Generative AI-Driven Context-Aware BDI-Based Smart Routing Protocol for Intelligent Transportation Systems

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***Abstract*— This research introduces a newly proposed Belief-Desire-Intention (BDI) agent-based Smart Routing Protocol for Intelligent Transportation Systems (ITS) that leverages context-aware decision-making inspired by Generative Artificial Intelligence (GAI) reasoning models. The protocol enhances routing decisions by considering real-time traffic conditions, weather, road blockages, peak-hour dynamics, and AI-generated predictions of future congestion. By incorporating BDI reasoning, the system dynamically adjusts routes based on both current and forecasted conditions, thereby improving the overall performance of vehicular networks. Our proposed system aims to optimise key performance indicators such as Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Control Overhead, Traffic Flow, Routing Decision Accuracy, and Energy Consumption. Simulation results demonstrate that the BDI-based system outperforms traditional routing protocols like Ad hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR), showing significant improvements in PDR, Throughput, and Energy Efficiency. For example, the BDI-based system achieved a PDR of 98%, compared to 85% for AODV and 80% for DSR. Additionally, the BDI protocol reduced end-to-end delay by 25% and energy consumption by 30% compared to the baseline protocols. These findings underscore the BDI-based system's capability for real-time, adaptive routing in ITS, enabling optimal network performance and resource efficiency through context-aware and predictive routing decisions.**

***Index Terms*— Generative artificial intelligence (GAI), BDI-based routing, intelligent transportation systems (ITS), context-aware routing.**

Received 8 December 2024; revised 14 April 2025; accepted 7 May 2025. This work was supported by the Deanship of Research and Graduate Studies at King Khalid University through the Small Group Research Project under Grant RGP1/251/46. The Associate Editor for this article was T. R. Gadekallu.
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Digital Object Identifier 10.1109/TITS.2025.3570237

I. Introduction

THE challenge of urban mobility has become a critical issue for modern society, where greater vehicular density, both predictable and unpredictable patterns of traffic, and more limited infrastructure make for congestion, delay, and accidents. Therefore, technology that would enable the control of urban transportation systems in an improved metabolism is highly sought, such as that of the Internet of Things and ITS. By incorporating various technologies such as the Internet of Things (IoT), machine learning and Vehicle-to-Everything (V2X) communication, ITS enables the real-time and dynamic management of traffic flow, reducing delays and enhancing road safety. However, the effectiveness of ITS largely depends on its ability to detect real-time incidents and provide travellers with contextualised and optimised routes. ITS is being implemented in many cities worldwide to alleviate road traffic congestion through the use of IoT technologies to ensure better traffic flow, especially in crowded urban areas [1]. However, today's technologies have some limitations in terms of efficiency. Besides traffic management, ITS also enhances transportation networks' efficiency, safety, and security through advanced technologies like electronic sensors, data transmission, and intelligent control technologies to provide better driver and rider services. To tackle these issues, BDI-based protocols developed after 2020 are being proposed to improve security and adaptive routing within ITS. These protocols are designed to handle the complexities of real-time data exchange and system integration, leading to safer and more efficient transportation networks [2].

Fig. 1 underscores the critical importance of obtaining real-time information about road conditions while driving. Context awareness is a cornerstone of ITS, as it allows for the dynamic acquisition, interpretation, and application of data related to road rules, traffic conditions, and potential blockages. Context-aware systems substantially amplify safety, efficiency, and the driving experience itself by facilitating informed decisions made by drivers and automated systems in light of the present conditions. Context awareness in ITS involves the fusion of heterogeneous data sources, such as real-time traffic data, road network status, meteorological data, user preferences, and such. Other data, such as road blockages or lane closures, have to be processed to reroute vehicles without creating longer delays or endangering safety. Similarly, visibility into traffic congestion allows systems to manage high capacity, freeing up

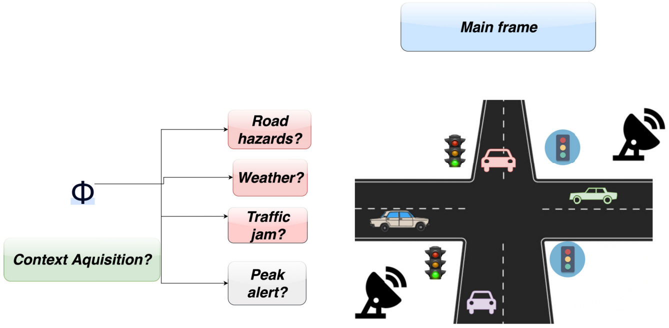


Fig. 1. Abstract view of the problem.

