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Integrating Dynamic Road Condition Sensors to Enhance Adaptability of Scenario-Specific Layers in Intelligent Transport Systems

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Abstract- The use of many sensors in vehicles allows us to study how road users interact. This is important for various applications in vehicle scenarios. In this context, we introduce a new training method called Sequential Training. This method divides the Neural Network (NN) layers of the Deep Neural Network (DNN) model into two sets. One set is tailored for the user, while the other is designed to work together, focusing on the road environment. We apply deep learning in situations where vehicle users, each with unique driving behaviors and styles, interact with their surroundings. We need to create specific models for each indi- vidual vehicle user in every environment. This process requires collecting relevant data to train the machine learning models. Such data collection can be expensive and, in many cases, may even be impossible. This approach aims to integrate dynamic road condition sensors, such as weather and real-time traffic data, to improve the adaptability of scenario-specific layers.

Keywords— Intelligent Transport Systems, Road Sensors, Weather Data, Traffic Monitoring, Cloud Computing, AI, ANN

I. INTRODUCTION

Road transportation is a key part of economic and social development in every country. In India, where roads con- nect millions of people across cities, towns, and villages, maintaining safe and efficient transport systems is a major challenge. With increasing urbanization, vehicle density, and unpredictable weather, traditional traffic management methods are not enough. Intelligent Transport Systems (ITS) have emerged as a modern solution to improve road safety, reduce congestion, and enhance travel experience.

ITS uses technologies like GPS, cameras, sensors, and Artificial Intelligence (AI) to monitor and manage traffic. However, many ITS setups still depend on static data like fixed maps and scheduled signals. These systems cannot respond quickly to sudden changes such as heavy rain, fog, traffic jams, or road damage. This limitation affects the performance and reliability of ITS, especially in dynamic and unpredictable road conditions [1].

To solve this issue, dynamic road condition sensors can be integrated into ITS. These sensors collect live data about weather, traffic flow, and road surface conditions. For example, they can detect potholes, slipperiness, waterlogging, or snow cover. This real-time data helps ITS to make smart decisions like changing routes, adjusting speed limits, sending alerts to drivers, or activating emergency protocols [1][2].

The sensor data can be transmitted to a central server or cloud platform using wireless communication. Cloud comput- ing provides storage, processing power, and remote access to sensor data. It also supports data fusion, analytics, and visu- alization for better decision-making [1][3]. Service Oriented Architecture (SOA) can be used to manage sensor data. In SOA, each sensor acts as a service provider, and applications act as service consumers. The sensor data is converted into web service messages and sent to the cloud for monitoring and control [1].

Artificial Intelligence (AI) plays a key role in analyzing sen- sor data. AI algorithms like Artificial Neural Networks (ANN) can classify road types and detect anomalies. Image processing techniques can be used to analyze road images captured by cameras. Morphological operations like thresholding, dilation, and erosion help in extracting features from images. These features are used as inputs to ANN models to identify road conditions such as wet, icy, snowy, or dry surfaces [1][4].

Scenario-specific layers in ITS refer to different modules that handle specific road situations. For example, urban traffic layer manages city roads and signals, highway layer handles long-distance travel and tolls, and emergency layer supports ambulances and police vehicles. Dynamic sensors help these layers adapt in real-time. For instance, if an accident occurs on a highway, the system can alert emergency services, divert traffic, and update navigation routes [1][2].

There are some challenges in integrating dynamic sensors into ITS. The cost of sensors and infrastructure can be high. Data privacy and security must be ensured while transmit- ting and storing sensor data. Compatibility with existing ITS systems and legacy devices can be difficult. Reliable internet connectivity is required for real-time communication [1][5].

In India, dynamic sensor integration can be very useful in hilly regions, snow-covered areas, flood-prone zones, and high-security military roads. It can help in monitoring road conditions during monsoon, winter, and peak traffic hours. It can also support smart city projects, public transport systems, and emergency response units. By using low-cost sensors, cloud platforms, and AI models, India can build adaptive and intelligent transport systems that respond to real-world conditions effectively [1][6].

This review paper focuses on the future integration of dynamic road condition sensors in ITS. It discusses current technologies, sensor types, cloud architecture, AI techniques, scenario-specific layers, challenges, and future scope. The aim is to provide a clear understanding of how dynamic sensors can enhance the adaptability of ITS and improve road safety and traffic management.

