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Robust Stochastic Model Predictive Control for Autonomous Vehicle Motion Planning

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Abstract—**This work presents a Robust Stochastic Model Predictive Control (RSMPC) framework for real-time motion planning autonomous vehicles, addressing the complex multi-modal vehicle interactions. The proposed framework involves adding expert policy from observations to the dataset and applying the Data Aggregation (DAgger) method to filter unsafe demonstrations and resolve expert conflicts. A Dual-Stage Attention-based Recurrent Neural Network (DA-RNN) model is integrated to predict dual class variables from the dataset, producing a set containing constraints collision-avoidance predicted to be active. The RSMPC framework enhances formulation optimization by eliminating irrelevant collision avoidance constraints, resulting in faster control signals. The framework is applied iteratively, continuously updating observations and solving the RSMPC optimization formulation in real-time. Evaluation of the DA-RNN model achieved a recall value of 0.97 and a high accuracy rate of 98.1% in predicting dual interactions, with a minimal false negative rate of 0.026, highlighting its effectiveness in capturing interaction intricacies. Validated through simulations of interactive traffic intersections, the proposed framework demonstrably excels, showing high feasibility of 99.84% and a 15-fold increase in response speed compared to the baseline. This approach ensures autonomous vehicles navigate safely and efficiently in complex traffic scenarios, paving the way for more reliable and scalable autonomous driving solutions.**

Keywords: ***autonomous vehicle, complex intersections, fast response control, motion planning, robust stochastic model predictive control,***

I. Introduction

Urban intersections are identified as significant sources of traffic congestion and primary contributors to bottlenecks in transportation systems [1]. Autonomous vehicles have the potential to alleviate traffic congestion through cooperative driving capabilities. However, navigating urban intersections presents a complex challenge due to the necessity for rapid and safe responses. These environments require vehicles to navigate safely through unstructured settings, demanding observation and reaction to various traffic entities, including human-driven and autonomous vehicles [2]. In such scenarios, motion planning for autonomous cars becomes particularly challenging due to uncertain, multi-modal behaviors from various traffic entities. Consequently, developing real-time and reliable solutions is essential in urban intersections [3].

Recent advancements in motion planning for autonomous vehicles at urban intersections have introduced various innovative approaches [4], [5], [6]. Existing methods, such as Merit-based motion planning, though innovative in evaluating multiple trajectories based on comfort, safety, and utility, struggle with real-time computational demands [7]. Ahmadi et al. proposed an innovative signal-free and path-free control strategy introduced for autonomous vehicles at intersections [8]. However, the strategy is limited to specific urban layouts modeled as Plazas, which may not generalize to all intersection types. Research by Nair et al. [9] focuses on predictive control that accounts for uncertainty and multi-modal predictions in urban driving scenarios research has limited practical validation, with a primary focus on theoretical models and less on real-world testing. Li et al. introduce edge computing-enabled intersections for signal control and path planning that adapt to traffic conditions [10] and exist in scalability and deployment across large urban areas. Hybrid Model Predictive Control (HMPC) strategy proposed by Jo et al. to enhance ride comfort and decision-making at urban signalized intersections [11]. This work has limitations of evaluation scenarios are limited and may not account for all real-world complexities. The study by Liu et al. presents an integrated system that includes behavior planning and motion control for autonomous vehicles, achieving high success rates in single-lane intersections with traffic rule compliance [12]. However, this approach is limited to single-lane intersections, and implementation with complex multi-lane scenarios is not fully addressed. This limitation hinders their practical application in highly dynamic urban settings, necessitating the development of more efficient real-time planners that can seamlessly adapt to diverse traffic scenarios.

Integrating deep learning methods into motion planning

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has shown significant promise, particularly in controlled environments [13], [14]. However, the reliability and generalization of these approaches in real-world urban scenarios remain challenging [15]. Deep learning-based behavioral prediction models require extensive datasets for training and robust mechanisms for real-time adaptation [16]. The unpredictability of urban intersections further complicates their application, indicating a need for hybrid approaches that combine deep learning's adaptability with the consistent reliability of rule-based methods [17].

Scalability and real-time efficiency are persistent challenges in applying advanced motion planning algorithms [18]. For instance, event-triggered path-tracking methods, which enhance disturbance rejection using tube model predictive control (MPC), face scalability issues in highly dynamic urban environments [19], [20], [21]. The complexity of real-time traffic scenarios often outpaces the computational capabilities of these systems, indicating a need for more scalable solutions that can operate efficiently in real-world conditions.

Despite significant autonomous vehicle motion planning advancements, current approaches face notable limitations. Many methods struggle with real-time computational demands and scalability across diverse urban environments and lack practical validation. Additionally, strategies tailored for specific urban layouts may not generalize well, and deep learning-based models often require extensive datasets and robust mechanisms for real-time adaptation. These limitations highlight the need for more efficient, scalable, and adaptable solutions to operate reliably in complex and dynamic traffic scenarios.

This work presents a robust real-time motion planning framework that offers multi-modal predictions in complex intersection traffic environments. Exploiting the cooperative nature of urban driving, the autonomous vehicle model prediction is transformed into a second-order cone programming (SOCP) to minimize the cost function while ensuring boundary satisfaction with desirable feasibility guarantees. Furthermore, a dual-stage attention-based recurrent neural network (DA-RNN) algorithm is employed to predict feasible dual solutions from environmental observation. To address distribution shifts in the model, the DAgger method is integrated, enhancing the model generalization to real-world traffic data filter unsafe demonstrations and resolving experts policy conflicts using a sensitivity-based vehicle and scenario selection method. Finally, a Robust Stochastic Model Predictive Control (RSMPC) problem optimization is formulated to reduce irrelevant collision avoidance constraints, thereby improving computational efficiency by using Lagrangian duality to identify which vehicle interactions are critical, allowing for the pruning of non-essential constraints and reducing computational complexity. Custom environment evaluation with OpenAI Gymnasium demonstrates the real-time application of the proposed motion planning framework approach in multi-modal complex traffic intersections.