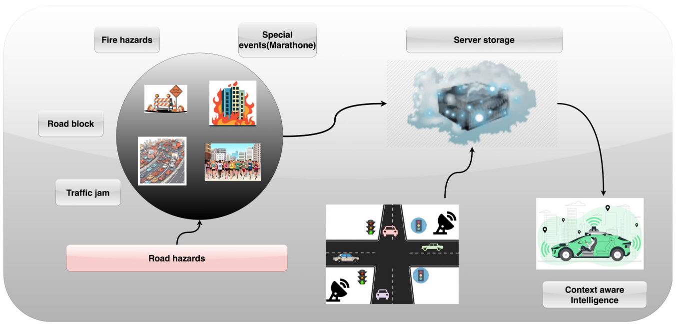


Fig. 2. Abstract view of the proposed system.

bottlenecks and allowing flow. This property of absorbing and processing constantly dynamic context data is critical to the success of ITS.

The main feature of ITS is the collection of real-time data using IoT-enabled sensors, V2X communication systems, and traffic surveillance cameras. Such technologies provide the opportunity for ITS to monitor changes in traffic and environmental conditions continuously. Furthermore, updating systems with traffic and infrastructure developments like accidents, construction areas, and road closures warrants systems to navigate around potential bottlenecks proactively, therefore offering safer and more optimised travel paths. Adverse weather events like rain, snow, or fog have a strong influence on road safety, making weather a key factor to consider in ITS. By the integration of weather-related data into ITS, drivers and systems are able to adjust themselves in relation to these threats, which consequently decreases the risk of accidents. Moreover, following road rules and regulations like speed limits and vehicle-specific regulations enables better traffic regulation and a safe travel atmosphere for all road users. To enhance the adaptability and user-friendliness of ITS, user-specific context must also be considered. ITS can provide personalised route recommendations that consider the user's hustle for expedience, safety, minimising environmental impact, and more from different domains. In addition, peak-hour traffic management is essential, as it enables forecasting and alleviating congestion during peak hours, leading to shorter travel times and less stress for commuters. By integrating these diverse elements, context-aware ITS systems can dynamically adapt to complex and evolving traffic scenarios. Hence, this is a crucial functionality in building sustainable, smart transportation solutions that cater to road safety, optimise congestion, and promote urban mobility as shown in Fig. 2.

One of the recent trends in ITS research is the improvement of traffic management in three different scopes, including individual demand management, traffic flow improvement, and infrastructure utilisation improvement. One example is that attention mechanisms from machine learning models were used to predict the dynamics of traffic flow in real-time, helping to enhance traffic forecasting systems [3]. Likewise, another field, such as V2X communication, has been integrated with reinforcement learning to further enhance the performance of signal control in the long term, especially during peak time, where it reduces traffic significantly [4]. Simultaneously, IoT-based solutions have been implemented in smart parking systems for resource allocation [5], highlighting the role of connected technologies in urban mobility. Graph neural networks (GNNs), which are used to represent relationships observed in traffic networks, have also been shown to be effective in predicting congestion [6]. When viewed together, these advancements demonstrate the increasing sophistication of ITS technologies.

However, the challenges posed by real-time, adaptive route planning are considerable. Most existing ITS solutions are limited to disparate components, like traffic prediction or signal optimisation, and do not incorporate holistic context awareness into their routing algorithms. For instance, even though there are real-time incident detection frameworks [7], they are often standalone systems and can, therefore, provide a divergent view for users. Path-planning systems for autonomous vehicles do consider dynamic obstacles, but they are mainly applicable to specific vehicle categories and may not be applicable to more general ITS applications [8]. Additionally, existing routing protocols generally do not consider multiple contextual factors, such as weather conditions, road blockages, and peak-hour traffic patterns, under a common framework. This fragmented structure can result in poor route suggestions, delays, and an inability to react in real time to disruptors.

