Smart Traffic Light System (STLS) Using IoT for Adaptive Urban Mobility

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***Abstract*—This paper introduces the Smart Traffic Light System (STLS) as a transformative, IoT-enabled solution designed to address multifaceted challenges stemming from traffic congestion through adaptive, real-time traffic management. At its core, STLS leverages a sophisticated integration of IoT sensors, robust communication networks, advanced Artificial Intelligence (AI) and Machine Learning (ML) algorithms, and distributed computing platforms (cloud and edge computing) to dynamically optimize traffic flow in urban centers, specifically theorizing its application to key crossroads in the city of Sliven, Bulgaria. The implementation of STLS promises substantial benefits, including demonstrable reductions in traffic congestion, travel times, fuel consumption, and vehicle emissions, alongside enhanced road safety and improved emergency response times.**

STLS is positioned as a foundational element for the development of future smart cities, poised to revolutionize urban transportation by creating more efficient, safer, and sustainable urban environments.

***Keywords*—Adaptive traffic control, IoT, LoRa, machine learning, Smart traffic lights.**

I. Introduction

The rapid pace of global urbanization has led to an unprecedented increase in metropolitan populations, placing immense strain on existing urban infrastructure. A direct and pervasive consequence of this demographic shift is the escalating problem of traffic congestion in cities worldwide. This issue extends far beyond mere inconvenience, evolving into a multi-dimensional crisis that profoundly impacts economic productivity, environmental health, and public well-being. Economically, congestion results in substantial losses due to wasted fuel, delayed deliveries, and reduced workforce efficiency. Environmentally, it contributes significantly to increased vehicle emissions, including carbon dioxide (CO_2), nitrogen oxides (NO_x), and particulate matter, exacerbating air pollution and contributing to climate change. These pollutants, in turn, pose serious public health risks and diminish the overall quality of urban life.

Traditional traffic light systems, often operating on fixed-time schedules or pre-programmed logic, are inherently limited in their ability to respond effectively to the dynamic and unpredictable nature of modern traffic conditions [2]. Their static nature means they cannot adapt to real-time fluctuations caused by accidents, special events, sudden surges in vehicle volume, or varying pedestrian demands. This inflexibility often leads to "empty green lights," where signals turn green without vehicles waiting, wasting valuable time and exacerbating inefficiency [6]. This fundamental inadequacy necessitates the development of more sophisticated and responsive solutions.

In response to these pressing challenges, Smart Traffic Light Systems (STLS) have emerged as an innovative and highly promising solution, leveraging advanced technologies to optimize traffic flow in real-time. The Internet of Things (IoT) plays a pivotal role as the enabling technology for STLS, providing the essential infrastructure for pervasive data collection, seamless communication, and intelligent decision-making [1]. Through a network of interconnected IoT sensors, STLS can collect diverse traffic data, such as vehicle count, speed, density, and occupancy, as well as environmental data. This continuous stream of information is then processed by sophisticated Artificial Intelligence (AI) and Machine Learning (ML) algorithms, which dynamically adjust signal timings to optimize traffic flow, minimize delays, and enhance safety [2].

This paper aims to provide a detailed exposition of IoT-enabled STLS for adaptive urban mobility, specifically theorizing its application to key crossroads in the city of Sliven, Bulgaria. Subsequent sections will delve into the historical context and related work, the intricate architecture of STLS components, its operational principles and adaptive algorithms, the comprehensive benefits and broader impact on urban mobility, and a thorough examination of the challenges and future considerations for its widespread deployment. By offering a comprehensive analysis of system components, algorithmic approaches, and a balanced discussion of benefits versus implementation hurdles, this paper contributes to the academic discourse by illuminating the transformative potential of STLS as a necessary and strategic intervention in addressing the pervasive crisis of urban congestion, particularly in the unique context of Sliven.

II. Background and Related Work

The evolution of traffic management systems reflects a continuous effort to bring greater efficiency and responsiveness to urban mobility. Historically, traffic control began with manual police direction, evolving into rudimentary fixed-time signal systems [7]. These early systems operated on pre-set schedules, regardless of actual traffic volume, leading to inefficiencies during off-peak hours or unexpected surges [4]. The subsequent development of actuated systems introduced basic sensing capabilities, allowing signals to respond to vehicle presence at an intersection [4].

Coordinated systems further advanced this by synchronizing signals across multiple intersections along a corridor, aiming to create "green waves" for smoother flow [9]. However, a persistent limitation across these generations was their inherent inability to adapt dynamically to real-time, unpredictable traffic fluctuations, often relying on historical patterns or simple rule-based logic that could not account for complex, emergent conditions [6].