The structure of the article is organized as follows: Section II discusses the modeling vehicle prediction into optimization problem as a second-order cone problem (SOCP) and proposed multi-modal motion planning with DA-RNN for dual-class predictions in an observation environment, with a Robust SMPC formulation optimization to ensures safe navigation of the autonomous vehicle in complex traffic environments. Section III outlines the evaluation environment in the multi-modal traffic intersection simulator employed for evaluating the proposed model and provides the results of model performance compared with the baseline. Section IV concludes with a comprehensive conclusion drawn from the work.

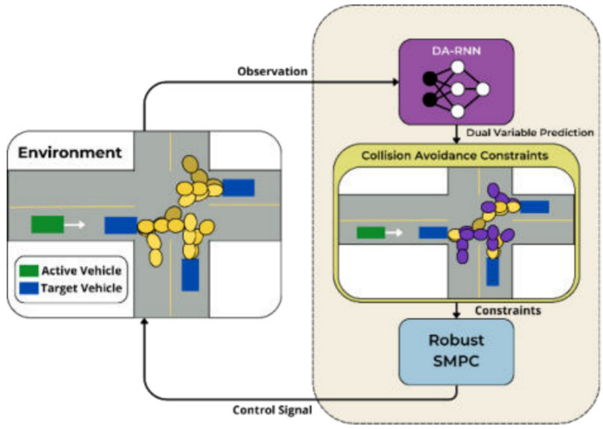

Figure 1. Block diagram of the RSMPC framework for motion planning with multi-modal prediction

II. METHODS

The proposed system framework of real-time motion planning is shown through a block diagram in Figure 1. This diagram block depicts a simulation environment at an intersection with interactive vehicles. The green box represents the active vehicle (AV), while the blue boxes signify the target vehicle (TV). The yellow ellipses illustrate the prediction constraints for active collision avoidance and the purple ellipses for inactive constraints. This framework is designed to be applied iteratively, continuously updating observations and solving the Robust Stochastic Model Predictive Control (RSMPC) optimization formulation in real-time to ensure safe and efficient motion planning for autonomous vehicles in highly interactive traffic scenarios.

The system framework for motion planning autonomous vehicles is divided into several stages:

1. Acquire data on initial conditions, state, and input constraints from environmental observations.
2. Calculate a set of constraints predicted to be active from the DA-RNN model.
3. Calculate the set of collision avoidance from the sensitivity criterion screening.
4. Reduced policy constraints with RSMPC framework formulation optimization.
5. Apply optimal control input signal from RSMPC optimization (to the system.

A. Vehicle Prediction Models

The vehicle prediction model, a discrete-time Linear Time-Varying (LTV) system, dynamically captures vehicle behavior and adapts to changing system dynamics and environmental conditions for robust predictions. The number of states and inputs depends on the vehicle's specific dynamics and control objectives, ranging from minimal states like position and velocity in SISO systems to additional states like acceleration, yaw rate, and steering angle in multivariable systems, which can increase computational complexity and affect real-time system performance. The state-space representation captures the system dynamics defined in equation (1) aligning with the principles outlined in [22], [23].

$$x_{t+1} = A_t x_t + B_t u_t + E_t w_t. \tag{1}$$

In this formulation, $(x_t) \in \mathbb{R}^{n_x}$ represents the state vector at time (t) where (n_x) is the number of state variables, $(u_t) \in \mathbb{R}^{n_u}$ denotes the control input vector at time (t) where (n_u) is the number of control input variables, and $(w_t) \in \mathbb{R}^{n_x}$ is the process noise vector at time (t), which has the same dimension as the state vector. The matrices (A_t), (B_t) and (E_t) are the current state transition, control input, and current noise input matrices, respectively, and they vary over time. The stability proof via Lyapunov functions confirms that as long as $\rho\ (A_t) < 1$, the system remains stable, making this model robust for real-time applications in dynamic settings. For simplicity, we consider the worst-case scenario where u_t=0 and w_t=0 defined in equation (2).

$$x_t^T \left(A_t^T P A_t - P \right) x_t < 0. \tag{2}$$

To satisfy this for all $x_t^T, A_t^T P A_t - P$ must be negative definite expressed in equation (3)

$$x_t^T \left(A_t^T P A_t - P \right) x_t < 0 \tag{3}$$

This implies $\rho\ (A_t) < 1$, ensuring the stability of the system. For the system to be stable, the eigenvalues of A_t must remain within the unit circle for all (t). The stability condition, $\rho\ (A_t) < 1$, where $\rho\ (A_t)$ denotes the spectral radius, is ensured by the RSMPC framework, which continuously monitors the eigenvalues of the time-varying system matrix (A_t), keeping them within the stable region. For the prediction of (V) target vehicles, each vehicle's motion is described by a discrete-time multi-modal model that varies over a prediction horizon (N) at time (t). The vehicle model is expressed in equation (4).

$$o^i_{k+1|t,j} = T^i_{k|t,j} o^i_{k|t,j} + q^i_{k|t,j} + E^i_{k|t,j} n^i_{k|t,j} \tag{4}$$

$(o^i_{k|t,j})$ represents the predicted state of the target vehicle and $(n^i_{k|t,j})$ denotes the noise for the target vehicle. The matrices $(T^i_{k|t,j})$, $(q^i_{k|t,j})$, and $(E^i_{k|t,j})$ represent the state transition, control input, and noise input matrices, respectively, for the target vehicle and are dependent on the time step (k), time (t), and mode (j). The noise $(n^i_{k|t,j})$is modeled as following a Gaussian distribution $\mathcal{N}(0, \Sigma^i_{k|t,j})$. The controlled autonomous vehicle is subject to state-input constraints, expressed as polytopic constraints in equation (5).

$$\mathbb{XU}_t = \left\{ (x,u) \mid +F_t^x x + F_t^u u \le f_t \right\} \tag{5}$$

Here, (F_x^t) and (F_x^u) are the boundary matrices and (f_t) is the boundary vector. Additionally, collision avoidance constraints are incorporated using potential field-based approximations, as specified in equation (6).