In the era of increased urbanisation and the emergence of smart cities, the need for holistic and real-time routing solutions is at an all-time high. Though IoT-based traffic management systems showcase the benefits of interconnected infrastructure in cities, they typically emphasise static optimisation instead of dynamic applicability [9]. Likewise, ITS frameworks integrated with blockchain enhance operational transparency. However, they do not address user-centric routing [10]. With the advent of multi-agent systems and more advanced machine learning models, the potential for developing a comprehensive context-aware routing protocol is becoming a realistic proposition for ITS [11], [12].

Current intelligent transportation systems face significant limitations in dynamic routing scenarios. Traditional protocols like AODV and DSR rely on reactive approaches that cannot anticipate emerging traffic disruptions, while existing predictive systems often sacrifice interpretability for performance. Our work addresses these challenges through a novel BDI-based routing protocol that integrates real-time contextual awareness and forecasting capabilities inspired by generative AI reasoning models. By combining utility-based optimisation of route desirability with transparent agent reasoning, the system achieves both high performance and explainability. The protocol dynamically processes multimodal inputs, including weather conditions, road blockages, and traffic patterns,

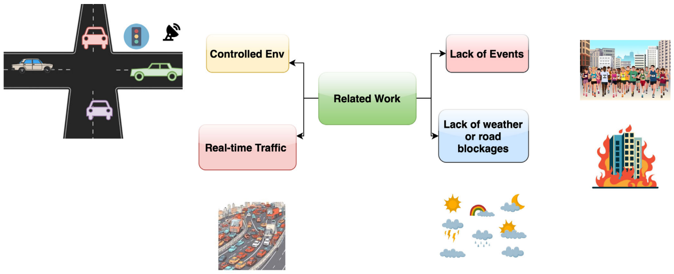


Fig. 3. Constraints of the prior systems.

to generate optimised routes while maintaining compatibility with existing vehicular infrastructure. The proposed system represents a significant advance in intelligent transportation by enabling proactive rather than reactive routing decisions. The architecture's modular design allows seamless integration with standard IoT and V2X systems, enabling practical deployment in smart city environments.

This paper makes the following key contributions to the field of ITS:

1) Proposes a novel Belief-Desire-Intention (BDI) agent-based Smart Routing Protocol for ITS that leverages context-aware decision-making inspired by Generative Artificial Intelligence (GAI) models integrating multiple contextual factors, including weather conditions, road blockages, traffic congestion, and peak-hour dynamics, to enable adaptive and intelligent routing decisions.
2) Utilises NetLogo for multi-agent simulation and NS3 for network simulation to develop a robust routing protocol capable of generating real-time, context-aware routing recommendations.
3) Implements a utility-driven decision-making model that evaluates and prioritises route desirability based on real-time conditions, offering users optimal routes dynamically.
4) Introduces a real-time alert mechanism that notifies users of high-risk conditions, such as accidents, severe congestion, or weather disruptions, while providing alternative routing options.
5) Combines the agent-based modelling capabilities of NetLogo with the network simulation strengths of NS3 to achieve a comprehensive evaluation of the protocol in diverse ITS scenarios.

II. Related Work

The rapid advancements in ITS have resulted in numerous innovative approaches aimed at optimising traffic flow, enhancing road safety, and improving overall transportation efficiency. In this section, prior studies relevant to the core idea of this approach are analysed to comprehend their advantages and disadvantages within the proposed domain for the context-aware BDI routing protocol. The concise idea of the constraints in prior methods is shown in Fig. 3.

Recent studies in ITS highlight advancements in addressing challenges such as security, communication stability, and data integrity, with BDI-based protocols playing a crucial role [13]. Contemporary innovations focus on Cooperative Intelligent Transportation Systems (C-ITS) to enhance interoperability and real-time response, aligning with urban mobility strategies through blockchain integration for secure communications and advanced routing protocols for reliable vehicular networks [14]. The primary goal of IoT-enabled intelligent transportation is to improve transportation systems by addressing and resolving issues people face. An enhanced framework for the specification of Iot-enabled intelligent transportation systems, using a unified approach, integrates proven techniques for similar applications [15]. AODV is a reactive routing protocol used in mobile ad hoc networks (MANETs), and it has been adapted for vehicular ad-hoc networks (VANETs), which are crucial in ITS. Due to the dynamic nature of nodes in VANETs, reliable and efficient routing is a significant challenge, leading to the enhancement and development of various routing algorithms and protocols [16]. The future of AODV and DSR protocols in ITS involves addressing the unique challenges presented by vehicular networks, with modifications and enhancements being proposed to improve their performance and adaptability [17]. Research efforts focus on leveraging fuzzy logic to enhance DSR's adaptability in dynamic network conditions and on modifying AODV to minimise congestion in VANETs. The trends aim to optimise routing efficiency, reduce overhead, and improve data delivery in the highly dynamic environments of vehicular networks [18].