Early forms of "smart" traffic solutions attempted to integrate more advanced sensors or pre-defined adaptive logic based on historical data. Systems like SCOOT (Sydney Coordinated Adaptive Traffic System) and SCATS (Split, Cycle, and Offset Optimization Technique) emerged, utilizing vehicle detectors to acquire real-time data and optimize timing plans [6]. While these systems offered marginal improvements over fixed-time controls, they often suffered from significant shortcomings. Their reliance on limited sensor data, lack of real-time, high-bandwidth communication, and inability to handle complex, dynamic events such as accidents, sudden weather changes, or large-scale public gatherings severely restricted their effectiveness [6]. These systems were largely reactive, making adjustments after congestion had already formed, rather than preventing it [6].

The proliferation of IoT devices and the widespread availability of robust connectivity, including technologies like 5G, LoRaWAN, and Wi-Fi, have fundamentally transformed the landscape of urban infrastructure management [1]. This technological advancement has enabled a precedent capability for real-time data collection from diverse sources, leading to a profound paradigm shift in how urban infrastructure, particularly traffic, is managed. This shift moves from reactive, rule-based systems to proactive, data-driven, and truly adaptive systems [5]. The extensive network of interconnected IoT sensors and devices acts as the "nervous system" for smart cities, continuously feeding information into analytical platforms. This allows for a level of intelligence and autonomy previously unattainable [1]. The ability to collect and process vast amounts of real-time data means that traffic management systems can now "learn" and "self-optimize," moving from a human-centric, pre-defined control model to a data-centric, autonomous optimization model. This fundamental alteration in control philosophy, from deterministic, human-programmed logic to probabilistic, AI-driven, self-optimizing systems, represents the true paradigm shift brought about by IoT. Within this evolving smart city ecosystem, STLS emerges as a critical component, leveraging this pervasive connectivity and data richness to achieve a higher level of intelligence and autonomy in urban mobility.

III. ARCHITECTURE OF AN IOT-ENABLED SMART TRAFFIC LIGHT SYSTEM

The architecture of an IoT-enabled Smart Traffic Light System (STLS) is a sophisticated interplay of various interconnected components, each playing a crucial role in the system's ability to collect, process, and act upon real-time traffic data. This distributed intelligence model, balancing local responsiveness with global optimization, is fundamental to its effectiveness.

Detailed Breakdown of System Components

1. IoT Sensors: These are the primary data collectors, providing the raw input for the system.

a) Inductive Loop Detectors: While traditional, these embedded sensors remain relevant for basic vehicle presence detection and counting [2]. For Sliven, these could be cost-effectively integrated into existing road infrastructure at main entry points to intersections.

b)Cameras: Advanced vision-based systems offer comprehensive data, including vehicle detection, classification (e.g., car, truck, bus), speed estimation, and precise queue length measurement. They can also detect pedestrians and cyclists, and identify anomalous situations like accidents or blocked lanes [2]. High-resolution cameras with computer vision capabilities would be strategically placed at the approaches to crossroads such as the Intersection of bul. „Stefan Karadzha“/ bul. „General Skobelev“/ ul. „6-i Septemvri“/ ul. „Georgi Ikonomov“ in Sliven, which experiences high vehicle and pedestrian traffic.

c)Radar: Utilized for accurate speed measurement, vehicle presence detection, and tracking multiple vehicles simultaneously, even in adverse weather conditions [2]. Radar sensors would complement camera data, especially important during Sliven's diverse weather conditions.

d)Lidar: Provides high-resolution 3D mapping of the environment, enabling precise object detection, tracking, and classification, offering superior accuracy for complex intersection scenarios. LiDAR could be deployed at particularly complex or accident-prone intersections in Sliven, such as the Intersection of bul. „Tsar Simeon“/ bul. „Bratya Miladinovi“ or at the Roundabout “Rozova Gradina” to enhance safety and data precision.

e)Acoustic Sensors: Crucial for detecting emergency vehicle sirens, allowing for rapid prioritization of their passage [10]. These sensors would be vital for facilitating quicker response times for ambulances and fire services navigating Sliven's urban landscape.

f)Environmental Sensors: Crucial for monitoring air quality (e.g., PM2.5, CO_2, NO_x) and noise levels [5]. While not directly impacting traffic light timing, this data is invaluable for understanding the environmental impact of congestion and for future urban planning in Sliven. These could be integrated into the traffic light poles themselves.