$$\mathbb{C}A^i_{k|t,j} = \left\{ (x,o) \mid L^{x,i}_{k|t,j} x + L^{o,i}_{k|t,j} o \le l^i_{k|t,j} \right\} \tag{6}$$

In this context, $(L^{x,i}_{k|t,j} x)$ and $(L^{o,i}_{k|t,j})$ are the boundary matrices and $(l^i_{k|t,j})$ is the boundary vector for collision avoidance. In the MPC formulation, the state-feedback control is determined as $u_t = \pi\,(x_t ob_t)$ aligning with the MPC algorithm formulation from Rawlings et al. [24]. In the SMPC formulation, the state-feedback control is determined as $u_t = \pi\ (x_t o_t)$, where (π) denotes the control policy that maps the current state (x_t) and observation (o_t) to the control input (u_t) . This is achieved by solving a finite-horizon optimal control formulation that minimizes a quadratic cost function while adhering to the system dynamics and constraints. This full-MPC problem optimization is formulated as a second-order cone program (SOCP) outlined in equation (7).

$$f(\theta_t) = \frac{1}{2} \left\| Q_t \theta_t \right\|_2^2 + C_t^T \theta_t \tag{7}$$

Equation (7) is subject to the constraints of equation (1), which define the constraints on the system dynamics and the decision variable to be optimized (θ_t) defined as,

$$\theta_t = \left\{ \left(h_{k|t}, \left\{ \left\{ K^i_{k|t,j} \right\}_{i=1}^{V} \right\}_{j=1}^{M} \right) \right\}_{k=t}^{t+N},$$

encapsulating a complex structure that incorporates multiple predictive elements over the horizon (t) from $(t+N)$ to . The positive definite matrix (Q_t) defines the quadratic cost, encapsulating the importance of different state variables through a weighted norm and vector (C_t) represents collision avoidance boundary, including the linear cost function associated with the decision variable, directly influencing the optimization objective. It leverages the Gaussian nature of the process noise to convert probabilistic constraints into deterministic ones. The objective is to solve the RSMPC formulation efficiently for real-time applications. This necessitates ensuring that the control is applied on time (t) is causally dependent on the current and past information rather than relying on the unknown future modes of the target vehicles. Lagrange duality is used to identify which vehicle interactions are critical, allowing for the pruning of non-essential constraints and reducing computational complexity. The resulting control policy ensures the safe navigation of the autonomous vehicle in complex traffic environments.

B. Dual Variables Prediction using Imitation Learning

The Dual-Stage Attention-based Recurrent Neural Network (DA-RNN) is proposed to predict the dual variables $(\tilde{\mu}_t^*)$ given the environmental observation (o_t). The system observation includes continuous and discrete data correlated with the dual variables, capturing various aspects crucial for motion planning in autonomous vehicles (AV). These include the current position of the autonomous vehicle, the distance and speed of target vehicles, environmental factors such as traffic conditions, and potential obstacles, which are incorporated to enhance the accuracy of the predictive model. These observations collectively aid in generating a comprehensive understanding of the driving environment, which is necessary for effective decision-making in a real-time motion planning framework. Several steps employed for the proposed models are detailed as follows.

1. Expert Dataset

An expert dataset is generated by obtaining optimal dual variables (u_t^*) from a simulation environment, where the formulation optimization is solved at each time-step (t) along a trajectory with a predefined length (T). This process ensures the acquisition of crucial data inputs necessary for integrating the DAgger method, facilitating interactive imitation learning with multiple imperfect experts for enhancing the safety of autonomous systems operating in critical environments. These dual variables are converted into binary class labels $(\tilde{\mu}_t^*)$ and stored as pairs $\{(o_t, \tilde{\mu}_t^*)\}_{t=0}^{B}$ in a dataset (D), where (B) denotes the dataset size defined by the user.

2. Input *Normalization* and Encoding

In complex driving scenarios, where robust scaling is employed for input normalization and encoding, environmental observations, including the current state of the autonomous vehicle, past system inputs, and target vehicle states, are robustly scaled using the interquartile range (IQR) to ensure resilience to outliers and noise. A graph encoding of the scene, incorporating graph neural networks (GNNs), captures interactions among entities, with nodes representing vehicles and directed edges indicating dynamic interactions based on time-to-collision (TTC) metrics. This process includes augmenting the observation per vehicle (o_t^i) with the TTC graph encoder and encoding it via a transformer-based encoder. The resulting scene representation features vector (f_i) ensures permutation invariance by summing the feature vectors of all vehicles before inputting them into the decoder.

3. DA-RNN Model

The normalized inputs are meticulously processed through a complex-designed DA-RNN framework, as depicted in Figure 2. This framework incorporates a multi-head attention mechanism, which excels in capturing diverse relationships between encoded inputs.

Each head within this mechanism is dedicated to discerning specific interactions between the ego and target vehicles, thus facilitating a nuanced understanding of the complex driving environment. Moreover, the framework integrates the power of GRU (Gated Recurrent Unit) functionality, which adeptly handles temporal dependencies in the data. The GRU ensures the efficient modeling of time-dependent interactions, contributing significantly to the framework's robustness. Dropout and layer normalization techniques are seamlessly integrated to mitigate overfitting risks and stabilize the training process. Complemented by a multi-layer perceptron (MLP) for discerning intricate interactions and the GRU's adeptness in capturing temporal nuances, the DA-RNN framework emerges as a formidable solution for modeling dynamic driving scenarios. The final output, a linear projection with sigmoid activation, predicts dual variable probabilities for collision avoidance constraints. These probabilities are combined and evaluated using a binary cross-entropy loss function, weighted to balance class representation.