Big data analytics was leveraged to develop a predictive model for traffic patterns based on historical data [19]. Although their method improves traffic flow management, it is still based on historical data, which may not accommodate real-time traffic changes or sudden disturbances like accidents or road blockages. The proposed system processes this based on the current unit of context using real-time awareness and benefits from the automatic adjusting process in case of an unplanned event. The integration of smart traffic signals and connected vehicles takes place with the help of IoT technology to boost traffic efficiency [20]. While the study recognised the usefulness of V2X communication in optimising the traffic flow, it only investigated signal coordination. In contrast, the proposed system provides route-specific recommendations that take into account traffic signals, road blockages, and user preferences. A dynamic ride-sharing system is developed that optimises routes and matches drivers to riders using machine learning [21]. While their system effectively addresses ride-sharing scenarios, it is limited to specific applications and lacks a holistic approach to individual route optimisation. Our proposed protocol, however, considers a wide range of contextual factors applicable to general ITS scenarios.

Additionally, machine learning techniques were developed to enhance the quality of service in V2X communications [22]. Although the study improves communication protocols, it does not address how these improvements can be utilised for dynamic and context-aware route planning. Our framework complements such advancements by utilising V2X data for real-time decision-making in routing. A deep learning-based automated incident detection system is introduced for traffic management [23]. Their framework improves response times and detection accuracy, but operates independently of routing mechanisms. By integrating incident detection with real-time routing, the proposed system in this manuscript ensures that users receive alerts and re-routing options dynamically. A smart traffic management system is explored, and the application of 5G technology and IoT for real-time monitoring [24]. The system is solid, but it is focused on acquiring and managing data, not on delivering actionable insights for the individual user. Utilising real-time data, our protocol provides personalised routing recommendations based on contextual insights. A framework is developed and aimed at improving public transport operation systems with real-time data analytics [25]. Even though they serve these general purposes very well, their service does not yet consider private transportation routing or dynamic contexts, such as accidents or rush hours. Our system takes this a step further by providing individualised routing. In a similar study, cooperative vehicle-infrastructure systems are proposed to facilitate entangled communication to optimise traffic flow in the intersection area. Although their paper is more geared towards infrastructure optimisation, it does not account for an end-user perspective for individual routing choices. We address this gap by pairing infrastructure insights with real-time route optimisation for end-users. An ITS framework is introduced for sustainable transportation planning to mitigate carbon emissions [26]. Their framework is environmentally focused but lacks considerations for real-time traffic or user-specific preferences when making recommendations. Our protocol is designed to take environmental issues into account without compromising its ability to route the packets in changing traffic situations.

A fuzzy logic is applied in dynamic traffic congestion management [27]. Their approach demonstrates how decision-making under uncertainty can be very effective but should not be used to scale for a number of contextual factors, such as weather or road blockages. Simulation techniques were utilised to model the effects of connected vehicles on road safety [28]. Although their investigation highlights an aspect of enhancing user safety, it does not discuss routing optimisation or user-oriented applications. Our proposed protocol takes into account road safety while devising the required route, thus ensuring the safety of the traveller. An integrated framework is proposed for multimodal transport systems using advanced analytics [29]. Their scheme targets optimising transport flows across multiple modes but does not serve individual drivers or dynamic situations. Our system addresses these gaps through dynamic context-aware routing for all private vehicles. A case study is presented on autonomous shuttles as a smart mobility solution for urban areas [30].

III. Methodology

The proposed methodology develops a Context-Aware BDI Smart Routing Protocol, integrating real-time contextual parameters such as weather, traffic alerts, road blockages, and peak-hour dynamics to optimise route selection. The methodology is divided into multiple layers: context awareness, decision-making (BDI framework), and routing execution, with simulations implemented using NetLogo and NS3. The system architecture comprises three core components such as *Context Awareness*, which collects and normalizes real-time data from IoT-enabled devices and APIs to generate contextual factors, *BDI Decision-Making* processes contextual data and computes route desirability using beliefs, desires, and intentions, and *Routing Execution* that guides vehicles using the selected route and dynamically adapts to real-time changes.