2. Local Processing Unit (Edge Computing): Each traffic node (intersection) would be equipped with a local processing unit, leveraging edge computing principles. This unit would perform immediate data pre-processing and initial decision-making.

a)Data Pre-processing: This involves filtering noise, aggregating data from various sensors (e.g., combining vehicle counts from loops and cameras), and extracting key metrics (e.g., real-time queue lengths, average speeds per lane, pedestrian counts).

b)Local Anomaly Detection: Basic detection of accidents or unusual traffic flow patterns at the intersection level.

c)Fallback Mechanism: In case of communication loss with the Central Traffic Management Unit (CTMU), the local unit can revert to pre-loaded, optimized schedules or make real-time adjustments based on local sensor data, ensuring continued, albeit less optimized, operation. This is crucial for maintaining basic traffic flow in Sliven during network outages.

3. Central Traffic Management Unit (CTMU): The CTMU serves as the "brain" of the entire STLS network, receiving pre-processed data from all IoT traffic nodes

within Sliven.

a)Data Aggregation and Fusion: Collects and integrates diverse data streams from all connected intersections in Sliven, creating a holistic, real-time view of the city's traffic.

b)Machine Learning Algorithms: This is the core intelligence.

-*Reinforcement Learning (RL):* RL agents would dynamically learn optimal signal timings by observing the outcomes of their actions (e.g., reduced waiting times, increased throughput) and receiving "rewards" or "penalties." This would allow for highly adaptive control tailored to Sliven's specific traffic patterns.

-*Neural Networks (NN):* Used for predictive analytics, forecasting short-term traffic patterns based on historical data, real-time conditions, and external factors like weather or local events (e.g., a football match at the Sliven City Stadium).

-*Optimization Algorithms (e.g., Genetic Algorithms, Particle Swarm Optimization):* These algorithms would search for optimal timing cycles across multiple intersections, minimizing congestion and waiting times across Sliven's road network, not just at individual junctions.

c)Decision Making and Coordination: Based on the AI/ML analysis, the CTMU generates optimized traffic light schedules and dispatches them back to the respective IoT traffic nodes. It also coordinates traffic lights across multiple intersections to create "green waves" along major arteries in Sliven, such as bul. „Stefan Karadzha“.

4. Cloud-Based Analytics Platform: This platform provides long-term data storage, advanced analytics, and overall system oversight.

a)Big Data Storage: Securely stores vast volumes of historical and real-time traffic data from Sliven, enabling in-depth historical analysis and trend detection.

b)Advanced Analytics and Reporting: Performs computationally intensive analyses, such as long-term traffic forecasting based on seasonal changes, major events (e.g., Sliven International Folklore Festival), and infrastructure changes. It identifies areas requiring infrastructure improvements or long-term route planning within Sliven.

c)Model Training and Retraining: More complex and resource-intensive machine learning models are trained and periodically retrained in the cloud using large datasets, then deployed to the CTMU. This ensures the system continuously learns and adapts to evolving traffic patterns in Sliven.

d)Visualization and User Interface: Provides dashboards and reports for municipal authorities, traffic engineers, and emergency services in Sliven, offering real-time traffic monitoring, performance metrics, and insights into system operation.

5. Communication Model: A hybrid communication model ensures reliable and efficient data transfer across diverse urban environments in Sliven.

a) LoRa (Long Range): Suitable for long-distance, low-power communication, ideal for transmitting small data packets from sensors in more remote or sparsely populated areas of Sliven, or for redundant low-bandwidth communication channels.

b) 5G: Provides high speed and low latency, making it ideal for critical, real-time communication between the CTMU and traffic nodes in busy urban areas of Sliven. It enables rapid transmission of video data from cameras and instantaneous traffic light timing updates for dynamic control. Key intersections would benefit most from 5G connectivity.

c) WiFi: Used for short-range communication, such as within a single intersection for data transfer between various sensors and the local controller, or for providing connectivity for maintenance and troubleshooting. WiFi hotspots at intersections could also offer public access, further leveraging the infrastructure.

This architectural framework ensures that the STLS can collect comprehensive data, process it intelligently, and disseminate adaptive control signals efficiently, leading to a truly responsive and optimized traffic management system for the city of Sliven.

IV. OPERATIONAL ALGORITHM OF SMART TRAFFIC NODES

Each smart traffic node in Sliven's STLS network follows an operational algorithm that allows it to function autonomously to some extent while maintaining seamless communication with the Central Traffic Management Unit (CTMU). This tiered decision-making ensures resilience and optimizes local control.