Challenges In Handling Dynamic Road Conditions

Lack of Real-Time Road Information

Autonomous vehicles mainly depend on pre-stored high- definition maps for navigation. However, road conditions are dynamic and can change due to temporary events such as traffic accidents, spontaneous road closures, or public gath- erings [11]. For example, a sudden vehicle breakdown on a highway can cause lane blockages that are not reflected in static maps. Without real-time updates from traffic monitoring systems or vehicle-to-infrastructure (V2I) communication, the vehicle may fail to reroute efficiently, leading to delays or unsafe maneuvers [13].

Unpredictability of Construction Zones and Weather Con- ditions

Construction zones often introduce temporary lane shifts, cones, and signage that differ from standard road layouts. These changes are difficult for autonomous systems to in- terpret, especially when visual cues like lane markings are inconsistent or obstructed [12]. For instance, a newly painted detour lane may not match the digital map, causing confusion in path planning. Similarly, adverse weather conditions such as heavy rain, fog, or snow can obscure road signs and lane boundaries, reduce LiDAR and camera visibility, and introduce slippery surfaces that affect braking and steering control [13]. In mountainous or rural areas, sudden weather shifts can be especially hazardous without predictive weather integration.

Delay in Data Processing and Decision Making

Autonomous vehicles rely on multiple sensors—cameras, radar, LiDAR—and onboard processors to interpret surround- ings and make decisions. However, high data volume and lim- ited computational bandwidth can cause latency in decision- making. For example, in a fast-moving urban scenario, a pedestrian suddenly crossing the road requires immediate braking. If sensor data is delayed or the system takes too long to process and respond, it can compromise safety. Network delays in cloud-based systems or edge computing bottlenecks also contribute to slower reaction times, especially in high- density traffic environments.

II. SOLUTIONS FOR HANDLING DYNAMIC ROAD CONDITIONS

AI-Driven Perception, Sensor Fusion, and V2X Communi- cation

Artificial Intelligence (AI) enhances vehicle perception by integrating data from multiple sensors such as LiDAR, radar, and cameras. Sensor fusion algorithms combine these inputs to create a unified and accurate environmental model, improving obstacle detection and lane tracking [13], [15]. Vehicle-to- Everything (V2X) communication enables vehicles to ex- change information with other vehicles (V2V), infrastructure (V2I), and pedestrians (V2P), allowing proactive responses to hazards and traffic changes [14]. For example, a vehicle detecting a pothole can alert nearby vehicles and traffic control systems to reroute or slow down.

Real-Time Sensor Technologies and Mapping

Modern autonomous systems use high-definition maps that are continuously updated by services like Waymo and Tesla. These maps are enriched with real-time data from LiDAR, radar, cameras, and infrared sensors, which detect lane mark- ings, traffic signs, and road anomalies. Advanced sensor fusion techniques ensure that overlapping data sources are reconciled to improve accuracy. For instance, radar can detect objects in poor visibility, while LiDAR provides precise 3D mapping, and cameras assist with color and texture recognition [12].

Cloud-Based Data Processing and Edge Computing

Cloud computing platforms such as IBM Bluemix and AWS IoT Core allow vehicles to access external databases for traffic, weather, and infrastructure updates [11]. Edge computing complements this by processing data locally at roadside units or onboard systems, reducing latency and bandwidth usage. Machine learning models deployed on edge devices can predict traffic congestion, detect anomalies, and suggest alternate routes in real time [14], [15]. This hybrid architecture ensures both scalability and responsiveness.

Regulatory and Infrastructure Support

Effective ITS deployment requires support from government and transport authorities. This includes establishing data- sharing policies, cybersecurity standards, and investment in communication infrastructure such as 5G and DSRC [11]. Public-private partnerships can accelerate sensor deployment and ensure interoperability across regions and manufacturers [13].