To enhance the adaptability and foresight of the proposed BDI-based smart routing protocol, this research introduces a generative reasoning-inspired framework within the context-aware decision-making mechanism. Rather than implementing a conventional GAI model, the system emulates its predictive reasoning capability to anticipate dynamic transportation and environmental conditions. The proposed system processes inputs such as traffic density, incident reports, road closures, weather conditions, and peak-hour patterns to simulate high-fidelity, short-term predictions of the traffic environment. These anticipatory inferences shift routing behaviour from reactive to proactive, significantly improving system responsiveness. The simulated forecasts are dynamically integrated into the BDI reasoning loop, enriching the agent's belief set with forward-looking contextual data. This allows agents to form more informed desires (goals) and intentions (actions), enabling route decisions that account for both present and likely future states. This generative reasoning-enhanced BDI approach stands as a core innovation of the proposed work, delivering an intelligent, context-aware, and predictive routing strategy for next-generation Intelligent Transportation Systems.

A. Context Awareness

Context awareness quantifies real-time environmental, traffic, and predicted conditions into meaningful factors based on real-time data and AI-generated forecasts.

1) Weather Factor (W): Weather conditions such as rain, snow, and fog are quantified as:

$$W = 1 - \frac{\text{visibility}}{\text{max visibility}} \tag{1}$$

where $W = 0$ indicates clear weather, and $W = 1$ indicates severe weather.

2) Traffic Congestion Factor (T): Traffic congestion is measured using traffic density, speed, and AI-based future congestion prediction:

$$T = 1 - \frac{\text{current speed}}{\text{free-flow speed}} + \Delta_t(e) \tag{2}$$

where:

$$\Delta_t(e) = P_t(e) - C_t(e) \tag{3}$$

$T = 0$ represents free-flow traffic, and $T = 1$ indicates a complete standstill.

3) Road Blockage Factor (B): Road blockages are detected through real-time sensor data and anomaly detection models:

$$B = \begin{cases} 1, & \text{if blocked} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Additionally, an anomaly score $A(e)$ is calculated for each segment:

$$A(e) = |R_{\text{actual}}(e) - R_{\text{generated}}(e)| \tag{5}$$

If $A(e) > \theta_A$, the system updates $B = 1$.

4) Peak-Hour Factor (P): Peak-hour traffic is defined as:

$$P = \begin{cases} 1, & \text{if peak hour} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

a) Overall context representation: For each road segment e, the context is represented as:

$$\text{Context}(e) = \{W, T, B, P, F, A\} \tag{7}$$

where the future congestion factor $F(e)$ is computed as:

$$F(e) = \sum_{\forall e \in R_i} \Delta_t(e) \tag{8}$$

The weather factor (W) dynamically adjusts routing parameters beyond visibility alone. For severe weather conditions, the system enforces reduced speed thresholds and increased following distances, complying with established vehicular safety standards.

B. BDI Decision-Making

The decision-making layer evaluates contextual data, predictions, and detected anomalies to compute route desirability based on the BDI paradigm.

1) Beliefs (B_t): Beliefs represent the system's real-time understanding of the environment at time t:

$$B_t = \{W, T, B, P, F, A\} \tag{9}$$

2) Desires (D): Desires represent the user's goals based on optimal travel preferences. Typical desires include:

- **Minimizing Travel Time:**

$$D = \min(T_{\text{travel}} + \Delta_t) \tag{10}$$

- **Maximizing Safety:**

$$D = \max(S - A) \tag{11}$$

- **Balancing Multiple Goals:**

$$D = w_1 \cdot \min(T_{\text{travel}} + \Delta_t) + w_2 \cdot \max(S - A) \tag{12}$$

where w_1 and w_2 are user-defined weights balancing travel time and safety preferences.