Table 1. DA-RNN model training hyperparameter

α	p_{dropout}	h_{MLP}	L	n_{h}
-0.1	0.1	128	6	1

The DA-RNN model integrates DAgger with an attention-based RNN for interactive imitation learning, initially training a novice policy using expert actions from the dataset. The model iteratively collects data by running trajectories in a simulation environment, recording observations and expert actions, and computing control actions based on the DA-RNN predictions. The aggregated dataset from multiple iterations trains the novice policy. The training process involves balancing the dataset using a weighted random sampler and applying a class bias in the loss function. The DA-RNN model, implemented in PyTorch, is trained over 3000 epochs with specified hyperparameters, optimizing the learning process for accurate and reliable dual variable prediction in dynamic environments. The training process, which spans 4 hours, utilizes the hyperparameters as detailed in Table 1.

These hyperparameters include (α) represents the learning rate controlling the magnitude of parameter updates during optimization. The parameter denotes the dropout probability, determining the proportion of units randomly dropped out during training to prevent overfitting. The parameter (h_{MLP}) specifies the hidden size of the multi-layer perceptron (MLP). The parameter (L) denotes the number of layers in the model, indicating the depth of the neural network architecture. Finally, (n_h) represents the number of attention heads in the multi-head attention mechanism, determining the model's capacity to capture diverse relationships in the input data.

C. *RSMPC Framework*

For online deployment, a hierarchical structure incorporating the Dual-Stage Attention-based Recurrent Neural Network (DA-RNN) model is utilized to predict the dual-class $(\tilde{\mu}_t)$ based on the environmental observation (o_t) as illustrated in Figure 1 and detailed in Algorithm 1.

Furthermore, Data Aggregation filters unsafe demonstrations and resolves expert conflicts, integrating

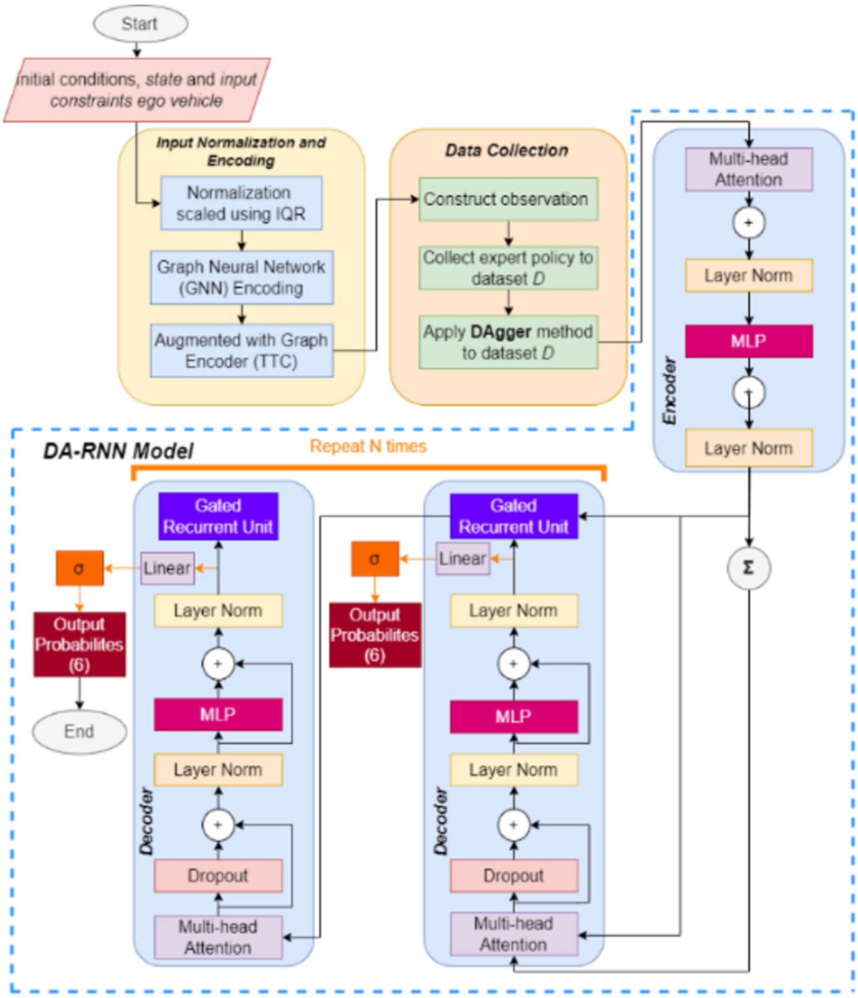

Figure 2. Flowchart of the proposed model DA-RNN

Algorithm 1. Robust Stochastic Model Predictive Control

1. T Define task horizon
2. $\mathcal{D} = \emptyset$ Initialize dataset
3. while $t < T$ do:
4. $o_t \leftarrow$ observation of the environment
5. $\mathcal{A}_t, \mathcal{R}_t, \mathcal{Q}_t, \mathcal{C}_t \leftarrow o_t$ constructed from observation
6. $expert \leftarrow (\mathcal{A}_t, \mathcal{R}_t, \mathcal{Q}_t, \mathcal{C}_t)$ collect expert policy
7. $\mathrm{D} \leftarrow \mathrm{D} \cup \{(\mathcal{A}_t, \mathcal{R}_t, \mathcal{Q}_t, \mathcal{C}_t)\}$ add $expert$ to dataset $\mathcal{D}$
8. $\mathrm{D} \leftarrow$ Apply DAgger to dataset D
9. $\hat{\mathbb{S}} \leftarrow$ computed using (13) from $\pi^{DA-RNN}(\tilde{\mu}_t|o_t)$
10. $\mathbb{S} \leftarrow$ computed from sensitivity criterion (8)
11. $u_t \leftarrow \pi^{\mathrm{RSMPC}}(\mathcal{A}t, \mathscr{R}t, \mathcal{Q}t, \mathcal{C}t, \mathbb{S})$
12. apply u_t to the system
13. $t \leftarrow t + 1$

seamlessly with the low-level MPC planner. The prediction process of the dual-class is specified in equation (8).