III. SYSTEM IMPLEMENTATION PLAN

- Sensor Network: Wireless mesh networks connect sen- sor nodes using protocols like Zigbee, LoRaWAN, and 5G. These networks ensure low-power, long-range com- munication suitable for urban and highway environments [13].
- Service-Oriented Architecture (SOA): Sensor data is encapsulated in XML or JSON web service messages, enabling interoperability across platforms and devices [15].
- Cloud Platform: Platforms such as IBM Bluemix, AWS IoT Core, and Azure IoT Hub support scalable data in- gestion, real-time analytics, and visualization dashboards [14].
- Artificial Intelligence (AI): AI models including ANN, CNN, and RL are used for classification, object detection, and route optimization [13].
- Scenario-Specific Layers: ITS layers manage conges- tion, prioritize emergency vehicles, and reroute traffic dynamically [14], [15].

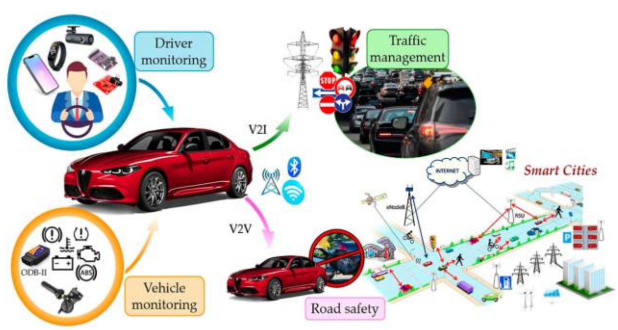

Fig. 1. Smart City Traffic and Safety Integration.

IV. DYNAMIC SENSOR INTEGRATION

Dynamic sensors such as weather stations, road surface detectors, and traffic monitors provide continuous updates on environmental and vehicular conditions [11]. These sensors are integrated through SOA, allowing modular communication between nodes and cloud services . Real-time data transmis- sion via 5G or edge computing enhances decision-making speed and accuracy [13]. For example, pavement condition systems using edge AI can instantly alert highway agencies about surface degradation, allowing timely repairs [14].

V. SCENARIO-SPECIFIC LAYERS

ITS architectures are increasingly layered to handle diverse traffic environments. Urban traffic layers focus on congestion management, pedestrian safety, and signal optimization. High- way layers prioritize lane discipline, speed regulation, and accident detection. Emergency response layers integrate with ambulance and fire services to provide priority routing and traffic clearance [14], [15]. These layers adapt dynamically using sensor inputs, enabling context-aware decision-making. For example, during a flood, the urban layer may reroute vehicles away from submerged zones while the emergency layer prioritizes rescue vehicle movement [13].

VI. INTEGRATION OF DYNAMIC ROAD CONDITION SENSORS

Modern Intelligent Transportation Systems (ITS) increas- ingly rely on dynamic road condition sensors to adapt to real-time changes in traffic, weather, and infrastructure. These include:

- Weather Detectors: Devices that monitor precipitation, temperature, humidity, and visibility. They help predict hazardous conditions like fog, ice, or heavy rain, enabling vehicles to adjust speed and routing accordingly [11], [13].
- Traffic Monitors: Radar, cameras, and inductive loops track vehicle flow, congestion levels, and incidents. These sensors support dynamic traffic light control and rerouting strategies [14], [15].
- Road Surface Analyzers: Vibration sensors, accelerom- eters, and surface cameras detect potholes, cracks, and slipperiness. This data is crucial for maintenance planning and vehicle suspension control [11], [13].

These sensors transmit data using Service-Oriented Archi- tecture (SOA) frameworks to cloud platforms, where it is processed and analyzed in real time. Edge computing enables local data processing at the sensor or roadside unit level, reducing latency and improving decision speed. For example, pavement condition monitoring systems using edge AI can instantly alert highway agencies about surface degradation, allowing timely repairs [13], [14].

Artificial Intelligence (AI) algorithms, particularly deep learning models, analyze sensor data to detect anomalies, predict traffic patterns, and classify road conditions. Combined with cloud connectivity, this enables scalable data aggregation and predictive modeling. Platforms like IBM Bluemix and AWS support these operations by offering real-time dash- boards and analytics pipelines [14].