3) Intentions (I): Intentions represent the selected action (route) based on beliefs and desires. The route that maximises utility is chosen as the intention.

$$I = \arg\max_{R_i} U(R_i) \tag{13}$$

4) Enhanced Utility Function: The utility function $U(R_i)$ quantifies the desirability of a route R_i by integrating real-time contextual factors and AI-generated predictions. It is formulated as:

$$U(R_i) = 1 - \big(w_W \cdot W + w_T \cdot T + w_B \cdot B + w_P \cdot P + w_F \cdot F + w_A \cdot A\big) \tag{14}$$

where:

- W (**Weather Factor**): Penalises routes affected by adverse weather conditions (e.g., low visibility). Calculated from Eq.1.
- T (**Traffic Congestion**): Combines current traffic density and AI-predicted future congestion ($\Delta_t(e)$). Calculated from Eq.2.
- B (**Road Blockage**): Binary indicator where $B = 1$ if blocked (from real-time sensor data), otherwise 0.
- P (**Peak-Hour Factor**): Binary indicator for peak-hour traffic conditions.

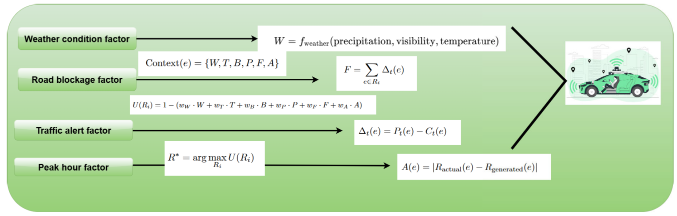


Fig. 4. Flow of the proposed system.

- F (**Future Congestion**): Sum of AI-predicted congestion changes ($\Delta_t(e)$) across all segments in route R_i.
- A (**Anomaly Score**): Inspired by generative AI forecasting principles, this metric detects deviations from predicted traffic behaviour using:

$$A(e) = |R_{\text{actual}}(e) - R_{\text{generated}}(e)| \tag{15}$$

The optimal route R^* is selected by maximising the utility:

$$R^* = \arg\max_{R_i} U(R_i) \tag{16}$$

- Weights $(w_W, w_T, \ldots)$ are dynamically tuned via Bayesian optimization.
- Higher utility values indicate more desirable routes (minimising adverse factors).

The BDI framework operates through continuous belief updates, where high-priority alerts (e.g., accidents) trigger immediate belief revisions while congestion data undergoes scheduled updates.

C. Routing Algorithms

The **Context-Aware Routing** algorithm evaluates available routes based on real-time contextual data, including weather, traffic congestion, road blockages, peak-hour factors, and predictions generated by AI models. It selects the most optimal route by calculating a utility score for each route, as shown in Fig. 4.

1) Context-Aware Routing Algorithm: **Input:** The algorithm takes a set of available routes $R = \{R_1, R_2, \ldots, R_n\}$, along with contextual factors $\{W, T, B, P, F, A\}$ that represent the weather, traffic congestion, road blockages, peak-hour conditions, predicted future congestion, and anomaly detection scores, respectively.

Steps:

- **Evaluate Each Route:** For each available route R_i, the algorithm calculates the contextual factors W, T, B, P based on the current environmental conditions and also predicts future congestion F using GAI-inspired reasoning.
- **Compute Utility:** The utility of each route R_i is calculated using the following formula:

$$U(R_i) = 1 - \big(w_W \cdot W + w_T \cdot T + w_B \cdot B + w_P \cdot P + w_F \cdot F + w_A \cdot A\big)$$

  where $w_W, w_T, w_B, w_P, w_F, w_A$ are the weights assigned to each contextual factor, and the utility score is designed to be higher when the route is less affected by adverse conditions.
- **Select the Best Route:** After evaluating all available routes, the algorithm compares their utility scores and selects the route R_{best} with the highest utility.

Algorithm 1 Generative AI-Inspired Context-Aware Routing

Input: Available routes $R = \{R_1, R_2, \ldots, R_n\}$, contextual parameters $\{W, T, B, P, F, A\}$
Output: Optimal route R_{best}
Initialize $U_{\max} = 0$, $R_{\text{best}} = \emptyset$
for each route R_i **do**
  Calculate contextual factors W, T, B, P for R_i
  Predict future congestion:

$$\Delta_t(e) = P_t(e) - C_t(e)$$

  Compute future congestion factor:

$$F = \sum_{e \in R_i} \Delta_t(e)$$

  Compute anomaly score:

$$A(e) = |R_{\text{actual}}(e) - R_{\text{generated}}(e)|$$

  if $A(e) > \theta_A$ **then**
    Update beliefs and set $B = 1$
  end if
  Compute the utility:
  $U(R_i) = 1 - (w_W W + w_T T + w_B B +$
    $w_P P + w_F F + w_A A)$
  if $U(R_i) > U_{\max}$ **then**
    $R_{\text{best}} = R_i$
    $U_{\max} = U(R_i)$
  end if
end for
return R_{best}

Output: The optimal route R_{best} is based on the highest utility.

