many researchers have focused on GPS trajectory generation [34], [35] due to the ability of GPS trajectory data to reflect traffic flow, which is crucial in ITS. Specifically, Zhu et al. [34] proposed a Traj-UNet structure within diffusion models for spatial-temporal modeling and embedding conditional information such as the trip region and departure time, thereby enabling controlled GPS trajectory generation. Subsequently, Diff-RNTraj [35] generates trajectories conditioned on the road network, with these trajectories represented in a hybrid format where each point is defined by a discrete road segment and a continuous moving rate.

Additionally, Rong et al. [120] proposed a cascaded graph denoising diffusion method to capture the joint distribution of nodes and edges within the origin-destination (OD) network. This method generates region-level OD flow for a new city by first generating the topology structure and then the corresponding mobility flows.

VI. DIFFUSION MODELS FOR TRAFFIC FORECASTING

Traffic forecasting is a critical component of intelligent transportation systems, facilitating the optimization of traffic flow, the reduction of congestion, and the enhancement of overall transportation efficiency. It involves predicting future traffic conditions, such as traffic flow rates and travel times, by analyzing historical data. However, traffic forecasting presents significant challenges due to the inherent complexities of transportation networks and concerns regarding the quality of traffic data [176].

Recent advancements in traffic forecasting have increasingly focused on leveraging diffusion models to address these challenges. Diffusion models have demonstrated significant promise in capturing the complex and dynamic nature of traffic systems. By incorporating diffusion processes, these models effectively account for the uncertainties and noise present in traffic data, making them particularly well-suited for handling incomplete or imperfect traffic datasets. As a result, the application of diffusion models in traffic forecasting is gaining momentum, especially in tasks such as traffic flow prediction and travel time estimation.

A. Traffic Flow Forecasting

Traffic flow forecasting entails predicting the future state of traffic on transportation networks, including vehicle speeds, traffic density, and flow rates, based on historical data and other relevant factors [176]. While significant progress has been made in this field, accurately forecasting traffic flow remains challenging due to the inherent uncertainties in flow distributions and the complex external factors that impact forecasting performance. Additionally, the collected urban flow data is often unreliable, noisy, and sometimes incomplete, further complicating the prediction task. Recent advancements have focused on addressing these challenges by leveraging diffusion models, which have shown promise in recovering traffic data [177], capturing the intricate spatial-temporal dependencies and handling the uncertainties associated with traffic flow data [36].

Graph-based approaches have proven effective in extracting spatial correlations in traffic networks [3], [4]. Naturally, integrating graph-based networks with diffusion models can enhance the modeling of intricate spatial-temporal dependencies. Wen et al. [36] proposed a GCN-based network called UGnet, which effectively captures multi-scale temporal dependencies and spatial correlations, thus significantly advancing traffic flow prediction tasks. However, GCN-based methods are computationally expensive, particularly for large-scale traffic networks. To address this issue, Lin et al. [122] incorporated a fast spectral graph convolution, which alleviates the computational inefficiencies of existing models.

Diffusion models have also been leveraged for fine-grained traffic flow inference from noisy and incomplete data. For example, Zheng et al. [43] and Xu et al. [123] focused on leveraging diffusion models for fine-grained traffic flow inference from noisy and incomplete coarse-grained traffic flow maps. Specifically, Zheng et al. [43] developed a transformerbased spatial-temporal feature extraction network along with a semantic feature extraction network designed to capture external factors and land features. These two types of features, serving as conditions for conditional diffusion models, facilitate the robust modeling of dynamic and long-range spatialtemporal dependencies. In contrast, Xu et al. [123] employed a relaxed structural constraint and a disentangled scheme for flow map and external factor learning. Additionally, Lablack et al. [124] proposed a vectorized state space module to decompose the historical signal of an ego-graph into the frequency domain, thereby reducing the impact of noise and data imperfections present in real-world traffic data.

Lastly, recent research has introduced novel approaches that transform the traffic flow forecasting task into a new domain. Chi et al. [126] introduced a novel concept of a spacetime image to incorporate physical meanings of traffic state variables. They transformed the traffic flow forecasting task into a conditional image generation problem by leveraging diffusion models.

B. Travel Time Estimation

Origin-Destination (OD) travel time estimation aims to predict the time required to travel between a specific starting point (origin) and a destination within a transportation network. This task is complex due to the variability in travel times for the same OD pair, influenced by factors such as traffic conditions and route choices [178]. Multiple historical trajectories with different travel times may connect an OD pair, and these trajectories can differ significantly, making accurate prediction challenging. To address this, it is crucial to mitigate the impact of outlier trajectories. The conditional diffusion model provides a promising solution to this challenge. For example, Lin et al. [44] proposed a conditional diffusion-based model for OD travel time estimation, which leverages historical trajectories. The model employs a pixelated trajectory representation and is conditioned on origin, destination, and departure time (ODT) queries to capture correlations between OD pairs and historical travel patterns, thereby aiding in the filtering of outlier trajectories.