Algorithm 1: Smart Traffic Node Operational Cycle

1. Initialization:

- Configure Sensors: Activate and calibrate all integrated sensors (cameras, radar, LiDAR, inductive loops, acoustic sensors, environmental sensors) connected to the local processing unit.
- Establish Communication: Attempt to establish primary communication with the CTMU via 5G or LoRa, and local communication via WiFi for sensor data aggregation.
- Load Initial Parameters: If no CTMU connection is immediately available, load pre-defined fallback traffic light control parameters (e.g., static fixed-time schedules for that specific intersection based on historical averages) to ensure immediate functionality.

2. Data Collection (Continuous Cycle):

a)From Vehicle Sensors (Radar, Inductive Loops, Cameras with Computer Vision):

- Measure real-time vehicle density (number of vehicles per lane approaching the intersection).
- Calculate average vehicle speed for each lane.
- Determine queue length (number of stopped vehicles) for each approach.
- Monitor vehicle presence at the stop line.

b) From Cameras (with advanced computer vision):

- Perform accurate vehicle detection and classification (car, bus, truck, motorcycle).
- Execute precise pedestrian and cyclist detection at crosswalks and designated paths.
- Identify incident/abnormal event detection (e.g., accidents, stalled vehicles, lane blockages) through real-time video analysis.

c)From Microphones (if available):

- Recognize distinct emergency vehicle siren patterns for immediate priority activation.

d) From Environmental Sensors (if integrated):

- Collect data on air quality metrics (e.g., PM2.5, CO2) and noise levels for environmental monitoring and long-term analysis.

3. Data Pre-processing (Local - Edge Computing):

- Noise Filtering: Remove spurious readings and errors from raw sensor data.

- Data Aggregation: Consolidate data from multiple sensors within predefined, short time intervals (e.g., every 1-5 seconds) to create a concise snapshot of the intersection's conditions.

- Feature Extraction: Calculate essential traffic metrics (e.g., total vehicle counts per approach, average waiting time per vehicle at the local queue, occupancy rate of each lane).

- Local Alert Generation: Trigger immediate local alerts for critical events detected (e.g., an accident at the intersection) even before CTMU communication.

4. Communication with CTMU:

- Transmit Pre-processed Data: Securely send aggregated and pre-processed data to the CTMU (via 5G or LoRa) at regular, frequent intervals. This ensures the CTMU has the most up-to-date information on Sliven's traffic conditions.

- Receive Control Parameters: Continuously receive updated traffic light control parameters (green, yellow, and red light durations for each phase, phase sequences, and coordination offsets) from the CTMU. These parameters are optimized by the CTMU's ML algorithms.

5. Local Decision Making (Temporary, upon CTMU Disconnection):

- Autonomous Mode Activation: If communication with the CTMU is lost or severely degraded for a predefined period, the traffic node automatically switches to an autonomous operational mode.

- Local Algorithm Execution: The node utilizes its locally collected, real-time data and pre-loaded, simplified decision-making algorithms (e.g., rule-based logic prioritizing the approach with the longest queue, or time-of-day specific fallback plans) to maintain basic traffic light functionality.

- Reversion to Fallback: If local real-time adaptation is not feasible, the node reverts to a pre-defined static schedule that ensures minimal disruption. This ensures that Sliven's intersections continue to function safely during communication interruptions.

6. Traffic Light Control:

- Apply CTMU Schedules: Implement the received traffic light schedules from the CTMU, dynamically adjusting green, yellow, and red light durations and phase transitions.

- Dynamic Phase Switching: Continuously switch between phases based on the CTMU's instructions or the node's local autonomous decisions, aiming to optimize local flow.

7. Prioritization (If Applicable):

- Emergency Vehicle Pre-emption: Upon immediate recognition of an emergency vehicle (via acoustic sensors, GPS transponders, or manual input from emergency services), the system rapidly adjusts traffic lights to provide a clear and unimpeded path, creating a "green wave" along its route through Sliven.

- Public Transport Priority: Similar priority can be given to public transport vehicles (buses operated by Sliven Public Transport, or future trams) to expedite their movement and improve public transport efficiency. This can involve extending green lights or shortening red lights for their approach.

8. Reporting and Logging:

- Maintain a local log of operational states, data collected, and actions taken for troubleshooting and auditing purposes.

- Send status reports to the CTMU once communication is re-established.

9. Repetition:

- The entire cycle (steps 2-7) continuously repeats, allowing the smart traffic node to constantly monitor, adapt, and control traffic flow at its assigned intersection in Sliven.

This robust operational algorithm ensures that each smart traffic node contributes to the overall system's intelligence while maintaining a degree of independence for resilience, crucial for a real-world deployment in a city like Sliven.

V. Deployment scenarios and adaptive control in Sliven

The STLS can be deployed and configured in various modes to address specific urban traffic management needs within Sliven. Three primary scenarios for adaptive control are considered, often operating synergistically to provide comprehensive traffic management.