This integration allows ITS to:

- Respond to emergencies faster (e.g., rerouting during accidents or floods)
- Improve safety by adapting to weather and surface changes
- Optimize traffic flow through predictive congestion man- agement
- Support autonomous vehicle navigation with up-to-date environmental context

VII. MATHEMATICAL MODELLING AND ANALYSIS

Efficient monitoring of dynamic road conditions requires the integration of multiple real-time parameters such as weather variations, traffic intensity, and road surface quality. Based on prior research in Intelligent Transport Systems (ITS) and Arti- ficial Intelligence (AI) [1], [8], [13], a structured mathematical framework is proposed to estimate road risk.

Input Parameters

Let:

- Sw denote the weather-related factor (including rain, fog, and temperature variations)
- St represent the traffic density level
- Sr indicate the condition of the road surface (such as potholes or slippery surfaces)

These parameters are obtained from sensor data and pro- cessed using machine learning models for accurate estimation [9], [10].

Risk Evaluation Function

R = W1Sw + W2St + W3Sr (1)

Here:

- R represents the calculated risk index
- W1, W2, W3 are weighting factors assigned to each pa- rameter based on their significance

This weighted formulation is commonly adopted in ITS- based risk assessment models [14], [15].

Normalized Risk Function

R − Rmin

VIII. LITERATURE REVIEW

Impact Assessment of Cooperative Intelligent Transport Systems (C-ITS)

The paper "Impact Assessment of Cooperative Intelli- gent Transport Systems (C-ITS)" published by IEEE/Springer (2023) presents an extensive literature review encompassing over one hundred studies to evaluate the effects of C-ITS technologies on modern transportation systems. The research primarily focuses on four major domains—safety, mobility, en- vironmental impact, and economic performance. The findings reveal that C-ITS considerably enhances road safety by reduc- ing crash frequencies and accident severity. Improvements in mobility were found to be moderate, resulting mainly from better traffic coordination and reduced congestion. However, environmental outcomes appeared inconsistent since energy usage and emission reductions varied across regions and technology types. Economically, C-ITS promises long-term benefits but requires substantial upfront investment. The paper identifies a major gap in the absence of standardized evalua- tion frameworks, which complicates cross-study comparisons. Hence, the authors recommend harmonized testing protocols and extensive real-world pilot trials to validate simulation

Rn =

Rmax − Rmin

(2)

outcomes. The study concludes that collaborative international efforts are essential to achieve consistent and measurable

The normalization process ensures that the computed risk value is scaled within a standard range (0 to 1), enabling consistent evaluation across different scenarios [2].

D. Decision Model

• • • Normal, Rn < 0.3

progress in C-ITS deployment. [1]

B. Modelling Interrelations Between C-ITS Impact Categories

The paper "Modelling Interrelations Between C-ITS Impact Categories" (IEEE/Springer, 2022) explores the complex in- terdependencies among safety, mobility, and emissions within Cooperative Intelligent Transport Systems. Utilizing system dynamics and simulation-based modeling, the authors examine

• • Emergency, Rn ≥ 0.7

This classification framework allows the system to catego- rize road conditions and initiate appropriate responses such as alerts or traffic control actions in real time [8], [13].

Sensor Data Analysis

Using real-time sensor inputs along with insights from pre- vious studies [11], [12], a sample risk evaluation is presented below:

Table 1: Dynamic Risk Evaluation Based On Sensor Inputs

Weather (S_w)	Traffic (S_t)	Road (S_r)	Risk (R)	Decision
0.2	0.3	0.2	0.23	Normal
0.5	0.6	0.5	0.53	Caution
0.9	0.8	0.9	0.86	Emergency

The results demonstrate that an increase in sensor parameter values leads to a higher computed risk level. This observation aligns with existing ITS research on real-time monitoring and safety enhancement [?], [14].

study identifies threshold effects, indicating that enhancements in safety or mobility eventually reach saturation points, and the phenomenon of induced demand, where improved traffic flow leads to additional vehicle usage and, consequently, higher emissions. The research highlights that evaluating each domain independently can yield misleading interpretations of system performance. Therefore, the paper proposes an integrated sim- ulation framework capable of assessing cross-domain trade-offs to inform data-driven transportation policies. The authors emphasize that future evaluations should implement multi- domain modeling approaches incorporating behavioral feed- back, secondary effects, and dynamic interactions. The study concludes that sustainable ITS deployment requires balanced optimization of safety, mobility, and environmental objectives under a unified analytical model. [2]