VII. DIFFUSION MODELS FOR TRAFFIC SAFETY

Traffic safety is a critical area of research within intelligent transportation systems, focusing on minimizing the risks associated with vehicular travel and reducing the frequency and severity of traffic accidents [179]. Recent advancements in diffusion models have opened new avenues for enhancing traffic safety. These models excel in generating high-quality samples from complex distributions and producing customizable samples conditioned on text descriptions, addressing the challenge of limited traffic accident or anomaly data. They have been effectively applied to various aspects of traffic safety, including traffic anomaly detection and accident prevention. The successful detection of traffic anomalies and the prevention of accidents are crucial for maintaining safe and efficient transportation systems.

A. Traffic Anomaly Detection

Traffic anomaly detection aims to identify irregular patterns in traffic data that deviate from normal behavior, such as unusual vehicle activity, accidents, or irregular traffic flow patterns. Detecting these anomalies is important for traffic management and safety. However, this task faces significant challenges due to the lack of large-scale labeled anomaly data and the difficulty in precisely defining the boundary between normal and abnormal patterns [180], [181]. Diffusion models, known for their powerful generative capacity, offer a promising solution. These models are well-suited for traffic anomaly detection, as anomalous events often exhibit a level of randomness and uncertainty that are inherently similar to the diffusion process. By leveraging diffusion models to reconstruct normal traffic patterns from Gaussian noise, researchers can effectively identify samples that deviate from these normal patterns, thereby flagging them as anomalies.

Building on this idea, Li et al. [127] formalized the vehicle trajectory anomaly detection problem as a noisy-to-normal paradigm, which leverages the generative capabilities of diffusion models to reconstruct near-normal trajectories and effectively identifies anomalies by comparing the difference between a query trajectory and its reconstruction. Similarly, Yan et al. [128] utilized diffusion models to learn the distribution of normal samples for video anomaly detection. Specifically, they employed two denoising diffusion modules to learn motion and appearance features from normal samples, ensuring the generative quality of the produced features.

B. Traffic Accident Prevention

Traffic accident prevention requires a deep understanding of accident causality and then designing strategies to reduce their likelihood. A significant challenge in this field is the lack of a large-scale and long-tailed accident dataset [182], which limits the ability to develop comprehensive and effective accident prevention. Diffusion models, with their powerful controllable generation capabilities, have emerged as a promising tool to overcome these challenges.

Recent advancements in diffusion models have enabled more innovative applications in traffic accident analysis and prevention. For example, Fang et al. [42] leveraged an abductive CLIP model within an Object-Centric Video Diffusion (OAVD) method to discern accident cause-effect chains, thereby enhancing the understanding of accident causality and improving accident prevention strategies. Specifically, this approach leverages diffusion models to generate new video frames conditioned on text descriptions, such as accident reasons and prevention advice. This allows for the visualization of how accidents might unfold based on these descriptions, aiding in understanding and potentially predicting accident outcomes, and contributing to better accident prevention.

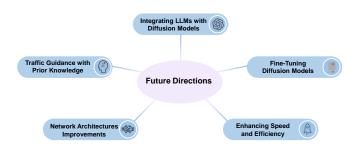


Fig. 7: Future research directions for diffusion models in intelligent transportation systems.

VIII. FUTURE DIRECTIONS

As diffusion models continue to evolve, their potential to address complex challenges in ITS becomes increasingly evident. However, several critical areas require further investigation and innovation to fully realize their capabilities. This section outlines key research directions for diffusion models in ITS that are worthy of further exploration, as shown in Fig. 7.

A. Integrating LLMs with Diffusion Models

The integration of large language models (LLMs) and diffusion models represents a promising new direction in ITS. Previous works, such as [32], [33], [64], have primarily relied on pre-trained CLIP [169] to encode textual information and generate outputs conditioned on these text feature representations. However, CLIP exhibits inherent limitations in processing long and complex sentences, which can negatively impact the quality of generated outputs. LLMs, with their strong capabilities in language understanding and knowledge-based reasoning, combined with the generative power of diffusion models, offer a compelling opportunity for enhanced performance. Recent studies, including MiniGPT-5 [183], which utilizes "generative vokens" to bridge LLMs and diffusion models, and EasyGen [184], which integrates these models via a projection layer, have demonstrated the potential for producing more realistic and reasonable outputs. Building on these advancements, integrating LLMs and diffusion models for various ITS tasks holds significant promise. In particular, in the field of traffic simulation, the use of LLMs for semantic comprehension, reasoning, and automated decision-making could lead to the generation of more realistic and contextually accurate driving images and videos. Moreover, another benefit of combining LLMs with diffusion models is their potential as a user interface. The natural language capabilities of LLMs can provide a more intuitive means for users to interact with these systems, enabling users to describe complex scenarios and receive tailored outputs without needing deep technical knowledge. This enhances the accessibility and usability of diffusion models in ITS applications.