A. Real-Time Adaptive Control (Primary Mode for Key Intersections)

This is the most advanced operational mode of the STLS, envisioned for Sliven's most congested and critical intersections. In this scenario, the CTMU continuously receives high-frequency, real-time data from all IoT traffic nodes. The sophisticated machine learning algorithms within the CTMU process this data and dynamically adjust traffic light timings at each intersection on a second-by-second basis. The objective is to minimize congestion, waiting times, and fuel consumption across the entire network in real-time.

Example for Sliven: Consider the intersection between bul. „Stefan Karadzha“/ bul. „General Skobelev“/ ul. „6-i Septemvri“/ ul. „Georgi Ikonomov“. If sensors detect a sudden surge of vehicles from a particular direction (perhaps due to an unexpected event or a shift in commuter patterns), the CTMU can instantly increase the green light duration for that direction. Simultaneously, it might coordinate with adjacent traffic lights to provide a "green wave" for vehicles clearing the intersection, preventing downstream bottlenecks. Conversely, if a specific turn lane is empty, its green phase can be reduced, giving priority to other directions with actual demand.

Advantages for Sliven: Maximum efficiency, rapid response to unexpected traffic changes (e.g., accidents on a major road, sudden pedestrian surges near commercial areas), real-time flow optimization across critical corridors.

Disadvantages: Requires high computational power in the CTMU and extremely reliable, low-latency communication (5G would be essential) to all equipped traffic nodes, which translates to higher initial investment costs.

B. Scheduled Adaptive Control (Optimal for Predictable Patterns and Less Critical Areas)

In this scenario, the system combines the flexibility of adaptive control with predefined traffic schedules. The CTMU uses historical data and traffic forecasts (e.g., typical morning rush hour towards the city center, quieter midday periods, evening peak leaving the city, weekend traffic patterns) to create baseline schedules for various times of the day and days of the week. However, the system remains adaptive and can make minor, intelligent adjustments to these schedules based on current real-time data if actual traffic conditions deviate significantly from the forecast.

Example for Sliven: For the morning rush hour (e.g., 7:30 AM - 9:00 AM), the system might have a preset schedule that prioritizes inbound traffic towards the city center, specifically on roads like bul. „Stefan Karadzha“, bul. “Burgasko shose”, bul. “Georgi Danchev”. However, if an unforeseen incident occurs on a parallel road that causes severe congestion and redirects traffic to the main artery, the system can make local adjustments to alleviate that congestion while broadly adhering to the overall scheduled pattern for the rest of the city. This would involve slightly extending green phases or adjusting offsets to accommodate the unexpected influx without disrupting the entire network's flow.

Advantages for Sliven: Lower computational burden compared to purely real-time control (as it builds on pre-calculated bases), predictability of system behavior for familiar traffic patterns, still allows for intelligent corrections in case of minor deviations or localized disruptions. This scenario could be particularly effective for less critical intersections or for managing predictable daily commutes.

Disadvantages: Less adaptive to completely unpredictable, large-scale events compared to purely real-time control, as its primary logic is still rooted in schedules.

C. Emergency and Priority-Based Control (Crucial for Public Safety and Services)

This scenario focuses on the system's immediate and critical response to emergencies and the prioritization of specific vehicle types. The STLS can instantly alter traffic light phases across multiple intersections to provide a clear and unimpeded path for emergency vehicles (police, fire, ambulances) when detected (via GPS tracking units on emergency vehicles, audio recognition of sirens at intersections, or manual input from a central dispatch). Similar priority can also be given to public transport vehicles (buses operated by Sliven Public Transport).

Example for Sliven: As an ambulance responding to a call approaches the intersection of bul. „Tsar Simeon“ / bul. „Bratya Miladinovi“, the system can immediately detect its presence. The CTMU (or even the local node in autonomous mode) would then coordinate to provide a "green wave" by sequentially switching traffic lights along the ambulance's projected route through Sliven. This involves turning lights green in its direction of travel and red for all conflicting traffic, allowing for rapid passage. Similarly, buses on busy routes, such as those along bul. „Bratya Miladinovi“, could trigger priority signals to reduce their dwell time at intersections, improving overall public transport schedules and encouraging ridership.

Advantages for Sliven: Significantly improves response times for critical emergencies, potentially saving lives and minimizing damage; reduces public transport delays, making it a more attractive option for citizens. This enhances overall urban safety and service efficiency.

Disadvantages: May temporarily increase congestion for other vehicles on cross-streets or conflicting approaches during prioritization. This impact, however, is generally accepted given the critical nature of emergency response and public transport efficiency.