Safety, Mobility and Comfort Assessment Methodologies of ITS Applications

This IEEE/Springer (2021) study introduces a hybrid assess- ment framework that integrates field experiments, simulation models, and driving simulators to evaluate Intelligent Trans- port System applications. It addresses the limitations of single-method evaluations by combining real driving data with surrogate safety indicators to enhance accuracy. A key insight of the study is the recognition of driver comfort—often neglected in ITS research—as a critical determinant of public acceptance and adoption. The framework encourages data-driven decision- making using standardized metrics and open-access datasets. Furthermore, the paper compares various evaluation tools to determine their fidelity in replicating real-world driving con- ditions. The authors advocate for harmonized testing protocols and global data-sharing standards to ensure the comparability of ITS performance metrics across nations. In conclusion, the study emphasizes that integrating quantitative safety measures with user experience parameters enables more holistic and realistic ITS evaluations. [3]

IoT Workload Offloading in Cooperative Edge-Cloud Net- works

The research article “IoT Workload Offloading in Coopera- tive Edge-Cloud Networks” (IEEE/Springer, 2022) focuses on reducing latency and improving energy efficiency in Intelligent Transport Systems through dynamic computational workload distribution between edge and cloud infrastructures. The pro- posed optimization framework allocates computational tasks according to network congestion, processing load, and com- munication delay. Simulation outcomes demonstrate that this dynamic offloading mechanism reduces response times, lowers energy consumption, and enhances overall scalability. The findings suggest that balancing computation between edge and cloud nodes supports real-time decision-making and improves data reliability for connected and autonomous vehicles. The authors recommend future exploration of federated learning for decentralized intelligence, secure data transmission for privacy protection, and adaptive compression to optimize bandwidth use. This cooperative architecture proves particularly usef

LPWAN-Based Hybrid Backhaul Communication for ITS

The paper “LPWAN-Based Hybrid Backhaul Communi- cation for ITS” (IEEE/Springer, 2023) introduces a hybrid communication model integrating Low Power Wide Area Networks (LPWAN) with cellular systems to enhance the efficiency of Intelligent Transportation Systems. The approach emphasizes low-bandwidth, delay-tolerant communication for transmitting data between roadside sensors and central control systems. The results indicate that this hybrid configuration ensures cost-effectiveness, long-range coverage, and low en- ergy consumption—making it suitable for extensive sensor de- ployments in smart cities. Nonetheless, the research identifies challenges such as potential security risks, latency constraints, and the limited suitability of LPWAN for time-critical safety applications. To address these issues, the authors propose implementing advanced encryption and traffic prioritization techniques for safety-critical operations. Overall, the paper demonstrates that hybrid LPWAN-cellular systems can effec- tively facilitate environmental monitoring, traffic management, and infrastructure maintenance in ITS frameworks. [5]

Simulator and On-Road Testing of Truck Platooning

The IEEE/Springer paper "Simulator and On-Road Testing of Truck Platooning" (2021) provides a detailed review of both simulation and real-world studies on truck platooning technologies. Truck platooning, which involves groups of vehicles driving in close formation via vehicle-to-vehicle (V2V) communication and adaptive cruise control, is shown to improve fuel efficiency and safety. The research reveals that platooning can achieve fuel savings between 5–15% and significantly lower greenhouse gas emissions. It also enhances traffic flow stability and reduces driver fatigue. However, challenges remain in communication reliability, driver trust, and the interoperability of systems produced by different manufacturers. The authors emphasize the need for standard- ized communication protocols and large-scale field testing to validate performance across diverse conditions. The study concludes that the widespread adoption of truck platooning can substantially enhance freight transport efficiency and reduce operationa

Influence of ITS on Vulnerable Road User Accidents

The study "Influence of ITS on Vulnerable Road User Acci- dents" by Johan Scholliers et al. (2020), conducted under the VRUITS project, examines how Intelligent Transport Systems enhance pedestrian and cyclist safety. The research evaluates multiple ITS-based detection and alert systems that identify vulnerable road users (VRUs) and issue timely warnings to drivers. Results show a significant reduction in collision occurrences and improved situational awareness, particularly in urban areas. However, the performance of these systems declines under poor visibility conditions such as rain, fog, or low light. The authors stress the importance of inclusive system design that accommodates users of all physical abilities and vehicle types. Additionally, they highlight the need for privacy-aware sensors and diverse datasets to ensure fairness and robustness. The paper concludes that progress in ITS for VRU protection requires collaboration between policymakers, engineers, and data scientists to achieve safety and in