$$\pi^{DA-RNN}\left(\tilde{\mu}_t \mid o_t\right) = \begin{cases} \left[\tilde{\mu}_t\right]_s = 1 \forall s \in \mathbb{I}_1^{n_c} \text{ if } \left[\mathcal{P}_t\right]_s \geq 0.5 \\ \left[\tilde{\mu}_t\right]_s = 0 \text{ otherwise} \end{cases} \tag{8}$$

where the DA-RNN output $(\mathcal{P}_t)$ determines the likelihood of each dual class being activated, given the environmental observation at time (t). Subsequently, a set containing all indices of constraints predicted to be active $(\hat{\mathbb{S}})$ as defined in equation (9).

$$\hat{\mathbb{S}} := \left\{ s \in \mathbb{I}_1^{n_c} \mid \left[\pi^{DA-RNN}\left(\tilde{\mu}_t \mid o_t\right] = 1\right\} \tag{9}$$

To derive a feasible dual candidate $(\hat{\mu}_t)$, a reduced linear system is solved via least-squares, yielding a suboptimal solution to the adjusted dual problem. Following this, a sensitivity-based method for vehicle and scenario selection is applied to refine the set $\mathbb{S}$, as specified in equation (10).

$$\mathbb{S} := \hat{\mathbb{S}} \bigcap_{\forall i \in \mathbb{I}_1^V : \left\| S^i [\hat{\mu}_t] \right\|_2 > \frac{\delta}{\mathcal{D}}} \mathbb{S}^i \bigcap_{\forall m \in \mathbb{I}_1^M \left\| S_m [\hat{\mu}_t] \right\|_2 > \frac{\delta}{\mathcal{D} \cdot V}} \mathbb{S}_m \tag{10}$$

This equation combines a sensitivity-based vehicle and scenario selection method, refining the set $(\mathbb{S})$ by iteratively removing interactions that contribute minimally to the optimal cost of the motion plan. The process involves intersecting the initial set $(\hat{\mathbb{S}})$ with subsets that satisfy specific conditions regarding the deviation in the optimal cost denoted by (δ), and the impact of violating collision avoidance constraints for individual vehicles and scenarios. The selection criteria ensure that only critical interactions, whose removal significantly affects the cost of the motion plan, are retained in the refined set $(\mathbb{S})$. Finally, the reduced constraints optimization is formulated and solved to obtain the RSMPC, as defined in equation (11).

$$u_t = \pi^{RSMPC}\left(\mathcal{A}_t, \mathcal{R}_t, \mathcal{Q}_t, \mathcal{C}_t\right) = u^*_{t|t,1} \tag{11}$$

Table 2. Device specifications

Description	Specifications
System Operating	Ubuntu 22.04 LTS
Processor	Intel Core i7-10700F
Graphic Card	NVIDIA RTX 3050
RAM	32GB DDR4
Library	CasADi, IPOPT, Gurobi

This equation signifies that at each time (t), the control input (u_t) is computed by the RSMPC framework based on the current observations ($\mathcal{A}_t$), system dynamics ($\mathcal{R}_t$), quadratic cost matrix ($\mathcal{Q}_t$), and collision avoidance constraints ($\mathcal{C}_t$). The notation ($u^*_{t|t.1}$) indicates the optimal control input obtained from solving the reduced optimization formulation. The availability of (o_t), which contains essential information for constructing ($\mathcal{A}_t, \mathcal{R}_t, \mathcal{Q}_t$) and ($\mathcal{C}_t$), is assumed to be sourced from a simulation environment or on-vehicle sensory devices.

III. Results and Discussion

This section presents the results from various test environments that have been evaluated. The evaluation step in this study was conducted to assess the designed system's performance and ensure that the system operates as expected and meets the established requirements. The system was evaluated by executing the program on a computer with specific specifications for testing purposes in this research, as listed in Table 2.

The imitation learning results from DA-RNN are presented, and subsequently, the performance of the Robust Stochastic Model Predictive Control (RSMPC) policy is compared with the full-MPC policy detailed in equation (5) with a prediction horizon (N) = 14 and a time step (Δt)=0.2s in 100 rollouts randomly generated in the OpenAI Gymnasium intersection traffic environment. During the evaluation of RSMPC and full-MPC simulations, the optimization problems are formulated using the CasADi backbone, a powerful computational tool known for its versatility in handling complex optimization tasks. Specifically, Second Order Cone Programming (SOCP) MPC is utilized, and the resulting optimization formulations are solved using Gurobi Optimization [25], a high-performance optimization solver widely recognized for its efficiency and accuracy in solving mathematical programming formulation.

A. *Simulation Environment Evaluation*

A custom Python and OpenAI Gymnasium simulation environment is designed to evaluate intersectional traffic interactions. This environment features four node zones (U, S, B, and T), with vehicles generated randomly, as shown in Figure 3.

The ego vehicle starts at a node in zone B and is assigned a target node (U or T), defining its mode. Up to three target vehicles are generated from zones B, S, and T, each with specific modes, acting as cross traffic or following different paths. Vehicles follow fixed reference trajectories, representing their states by displacement and speed. The Frenet-frame Intelligent Driver Model (FIDM) is used for target vehicles to simulate human-like driving behaviors, including safe acceleration and yielding at intersections. Observations available to the ego vehicle include its state, previous control inputs, mode, and the states, modes, and target vehicle time-to-collision (TTC) metrics. The simulation continues until the autonomous vehicle reaches its target node or a collision occurs, with the environment designed to capture complex traffic dynamics and collision avoidance scenarios.