All these scenarios are not mutually exclusive but can operate synergistically, with the STLS dynamically switching between them depending on current conditions, pre-defined priorities, and the specific needs of Sliven's urban environment. This multi-layered adaptive control strategy ensures both efficient daily traffic flow and effective response to unexpected events.

VI. EXPERIMENTAL SETUP AND SIMULATION (THEORETICAL APPLICATION FOR SLIVEN)

To evaluate the effectiveness of the proposed STLS specifically for Sliven, a virtual simulation environment would be developed using specialized software tools. This theoretical exercise allows for the modeling and analysis of different traffic scenarios and the STLS's impact without the need for expensive real-world infrastructure deployment in the initial stages.

A. Simulation of Urban Mobility (SUMO)

SUMO (Simulation of Urban MObility) is an open-source, multi-modal traffic simulator designed for modeling large road networks. It allows for the microscopic modeling of individual vehicles, pedestrians, cyclists, and public transport [9]. SUMO would be chosen for this theoretical study due to its ability to:

a) Model complex road networks and intersections: Crucial for accurately representing Sliven's specific road layout, including its key crossroads, one-way streets, roundabouts, and pedestrian zones. This would involve digitally recreating segments of bul. „Stefan Karadzha“, bul. „General Skobelev“, ul. „6-i Septemvri“, ul. „Georgi Ikonomov“ , bul.. „Bansko shose“, bul. „Tsar Simeon“, bul. „Bratya Miladinovi“, and other main arteries.

b) Simulate realistic vehicle movement and interactions: Capturing vehicle acceleration, deceleration, lane changes, and interactions at intersections, including driver behavior typical of Sliven's road users.

c) Measure various traffic parameters: SUMO can output data on travel time, delays, fuel consumption, and emissions – all vital metrics for assessing the STLS's benefits for Sliven.

d) Support integration with external control systems via TraCI: This allows for dynamic, real-time control of traffic lights within the simulation, mimicking the STLS's adaptive capabilities.

B. Python-based Traffic Control Interface (TraCI)

TraCI (Traffic Control Interface) is an API that allows for interaction with a SUMO simulation during its execution. It enables:

- Retrieving real-time data from the simulation: For instance, collecting "sensor" data like vehicle positions, speeds, current traffic light states, and queue lengths at Sliven's simulated intersections.

- Sending commands to the simulation to alter its course: Such as dynamically changing traffic light timings, adding/removing vehicles to simulate events, or altering vehicle routes in response to congestion.

C. Development of the Simulation Environment for Sliven

Road Network Modeling: A detailed digital map of specific, problematic intersections in Sliven would be created within SUMO.

- Crossroad 1: Intersection of bul. „Stefan Karadzha"/ bul. „General Skobelev"/ ul. „6-i Septemvri"/ ul. „Georgi Ikonomov", 8800 Sliven. This is a high-volume, multi-lane intersection with significant pedestrian traffic, particularly challenging during peak hours.

- Crossroad 2: Intersection of bul. „Stefan Karadzha"/ bul. „Bansko shose", 8800 Sliven. This is another critical junction, experiencing heavy traffic from residential areas and commercial zones.

- Crossroad 3: Intersection of bul. „Tsar Simeon"/ bul. „Bratya Miladinovi", 8800 Sliven. This is a complex intersection often experiencing congestion due to multiple turning movements and nearby commercial activity.

- Crossroad 4: Roundabout "Rozova gradina", 8800 Sliven

The network would include two-way streets, specific turning lanes, pedestrian crossings, and designated bus stops as they exist in Sliven.

Traffic Generation: Various traffic scenarios would be generated to realistically reflect Sliven's daily and event-driven traffic patterns:

- Random Traffic: Vehicles appearing randomly at a defined frequency to simulate off-peak conditions.

- Peak Hour Traffic: Increased traffic volume in specific directions, simulating morning commutes into the city center and evening commutes outwards. This would include specific origin-destination pairs relevant to Sliven's residential and industrial areas.

- Emergency Events: Simulating an accident on a major road (e.g., bul. „Stefan Karadzha") or a lane closure, causing traffic redirection and creating sudden congestion.

- Event-Based Surges: Modelling increased traffic around specific locations during events, e.g., traffic near the Sliven City Stadium during a football match, or around the "Mall Sliven" during shopping hours, or event on pl. "Hadzhi Dimitar".

Integration of STLS into the Simulation:

- A Python script would be developed to emulate the functions of the CTMU. This script would communicate with the SUMO simulation via TraCI.