Machine Learning in ITS Applications

The review article "Machine Learning in ITS Applications" by Azad et al. (2024), published in the Open Transportation Journal, provides a comprehensive analysis of forty-eight machine learning (ML) and deep learning (DL) based ITS research studies. The paper categorizes applications into areas such as traffic flow prediction, road safety, infotainment, and autonomous driving. It discusses a variety of models including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and the YOLO object detec- tion framework. The findings confirm that ML algorithms substantially improve system efficiency, prediction accuracy, and decision-making capabilities within ITS. Despite these advancements, persistent challenges remain regarding data quality, real-time deployment, and scalability. The authors identify ten major research gaps and recommend future direc- tions such as transfer learning, federated learning, and hybrid AI frameworks to achieve adaptive, intelligent, and secure ITS ecosystems. The study concludes that ML-based approaches are pivotal to realizing autonomous, data-driven transportation infrastructures. [8]

DeepTrack: Lightweight Deep Learning for Vehicle Trajec- tory Prediction

The IEEE Transactions paper "DeepTrack: Lightweight Deep Learning for Vehicle Trajectory Prediction" by Katariya et al. (2022) proposes an efficient deep learning model for real- time vehicle trajectory prediction. The framework integrates Temporal Convolutional Networks (TCN) with Long Short-Term Memory (LSTM) architectures to effectively capture both motion dynamics and temporal dependencies. The pro- posed model achieves comparable accuracy to conventional deep architectures while being 40% smaller in size, making it suitable for embedded and edge-device deployment. It ac- curately predicts vehicle trajectories up to five seconds ahead, which is vital for crash prevention, autonomous navigation, and traffic control. The results demonstrate that lightweight deep learning models provide high computational efficiency with reduced energy consumption. The authors recommend further exploration into adaptive model updating and cross-domain generalization to enhance prediction reliability under diverse road and

RoadSegNet: Deep Learning Framework for Urban Road Detection

The paper "RoadSegNet: Deep Learning Framework for Urban Road Detection" by Pal et al. (2022), published in the Journal of Engineering and Applied Science, introduces a deep learning-based semantic segmentation framework for detecting drivable regions in complex urban environments. The model leverages DeepLabV3+ architecture with ResNet50, Xception, and MobileNet-V2 backbones, trained on the KITTI dataset. Among these, the MobileNet-V2 backbone demonstrated the best performance balance, achieving 96% segmentation accu- racy with minimal computational demand, thereby enabling efficient edge deployment in autonomous vehicles. The paper emphasizes that precise road segmentation is essential for lane detection, path planning, and obstacle avoidance. It concludes that deep learning-driven segmentation models are integral to advancing perception systems in self-driving vehicles and facilitating real-time, reliable decision-making within urban Intelligent Transport Systems. [10]

IX. CONCLUSION

The integration of dynamic road condition sensors with Intelligent Transportation Systems (ITS) represents a trans- formative step toward safer, smarter, and more efficient mo- bility solutions. By combining advanced sensors such as LiDAR, radar, and IoT-enabled weather detectors with AI- driven analytics, vehicles and infrastructure can collaboratively interpret environmental conditions in real time. This integra- tion enhances road awareness, supports predictive decision- making, and reduces the likelihood of accidents caused by poor visibility, surface hazards, or traffic congestion. Cloud computing platforms further strengthen ITS by pro- viding scalable data storage, analytics, and real-time com- munication frameworks that enable continuous learning and adaptation. Through the fusion of AI, sensor data, and Vehicle- to-Everything (V2X) communication, traffic systems can dy- namically adjust to changing conditions and improve overall urban mobility.

In conclusion, integrating dynamic road condition sensors with ITS holds significant potential for advancing autonomous vehicles, supporting smart city development, and enhancing road safety across India and beyond. With continued innova- tion in AI, IoT, and cloud infrastructure, the vision of a re- sponsive, intelligent, and sustainable transportation ecosystem is well within reach.

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