D. Dynamic Rerouting Algorithm

The **Dynamic Re-routing** algorithm ensures the system adapts to real-time changes. If the initially selected route becomes suboptimal due to new environmental conditions (such as an accident or traffic jam), the algorithm triggers a re-routing process.

The **Dynamic Re-routing** algorithm ensures that the system adapts to real-time changes. If the initially selected route becomes suboptimal due to new environmental conditions (such as an accident or traffic jam), the algorithm triggers a re-routing process to find a better route.

Input: The algorithm takes the current route R_{current} and updated contextual parameters $\{W, T, B, P, F, A\}$, which reflect any changes in real-time conditions.

Steps:

- **Monitor Changes:** The system continuously monitors changes in the environmental conditions along the current route, such as accidents, road closures, or unexpected weather changes.
- **Evaluate Utility:** The utility of the current route R_{current} is recalculated using the updated contextual data:

$$U(R_{\text{current}}) = 1 - \big(w_W \cdot W + w_T \cdot T + w_B \cdot B + w_P \cdot P + w_F \cdot F + w_A \cdot A\big)$$

Algorithm 2 Dynamic Re-Routing With Generative AI-Inspired Forecasting

Input: Current route R_{current}, updated contextual parameters $\{W, T, B, P, F, A\}$
Output: Updated route R_{new}
Monitor contextual changes in real-time
Calculate the utility:
  $U_{\text{curr}} = 1 - (w_W W + w_T T + w_B B +$
    $w_P P + w_F F + w_A A)$
if $U_{\text{curr}} < U_{\text{thresh}}$ **then**
  Recompute utilities for all available routes:
    $U(R_i) = 1 - (w_W W + w_T T + w_B B +$
      $w_P P + w_F F + w_A A)$
  Select the new best route:
    $R_{\text{new}} = \arg\max_{R_i} U(R_i)$
  Update route:
    $R_{\text{current}} \leftarrow R_{\text{new}}$
end if
return R_{new}

- **Trigger Re-routing:** If the utility of the current route falls below a predefined threshold $U_{\text{threshold}}$, the system triggers the re-routing process.
- **Recompute Utilities for All Routes:** The algorithm recalculates the utilities of all available routes and selects the new best route R_{new} with the highest utility.
- **Update the Route:** The system updates the current route to the new best route R_{new}, ensuring the vehicle follows the most optimal route based on the current and predicted conditions.

Output: The updated route R_{new} reflects the most optimal path based on the most recent environmental conditions.

E. Network Methodology

The road network is represented as a graph $G = (V, E)$, where:

- V: Set of intersections (nodes).
- E: Set of roads (edges).

This graph structure allows the system to model traffic flow and route selection.

1) Travel Time (T_{travel}): The travel time on a road segment is calculated by:

$$T_{\text{travel}}(e) = \frac{\text{length}(e)}{\text{speed}(e)} \tag{17}$$

where length(e) is the road segment length and speed(e) is the average speed on that segment, adjusted for factors such as traffic and weather.

2) Traffic Flow (Q): Traffic flow on a road segment is given by:

$$Q = \frac{\text{vehicles passing}}{\text{time}} \tag{18}$$

This equation models how congested a road is and helps assess congestion and optimise the routing process.