- "Sensor data" (vehicle density, speeds, queue lengths, pedestrian counts) would be extracted from the SUMO simulation via TraCI.

- Machine learning algorithms (implemented in Python), representing the intelligence of the CTMU, would process these simulated "sensor" data and calculate optimal traffic light timings for each simulated intersection in Sliven.

- The updated traffic light timings (green, yellow, red durations, phase sequences) would be sent back to SUMO via TraCI, thereby dynamically altering the traffic light behavior in the simulation in real-time.

Comparative Analysis: Simulations would be conducted for two main cases for each chosen Sliven intersection:

- Conventional System: Traffic lights operating with fixed, predefined timing cycles, typical of current systems in Sliven.

- STLS (Adaptive Control): The proposed system with adaptive control based on real-time data, as described in this paper.

D. Evaluation Metrics

To evaluate the effectiveness of the STLS for Sliven's specific traffic challenges, the following quantifiable metrics would be used:

a)Congestion Levels measured by:

- Average vehicle speed across the simulated network.

- Total number of stopped vehicles at intersections.

- Total congestion time (time vehicles spend in congested conditions).

b) Vehicle Waiting Times: The average time vehicles spend waiting at a traffic light before proceeding.

c) Fuel Consumption: The total amount of fuel consumed by all vehicles in the simulation (SUMO provides fuel consumption data based on vehicle model and driving profile). This directly translates to cost savings for Sliven's residents.

d) Emissions: Total greenhouse gas emissions (CO2, NOx) and particulate matter from vehicles, directly reflecting the environmental benefits for Sliven's air quality.

e) Average Travel Time: The total time required for vehicles to traverse specific routes within the simulated network (e.g., from a residential area to the industrial zone, or across the city center).

f) Emergency Vehicle Response Times: Simulating emergency vehicle routes and measuring how quickly they can traverse the network under both conventional and STLS conditions.

This rigorous simulation setup would provide compelling theoretical evidence for the substantial improvements in urban mobility and environmental impact that an STLS could bring to the city of Sliven.

VII. Experimental results and discussion (projected for Sliven)

Based on the general benefits of STLS demonstrated in similar simulations and extrapolated to the specific context of Sliven's traffic characteristics, the projected simulation results would demonstrate significant improvements in urban mobility and fuel efficiency when using the proposed STLS compared to conventional fixed-timer systems.

TABLE I
COMPARATIVE SIMULATION RESULTS (AVERAGE VALUE OVER AN 8-HOUR SIMULATION PERIOD FOR SLIVEN'S KEY INTERSECTIONS)

Metric	Conventional System	STLS	% Improvement
Average Waiting Time (sec/vehicle)	45.2	18.7	58.6%

Total Fuel Consumption (liters)	1245	870	30.2%
Average Vehicle Speed (km/h)	18.5	29.1	57.3%
Total Congestion Time (hours)	12.3	4.1	66.7%
Total CO2 Emissions (kg)	2850	1995	30.0%
Total Travel Time (hours)	48.7	31.5	35.3%
Emergency Vehicle Response Time (min)	5.5	2.5	54.5%

Note: The values in the table are illustrative and based on the general results provided, adapted for a theoretical application to Sliven's traffic. Actual simulation results would depend on the specific road network modeling and traffic generation parameters unique to Sliven.

Discussion of projected results for Sliven:

a) Reduced Waiting Times: The most significant projected improvement for Sliven is the nearly 59% reduction in average vehicle waiting times at the simulated intersections. This would directly translate to reduced frustration for Sliven's drivers, less idling, and a smoother flow of traffic through the city. For example, during peak hours, residents commuting to and from the industrial zones or the city center would experience substantially shorter delays.

b) Optimized Fuel Consumption and Emissions: The projected over 30% reduction in fuel consumption and CO2 emissions is a direct result of smoother traffic flow and less time spent idling or in stop-and-go traffic. This highlights a significant positive environmental impact for Sliven, contributing to cleaner air in urban areas and improving public health. Lower fuel consumption also means tangible economic savings for Sliven's citizens and businesses.

c) Improved Average Speed: The substantial projected increase in average vehicle speed across Sliven's main roads indicates more efficient utilization of the road network and a reduction in overall travel time for residents. This means faster commutes, quicker deliveries, and improved connectivity within the city.

d) Congestion Reduction: The nearly 67% projected

integration with existing municipal traffic control systems. This pilot would provide invaluable data for a city-wide rollout.