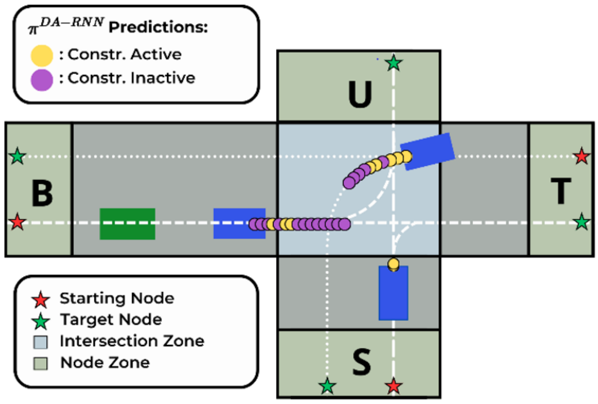

Figure 3. Evaluation environment in the custom unsignalized intersection

B. *DA-RNN Model Evaluation*

The trained DA-RNN model was evaluated in randomly initialized novice policy during 3000 rollouts, with the network being saved and evaluated every 100 training rollouts for experiments with the data filter. The statistical comparison of the normalized loss of DA-RNN with the MLP network (π^{MLP}), trained under the same configuration as DA-RNN with the parameters (h_{MLP}) = 128 and (L) = 6, is illustrated in Figure 4a. The normalized confusion matrix of DA-RNN is shown in Figure 4b. The complex interaction predictions between the autonomous vehicle and the target vehicle are effectively captured by the DA-RNN model, surpassing the capabilities of the MLP network. Additionally, the DA-RNN model achieved a recall value of 0.97 and a precision value of 0.44, signifying an accurate prediction of interactive constraints in 44% of observed instances in the test dataset. The DA-RNN training was configured to sacrifice precision to achieve high recall, as false positive classifications are not critical for safety. During the evaluation of the test dataset, a high accuracy rate of 98.1% was achieved in predicting total dual interactions, with a minimal false negative rate of 0.026.

This evaluation highlights the superiority of the DA-RNN model over the MLP network [26], which achieved only 92% accuracy compared to DA-RNN's high accuracy rate of 98.1%. The DA-RNN model's ability to capture

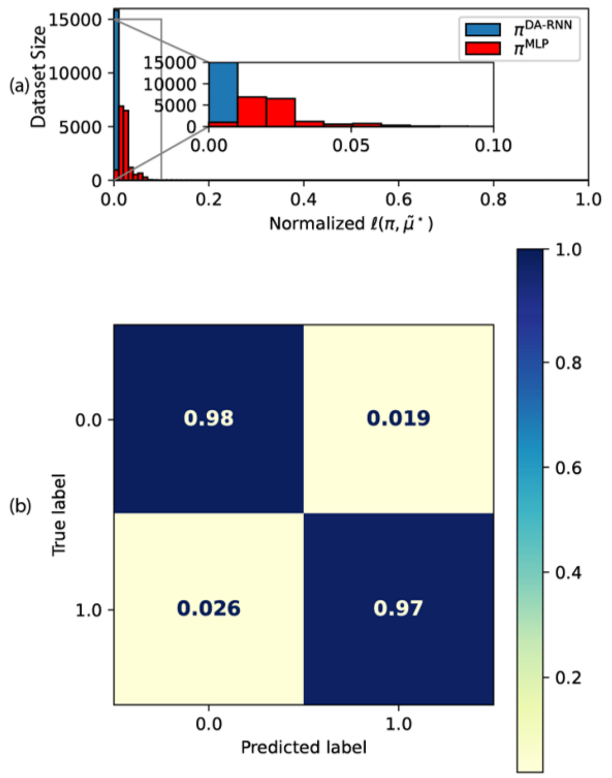

Figure 4. DA-RNN evaluation results: (a) normalized loss values, (b) confusion matrix of DA-RNN

Table 3. Comparison of Full-MPC with RSMPC policy

Metrics	Full-MPC (5)	RSMPC (9)
Feasibility (%)	96.85	99.84
Collision (%)	0	2.0
Average active constraints (%)	100	17.18
Average solving time (s)	1.01±0.166	0.042±0.037
Average time query DA-RNN (s)	–	0.022±0.007
Average total processing time (s)	1.01±0.166	0.064±0.044
Average normalized time to complete tasks	1	0.89

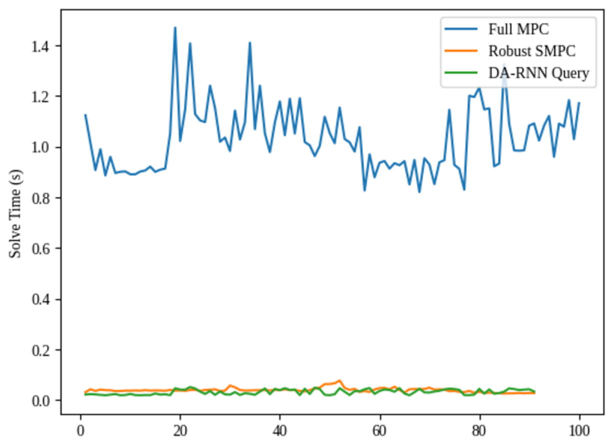

Figure 5. Solving time comparison of the proposed model

complex patterns and accurately predict interactions between autonomous vehicles and targets results in good recall values and high accuracy. Effectiveness in handling complex vehicle interactions is demonstrated by the DA-RNN model, which consistently produces accurate and satisfactory predictions. With its high recall results and excellent accuracy in predicting various vehicle interactions, the proposed model proves its robustness in navigating diverse dynamic and complex traffic scenarios. Despite some false positives, the model prioritizes improving recall to ensure the accurate detection of significant interactive obstacles, thereby ensuring high safety in autonomous vehicle navigation.

C. Framework Performance Comparison

Table 3 provides comparison insights into the performance metrics of Full MPC and RSMPC algorithms over 100 rollouts. It records the percentage of time steps indicating RSMPC feasibility and collisions with target vehicles alongside the average rate of constraints enforced in RSMPC. Additionally, it captures the average time to solve expert policy (5) and RSMPC (9) and the average query time for the DA-RNN model. Finally, it presents the average total processing time until reaching the target node for RSMPC by full MPC. The analysis reveals that RSMPC outperforms Full MPC in feasibility and collision avoidance, with significantly lower collision rates (2.0% compared to 0%). Despite enforcing a smaller percentage of constraints (17.18% compared to 100% in Full MPC), RSMPC demonstrates higher feasibility, suggesting more efficient boundary utilization.

