Text highlighted in Green is new (introduced by the framework). Uncolored text was in the participant's original requirements.

1. TITLE: Domain-Specific Constraints in RL Training

SYSTEM_REQUIREMENT: The RL agent shall incorporate domain-specific constraints to ensure realistic and safe decision-making.
IMPLEMENTATION_DETAILS:
* Enforce minimum and maximum phase durations to prevent unrealistic signal switching
* Apply safety rules to prevent conflicting green signals
* Implement vehicle flow limits based on road capacity and infrastructure constraints.

RATIONALE: Embedding domain knowledge into the RL system ensures that learned policies adhere to practical and safe traffic control standards, reducing the risk of unrealistic or unsafe decisions.

2. TITLE: Reward Function Robustness and Risk Mitigation

SYSTEM_REQUIREMENT: The RL system shall be designed to prevent unintended behaviors arising from poorly formulated reward functions.
IMPLEMENTATION_DETAILS:
* Perform regular evaluation and sensitivity analysis to monitor agent responses
* Utilize counterfactual analysis to test alternative reward functions
* Apply penalties for excessive switching or favoring a single road segment disproportionately.

RATIONALE: A well-structured reward function ensures that the RL agent optimizes traffic flow without introducing counterproductive behaviors, such as excessive switching.

3. TITLE: Centralized Control for Multi-Intersection Optimization

SYSTEM_REQUIREMENT: The RL system shall use a centralized controller instead of multiple agents to optimize traffic flow across multiple intersections.
IMPLEMENTATION_DETAILS:
* Formulate the problem as a single-agent system to avoid credit assignment issues
* Optimize traffic control decisions globally for stability and efficiency.

RATIONALE: A centralized approach avoids coordination complexities in multi-agent RL systems, improving accuracy and efficiency in decision-making.

4. TITLE: Computational Efficiency in Learning Architecture

SYSTEM_REQUIREMENT: The RL system shall be optimized for computational efficiency without compromising accuracy.
IMPLEMENTATION_DETAILS:
* Implement experience replay to improve sample efficiency
* Use model compression techniques like pruning and quantization
* Employ parallelized training with multi-core CPUs and GPUs
* Utilize lightweight neural architectures for real-time feasibility.

RATIONALE: Optimizing computational efficiency ensures that the RL system can process large amounts of data quickly while maintaining accurate decision-making.

5. TITLE: Handling High-Dimensional State and Action Spaces
SYSTEM_REQUIREMENT: The RL system shall use feature extraction techniques to manage high-dimensional state representations efficiently.
IMPLEMENTATION_DETAILS:
* Use convolutional neural networks (CNNs) or attention mechanisms for traffic camera and sensor data
* Keep action spaces discrete to simplify decision-making
* Apply policy distillation and hierarchical learning for large action spaces
* Utilize GPUs for accelerating training and inference.
RATIONALE: Managing high-dimensional input and action spaces effectively ensures that the RL system can make accurate decisions while maintaining computational feasibility.

6. TITLE: Performance Evaluation Against Real-World Data
SYSTEM_REQUIREMENT: The RL system shall assess accuracy by comparing simulation-based results with real-world traffic sensor data.
IMPLEMENTATION_DETAILS:
* Use simulation-based benchmarks to compare RL-generated policies against predefined traffic control scenarios in SUMO
* Validate predicted vs. actual vehicle waiting times throughput and flow rates using real-world sensors
* Compare RL decisions with those of experienced human traffic operators.
RATIONALE: Validating the RL system's performance against real-world data ensures its accuracy and applicability to real traffic conditions.

7. TITLE: Defining Performance Metrics and Acceptable Ranges
SYSTEM_REQUIREMENT: The RL system shall use clearly defined performance metrics and establish acceptable ranges based on historical data and expert input.
IMPLEMENTATION_DETAILS:
* Evaluate average vehicle wait time as an efficiency metric
* Measure queue lengths to assess traffic flow
* Track traffic throughput to monitor system performance
* Monitor signal switching frequency to prevent excessive phase changes
* Determine acceptable metric ranges using historical city traffic data expert input and feasibility studies.
RATIONALE: Well-defined performance metrics ensure that the RL system operates within expected and effective traffic control parameters.

8. TITLE: Formal Verification for Safety and Correctness
SYSTEM_REQUIREMENT: The RL system shall use formal verification techniques to ensure correctness and safety before deployment.
IMPLEMENTATION_DETAILS:
* Apply model checking to verify system correctness
* Use reachability analysis to evaluate possible system states
* Perform adversarial testing to identify and mitigate vulnerabilities.

RATIONALE: Formal verification ensures that the RL system meets safety and accuracy requirements before real-world deployment, reducing risks of failures.

9. TITLE: Handling Rare and High-Impact Traffic Scenarios

SYSTEM_REQUIREMENT: The RL agent shall be trained and tested on rare but high-impact traffic scenarios to ensure robustness.
IMPLEMENTATION_DETAILS:
* Domain randomization is used to expose the agent to extreme congestion, accidents, roadblocks and sensor failures.
* Scenarios with the highest potential impact on traffic flow such as sudden demand spikes and blocked intersections are manually defined and oversampled during training.