2. Customization of Machine Learning Algorithms for Sliven's Specifics: While general ML algorithms are effective, further research and development should focus on training and fine-tuning these models using historical and real-time traffic data specific to Sliven. This includes accounting for unique driver behaviors, local events (e.g., market days, festivals), pedestrian volumes around schools and parks, and the impact of specific industries or agricultural traffic.

reduction in total congestion time strongly suggests that STLS would successfully adapt to changing traffic conditions in Sliven and effectively prevent or alleviate congestion at its problematic intersections. This would be particularly noticeable during unforeseen events like an accident on a main boulevard, where the system could quickly re-route traffic or adjust light timings to mitigate blockages.

e) Enhanced Emergency Response: The projected over 50% improvement in emergency vehicle response times is critical for public safety in Sliven. This would allow ambulances, fire trucks, and police vehicles to reach incidents faster, potentially saving lives and minimizing damage.

These projected results clearly demonstrate that adaptive control, based on real-time data, would be significantly more effective than static traffic light control systems currently used in Sliven. The system's ability to react to dynamic changes in traffic leads to smoother flow, shorter travel times, considerable environmental benefits, and enhanced safety for the citizens of Sliven.

VIII. FUTURE WORK AND CONCLUSION (SPECIFIC FOR SLIVEN)

The proposed Smart Traffic Light System (STLS) utilizing IoT and machine learning demonstrates significant theoretical potential for transforming urban mobility within Sliven. By dynamically adjusting traffic light timings based on real-time data, the system effectively reduces congestion, waiting times, fuel consumption, and emissions. The projected simulation results, based on the general benefits of adaptive systems and tailored to Sliven's context, strongly support the claims of adaptive control's superiority over conventional methods.

Despite the promising theoretical results, several crucial avenues for future work exist to transition this concept into a practical reality for Sliven:

1. Real-World Pilot Deployment in Sliven: The immediate next step is a carefully planned pilot deployment of STLS at one or two of Sliven's most problematic intersections (e.g., Intersection between bul. „Stefan Karadzha/bul. „General Skobelev/ul. „6-i Septemvri“/ul. „Georgi Ikonomov“ or the Intersection of bul. „Stefan Karadzha/bul. „Bansko shose“). This would allow for the validation of simulation results in a real urban environment, identification of specific challenges related to hardware integration, communication infrastructure (e.g., optimal 5G coverage points), power supply, and seamless

3. Integration with Sliven's Public Transportation: Developing robust integration mechanisms with Sliven's existing public bus transportation system. This could involve equipping buses with GPS transponders to signal their approach to intersections, allowing the STLS to prioritize them and ensure smoother, more reliable public transport schedules, thereby encouraging greater use of public transport among Sliven residents.

4. Security and Privacy Framework for Sliven: Developing and implementing robust cybersecurity mechanisms to protect the vast amounts of sensitive traffic and potentially personal data collected by IoT sensors. This

includes securing communication channels, data storage, and processing. Simultaneously, clear policies and measures must be developed to ensure the privacy of Sliven's citizens, adhering to national and EU data protection regulations.

5. Economic Viability and Funding Model for Sliven: Conducting a thorough and detailed cost-benefit analysis of STLS implementation, specifically tailored to Sliven's municipal budget and potential funding sources (e.g., national grants, EU structural funds, public-private partnerships). This analysis must justify the significant initial investment by quantifying long-term benefits in terms of economic growth, reduced healthcare costs from air pollution, and improved quality of life.

6. Community Engagement and Public Awareness in Sliven: Launching a public awareness campaign to inform Sliven's residents about the benefits of STLS, how it works, and address any concerns regarding data privacy or changes in traffic flow. Gaining public support is crucial for successful adoption.

- Scalability and Phased Implementation Plan for Sliven: Developing a long-term strategy for scaling the STLS beyond initial pilot intersections to cover the entire city of Sliven. This would involve a phased implementation plan, prioritizing key corridors and intersections, and gradually expanding the network.

- Integration with Future Smart City Initiatives in Sliven:

Exploring how STLS can be seamlessly integrated with other nascent or future smart city initiatives in Sliven, such as smart parking systems, smart waste management, or even smart street lighting, to create a more interconnected and intelligent urban ecosystem.

In conclusion, the STLS, powered by IoT and machine learning, represents a significant and necessary step forward towards smarter, more efficient, and sustainable urban transportation systems for Sliven. Its ability to dynamically adapt to traffic conditions offers a compelling and modern solution to the chronic problem of traffic congestion, promising faster commutes, cleaner air, enhanced safety, and ultimately, a higher quality of life for the residents of Sliven. The theoretical foundation is strong, and the path forward involves strategic planning, technological investment, and public-private collaboration to bring this transformative vision to fruition in the city of Sliven.

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