Moreover, RSMPC exhibits a substantially shorter average total processing time compared to Full MPC (0.89 seconds compared to 1 second), indicating its efficacy in achieving task objectives promptly. Furthermore, RSMPC incurs a negligible query time for the DA-RNN model (0.022 seconds), contributing to its computational efficiency. These findings underscore the effectiveness of RSMPC in achieving safe, faster response and efficient autonomous driving behavior, offering a promising alternative to Full MPC with notable improvements in feasibility and computational efficiency.

An analysis of the solving times presented in Figure 5 illustrates a clear difference between the expert policy using Full MPC and the learned policy employing RSMPC combined with DA-RNN queries. The expert policy exhibits an average solve time of 1.01 seconds, with a standard deviation of 0.166 seconds. In contrast, RSMPC achieves an average solve time of 0.042 seconds, with a standard deviation of 0.037 seconds. The average NN query time is 0.022 seconds, with a standard deviation of 0.007 seconds. This substantial reduction in solving time underscores the computational efficiency of the RSMPC approach, indicating a notable improvement in response time from 1.01 to 0.064 seconds, marking a 15-fold enhancement.

The control input plot in Figure 6 shows how the control

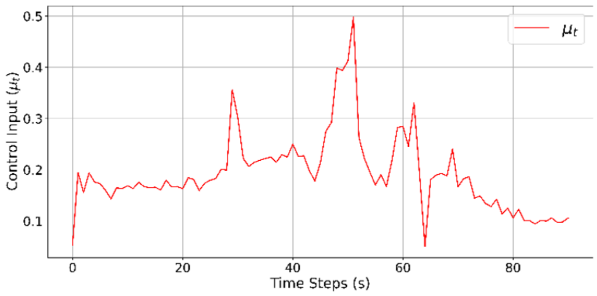

Figure 6. Control input over time

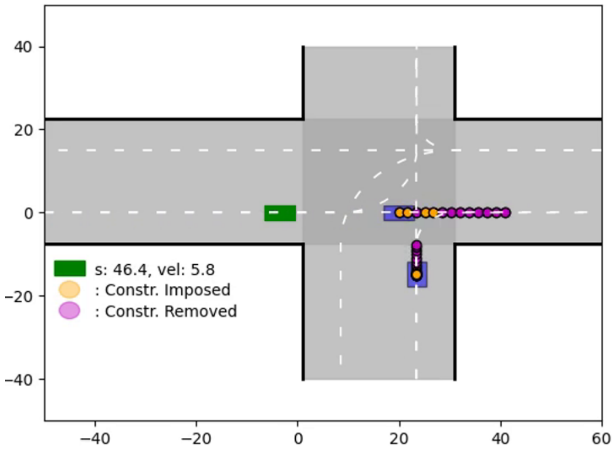

Figure 7. Motion planning of $\pi^{\text{DA-RNN}}$ in multi-modal intersections traffic environment

input (μ_t) varies over time, computed by the RSMPC framework. Initially, minor fluctuations indicate responses to less complex traffic. Significant peaks in the middle time steps correspond to critical maneuvers needed for collision avoidance and navigating dense traffic, reflecting real-time adaptability. Towards the end, the control input stabilizes and reduces, indicating successful negotiation through challenging traffic and entry into stable flow. This demonstrates the system's ability to minimize control effort, ensuring efficient energy use and smooth motion, validating the RSMPC framework's effectiveness in maintaining safety and efficiency.

The visualization provided in Figure 7 offers a qualitative representation of a scene in the multi-modal intersection environment, showcasing the motion planning of $\pi^{\text{DA-RNN}}$. Supplementary videos showcasing the RSMPC algorithm's performance in various environments are available at https://youtu.be/V1TcGfFPsY8. The RSMPC code is accessible for further examination and replication at https://github.com/Xhydracore/RSMPC_DARNN.

The constraints within the RSMPC formulation for multi-modal traffic intersections have been streamlined to accelerate the response time significantly, as shown in Figure 6. The proposed DA-RNN model shows the effectiveness of the model in the forecast, which targets vehicles and interaction modes that will influence the ego vehicle through impressive performance metrics, with a recall value of 0.97 and a precision value of 0.44, alongside a high rate accuracy level of 98.1%, surpassing the MLP network by 6%. Overall, there is a notable improvement in the proposed framework performance in most scenarios. Focusing on relevant, with a smaller percentage of constraints of 17.18% compared to 100% in Full-MPC, has led to a higher feasibility rate at 99.84% and more than 15 times improvement in response time for the control system while maintaining rigorous safety standards. Furthermore, this framework improves computational efficiency and enhances autonomous vehicle operations' overall robustness and reliability in real-world implementation. This method ensures that autonomous vehicles navigate safely and efficiently through intricate traffic scenarios, laying the groundwork for more dependable and scalable autonomous driving solutions.

IV. Conclusion

This work presents a robust framework for real-time motion planning in complex, multi-modal traffic intersection environments. Utilizing the cooperative nature of urban driving, the autonomous vehicle model prediction transforms into a robust stochastic model predictive control (RSMPC) approach, which minimizes the cost function while ensuring feasibility and safety guarantees. The Dual-Stage Attention-based Recurrent Neural Network (DA-RNN) algorithm is employed to predict feasible dual solutions for the RSMPC optimization formulation, enhanced by the Data Aggregation (DAgger) method to address distribution shifts and improve generalization to real-world traffic data. Finally, an RSMPC problem optimization is formulated to reduce irrelevant collision avoidance constraints, achieving faster response through Lagrangian duality. The proposed DA-RNN model demonstrates a notable accuracy rate of 98.1% in predicting total dual interactions, accompanied by a minimal false negative rate of 0.026. This achievement underscores the model's effectiveness in capturing the intricacies of interactions. This innovative framework approach excels in a simulated multi-modal traffic intersection, resulting in real-time performance and a high feasibility rate at 99.84%, with a 15-times increase in response speed compared to the baseline.

References

[1] M. S. Shirazi and B. T. Morris, "Looking at intersections: A survey of intersection monitoring, behavior, and safety analysis of recent studies," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 1, pp. 4–24, 2017

[2] I. Kamal, K. Housni, and M. Y. Hadi, "A survey of autonomous vehicles for traffic analysis," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 33, no. 2, pp. 1016–1029, 2024.