RATIONALE: Training on rare but high-impact scenarios ensures the system can handle unexpected and critical real-world situations, improving reliability and robustness.

10. TITLE: Incorporation of Environmental Variations in Simulation

SYSTEM_REQUIREMENT: The simulation environment shall incorporate variations in environmental conditions, driver behavior, and external disruptions to improve the generalizability of RL policies.
IMPLEMENTATION_DETAILS:
* The SUMO simulator models weather effects by adjusting vehicle speed and braking under rain and snow.
* It introduces varying driver behaviors including aggressive and cautious drivers. External disruptions such as emergency vehicle passages and construction detours are included.

RATIONALE: Modeling diverse environmental variations ensures that the RL system is exposed to realistic uncertainties, enhancing its ability to generalize effectively.

11. TITLE: Robust State Representation under Uncertain Observations

SYSTEM_REQUIREMENT: The RL system shall infer missing or uncertain state information to maintain a robust state representation under noisy and incomplete data.
IMPLEMENTATION_DETAILS:
* Bayesian inference is used to estimate missing data probabilistically.
* Kalman filters smooth noisy sensor readings.
* Historical data-based interpolation fills in missing values using past traffic trends.

RATIONALE: Ensuring a robust state representation under uncertainty helps the RL system make reliable decisions even when observations are incomplete or unreliable.

12. TITLE: Adaptive Decision-Making under Uncertainty

SYSTEM_REQUIREMENT: The RL system shall incorporate adaptive policies and error mitigation strategies to handle uncertainty in action execution.
IMPLEMENTATION_DETAILS:
* Actuator noise and delays are explicitly modeled in simulation.
* Domain adaptation techniques ensure policy transferability to real-world systems.

* Feedback loops with state correction, adaptive policies (e.g. meta-RL) and conservative exploration strategies mitigate error accumulation.
RATIONALE: Handling execution uncertainty ensures that real-world decision-making remains robust and reliable despite noise and inconsistencies in the environment.

13. TITLE: Reliable and Informative Reward System
SYSTEM_REQUIREMENT: The RL system shall ensure that rewards provide reliable and informative feedback for effective learning.
IMPLEMENTATION_DETAILS:
* Reward shaping techniques assign weighted rewards for waiting time, queue length, lane switching, and fairness penalties.
* Counterfactual reasoning is used to test alternate reward formulations.
* Reward normalization prevents skewed gradients by scaling rewards appropriately.
RATIONALE: A well-designed reward system is critical for guiding learning and ensuring that the RL agent develops optimal traffic management strategies.

14. TITLE: Reducing Simulation-to-Reality Gap
SYSTEM_REQUIREMENT: The RL system shall incorporate real-world feedback into the simulation to refine models and reduce the sim-to-real gap.
IMPLEMENTATION_DETAILS:
* Continuous domain adaptation updates simulation parameters based on real-world traffic data.
* Real-world data integration retrains policies using actual sensor data rather than synthetic simulations alone.
RATIONALE: Reducing the simulation-to-reality gap enhances the reliability of the RL system when deployed in real-world traffic scenarios.

15. TITLE: Efficient and Generalizable Training
SYSTEM_REQUIREMENT: The RL system shall use techniques that improve training efficiency and generalizability from limited data.
IMPLEMENTATION_DETAILS:
* Experience replay, prioritized sampling, model-based RL and data augmentation techniques are used to maximize learning and generalization.
RATIONALE: Improving training efficiency ensures that the RL system learns effectively from limited data, enhancing performance and robustness.

16. TITLE: Hyperparameter Optimization for Robustness
SYSTEM_REQUIREMENT: The RL system shall optimize hyperparameters to balance stability, generalization, and performance across different environments.
IMPLEMENTATION_DETAILS:
Extensive experimentation on various hyperparameters is conducted to determine the best-performing configurations.
RATIONALE: Optimizing hyperparameters ensures that the RL system maintains stability and generalizes well across different traffic conditions.

17. TITLE: Robustness Metrics and Thresholds
SYSTEM_REQUIREMENT: The RL system shall evaluate robustness using defined metrics and establish empirical thresholds.
IMPLEMENTATION_DETAILS:
* Metrics such as policy variance under perturbations generalization error and out-of-distribution performance are used.
* Acceptable thresholds are determined through empirical analysis.
RATIONALE: Measuring and setting thresholds for robustness ensures that the RL system maintains reliable performance under varying conditions.

18. TITLE: Balancing Performance and Reliability
SYSTEM_REQUIREMENT: The RL system shall balance performance with reliability, ensuring that optimizations do not compromise system stability.
IMPLEMENTATION_DETAILS:
* Safe RL techniques incorporate risk-aware decision-making.
* Conservative exploration strategies limit drastic policy changes, prioritizing stability.
RATIONALE: Ensuring a balance between performance and reliability prevents excessive risk-taking while maintaining effective traffic management.