B. Traffic Guidance with Prior Knowledge

Traffic-related tasks often require reasoning that integrates both scenario-specific features and domain-specific knowledge. Rather than relying on a large, and computationally expensive diffusion model, the development of more efficient traffic guidance that incorporate prior knowledge about traffic systems can significantly enhance the generative process. Existing research has primarily focused on designing guidance to guide sampling in autonomous driving contexts, particularly in planning and decision-making. These guidance are often based on reinforcement learning techniques or cost functions grounded in traffic rules [46], [47]. Beyond autonomous driving, other domains within ITS, such as traffic flow prediction and traffic safety analysis, also rely heavily on domain knowledge. For instance, factors like the relationship between traffic flow, urban population density, public holidays, weather conditions, and landmark locations are critical for accurate traffic forecasting. By leveraging this extensive domain knowledge, task-specific guidance can be developed to improve the prediction of traffic patterns and congestion levels. Future research could focus on creating guidance that more effectively mine and utilize relevant prior knowledge for specific trafficrelated tasks, thereby advancing the performance of diffusion models in these domains.

C. Network Architectures Improvements

The architectures of diffusion models present substantial opportunities for improvement. U-Net [17], while demonstrating remarkable performance as a denoising network backbone across various traffic-related tasks and being combinable with methods such as GCNs to model spatial-temporal dependencies [36], still has considerable potential for further optimization. Recent advancements in transformer-based denoising networks, such as DiT [185], U-ViT [186], and their applications in diffusion models like Sora [8] and Stable Diffusion 3 [187], have gained significant attention. Transformer-based architectures excel in capturing long-range spatial-temporal relationships and offer greater scalability. Therefore, leveraging or refining transformer-based denoising networks holds significant potential for enhancing spatial-temporal-related traffic applications, such as traffic flow forecasting and traffic trajectory prediction. Furthermore, designing novel network architectures specifically tailored to particular tasks within intelligent transportation systems, as backbones for diffusion models, presents a promising direction for future research.

D. Fine-Tuning Diffusion Models

Large diffusion models, such as Stable Diffusion [38], pretrained on extensive image datasets, have demonstrated considerable promise across various domains. Fine-tuning these models on traffic-specific data or for traffic-related condition control can further enhance their applicability within ITS. Recent research has explored methods to fine-tune large pretrained diffusion models for more fine-grained control. For example, ControlNet [162] adds spatial conditioning controls to large and pre-trained diffusion models through efficient fine-tuning techniques. Similarly, T2I-Adapter [188] learns simple and lightweight adapters to align internal knowledge in large diffusion models with external control signals. Building on these advancements, developing effective fine-tuning methods tailored to traffic data or traffic scenes holds the potential to significantly enhance the flexibility and control of these models in generating traffic-related outputs. These approaches promise to improve the models' utility in various ITS applications, particularly in traffic simulation and incident detection.

E. Enhancing Speed and Efficiency

Although diffusion models have demonstrated significant potential in generating high-quality results, their computational cost and slow inference speeds remain major bottlenecks. To enable real-time applications in ITS, such as autonomous driving, future research should improve the efficiency of these models. Although recent advancements, including sampling acceleration [73], [189], [190], network architecture optimization [74], [38], and approach improvements [191], have contributed to mitigating these challenges, further innovation is necessary. Future research should explore the development of more adaptive and lightweight network architectures, as well as parallel sampling techniques. Additionally, hybrid models that integrate the strengths of diffusion models with faster, more deterministic approaches might also prove valuable for real-time applications in ITS.

IX. CONCLUSION

In this paper, we provide a comprehensive review of diffusion models in ITS. We outline the theoretical foundations of diffusion models, discuss their key variants, and demonstrate how they can effectively address the complex challenges of ITS. Our review also highlights the advantages of diffusion models, especially in handling multi-modal, noisy, and incomplete traffic data. By investigating their current applications in ITS domains, including autonomous driving, traffic simulation, traffic forecasting, and traffic safety, we highlight the versatility and potential of diffusion models in enhancing various aspects of ITS. Additionally, we summarize several key research directions that warrant further investigation, including the integration of other approaches and the development of more efficient and scalable diffusion models tailored to various traffic-related tasks. We hope this review encourages further interdisciplinary collaboration, paving the way for the continued evolution of diffusion models as a pivotal tool in future ITS.

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