[3] S. Baccari, M. Hadded, H. Ghazzai, H. Touati, and M. Elhadef, "Anomaly detection in connected and autonomous vehicles: a survey, analysis, and research challenges," *IEEE Access*, vol. 12, pp. 19250–19276, 2024.

[4] F. Sana, N. L. Azad, and K. Raahemifar, "Autonomous vehicle decision-making and control in complex and unconventional scenarios—a review," *Machines*, vol. 11, no. 7, pp. 1-29, 2023.

[5] K. Wang, G. Zhao, and J. Lu, "A deep analysis of visual SLAM methods for highly automated and autonomous vehicles in complex urban environment," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 9, pp. 10524 – 10541, 2024,

[6] M. Reda, A. Onsy, A. Ghanbari, and A. Y. Haikal, "Path planning algorithms in the autonomous driving system: A comprehensive review," *Robotic and Autonomous System*, vol. 174, pp. 104630, 2024.

[7] J. Medina-Lee, A. Artuñedo, J. Godoy, and J. Villagra, "Merit-based motion planning for autonomous vehicles in urban scenarios," *Sensors,* vol. 21, no. 11, pp. 3755, 2021.

[8] E. Ahmadi, A. Olama, R. C. Carlson, and E. Camponogara, "Signal-free path-free intersection control for connected vehicles under automated driving," *IEEE Transactions on Intelligent Vehicles*, pp. 1 – 13, 2024.

[9] S. H. Nair, H. Lee, E. Joa, Y. Wang, H. E. Tseng, and F. Borrelli, "Predictive control for autonomous driving with uncertain, multi-modal predictions," Oct. 2023, Accessed: May 22, 2024. [Online]. Available: https://arxiv.org/abs/2310.20561v1.

[10] J. Li, L. Peng, S. Xu, and Z. Li, "Distributed edge signal control for cooperating pre-planned connected automated vehicle path and signal timing at edge computing-enabled intersections," *Expert Syst Appl*, vol. 241, pp. 122570, 2024.

[11] A. Jo, S. Kim, H. Lee, and K. Yi, "Ride comfort-enhanced optimal decision and planning strategy at urban signalized intersections based on hybrid model predictive control," in Proc. IEEE Conference on Intelligent Transportation Systems, 2023, pp. 4866–4873.

[12] H. Liu, K. Chen, Y. Li, Z. Huang, J. Duan, and J. Ma, "Integrated behavior planning and motion control for autonomous vehicles with traffic rules compliance," in Proc. IEEE International Conference on Robotics and Biomimetics, 2023

[13] S. Zhou, H. Xu, G. Zhang, T. Ma, and Y. Yang, "Deep learning-based pedestrian trajectory prediction and risk assessment at signalized intersections using trajectory data captured through roadside LiDAR," *Journal of Intelligent Transportation System*, pp. 1-3, 2023.

[14] K. Yu, L. Lin, M. Alazab, L. Tan, and B. Gu, "Deep learning-based traffic safety solution for a mixture of autonomous and manual vehicles in a 5G-enabled intelligent transportation system," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 7, pp. 4337–4347, 2021

[15] S. Chen, X. Hu, J. Zhao, R. Wang, and M. Qiao, "A Review of Decision-Making and Planning for Autonomous Vehicles in Intersection Environments," *World Electric Vehicle Journal,* vol. 15, no. 3, pp. 99, 2024.

[16] J. Sun, X. Qi, Y. Xu, and Y. Tian, "Vehicle turning behavior modeling at conflicting areas of mixed-flow intersections based on deep learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 9, pp. 3674–3685, 2020.

[17] R. Yao, W. Zeng, Y. Chen, and Z. He, "A deep learning framework for modeling left-turning vehicle behaviour considering diagonal-crossing motorcycle conflicts at mixed-flow intersections," *Transportation Research Part C: Emerging Technologies*, vol. 132, pp. 103415, 2021.

[18] B. Li, X. Chen, T. Acarman, X. Li, and Y. Zhang, "Recent advances in motion planning and control of autonomous vehicles," *Electronics,* vol. 12, no. 23, pp. 4881, 2023.

[19] Y. Chen, Y. Bian, Y. Chen, and Y. Bian, "Tube-based event-triggered path tracking for AUV against disturbances and parametric uncertainties," *Electronics*, vol. 12, no. 20, pp. 4248, 2023.

[20] H. Sun, C. Zhang, C. Hu, and J. Zhang, "Event-triggered reconfigurable reinforcement learning motion-planning approach for mobile robot in unknown dynamic environments," *Engineering Application of Artificial intelligence*, vol. 123, pp. 106197, 2023.

[21] J. Hu, R. Chen, W. Xu, and R. Lu, "An event-triggered real-time motion planning strategy for autonomous vehicles," vol. 236, no. 19, pp. 10332–10348, 2022.

[22] B.Novel and M. D. Lara, "Discrete-time linear dynamical systems," In: Control Theory for Engineers. Springer, Berlin, Heidelberg, 2013.

[23] Z. Ma, L. Liu, S. Zhou, F. Naets, W. Heylen, and W. Desmet, "Dynamic stability analysis of linear time-varying systems via an extended modal identification approach," *Chinese Journal of Mechanical Engineering*, vol. 30, no. 2, pp. 459–471, 2017.

[24] J. B. Rawlings, D. Q. Mayne, M. M. Diehl, and S. Barbara, "Model Predictive Control: Theory, Computation, and Design 2nd Edition," 2022. [Online]. Available: http://www.nobhillpublishing.com

[25] L. Gurobi Optimization, "Gurobi Optimizer Reference Manual," 2023. Accessed: May 08, 2024. [Online]. Available: https://www.gurobi.com/

[26] T. Tran, J. Denny, and C. Ekenna, "Predicting Sample Collision with Neural Networks," Jun. 2020, Accessed: Jun. 02, 2024. [Online]. Available: https://arxiv.org/abs/2006.16868v1.