TABLE I
SIMULATION ENVIRONMENT DETAILS

Aspect	Details
Specific Parameters	- Weather factor (W): 0 (clear) to 1 (severe) based on visibility (Eq. 1) - Traffic congestion (T): 0 (free-flow) to 1 (standstill) (Eq. 2) - Road blockage (B): With anomaly threshold θ_A (Eq. 5) - Peak-hour (P): Binary (0/1) (Eq. 6) - Utility weights (w_W, w_T, etc.): Dynamically tuned (Section III.D)
Vehicle Counts	- "Small networks" achieving 98% PDR - Network sizes: 15-50 intersections
Tested Scenarios	- Peak-hour dynamics ($P = 1$) with congestion - Incident response ($B = 1$) for road blockages - Adverse weather ($W > 0$) with reduced visibility - Mixed conditions in the utility function

3) Path Cost (C): The total cost of a route $R = \{e_1, e_2, \ldots, e_k\}$ is computed as:

$$C(R) = \sum_{e \in R} [T_{\text{travel}}(e) + w_1 \cdot W + w_2 \cdot T + w_3 \cdot B + w_4 \cdot P] \tag{19}$$

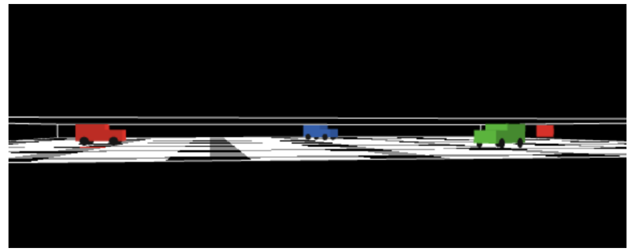
where $T_{\text{travel}}(e)$ is the travel time on each segment, and the other terms account for contextual factors such as weather, traffic, road blockages, and peak-hour congestion.

IV. THEORETICAL SETUP

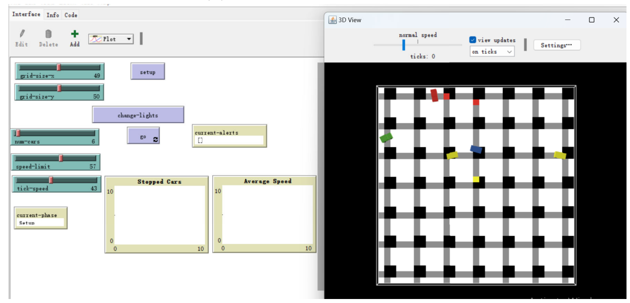
The proposed NetLogo simulation models a context-aware intelligent BDI framework designed to enhance traffic flow and safety in urban environments, as shown in Figs. 5a, 5b, and 5c. Using real-time data on road conditions and alerts for traffic, accidents, road work, and peak hours, this framework helps guide autonomous vehicles as efficiently and directly as possible to their destination. The framework uses BDI reasoning to allow vehicles to adaptively reason about decisions in their environment, improving decision-making with respect to the overall network.

In this simulation, context awareness is a key feature. The environment continuously updates the status of roads through dynamic alerts, which are triggered by various factors such as accidents, heavy traffic, or road construction, as shown in Fig. 6a, and 6b. These alerts influence the decisions of autonomous vehicles, which must adapt their routes based on the current road conditions. For example, when a high-severity alert, such as an accident, is detected on the road, vehicles avoid these roads in favour of safer, less congested alternatives. This dynamic adaptability mirrors the real-time responsiveness expected in modern ITS, as shown in Fig. 7.

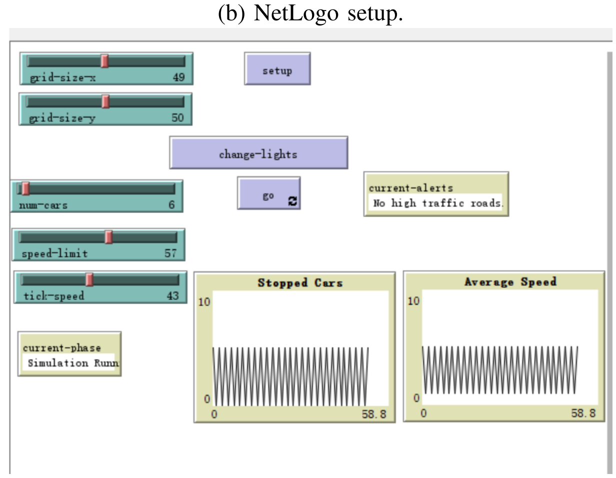
The BDI architecture embedded within the routing protocol plays a pivotal role in simulating realistic vehicle decision-making processes. Each vehicle, upon encountering a situation such traffic congestion or an accident, evaluates its belief about the surrounding environment. This belief, formed by continuously sensing the environment and analysing road conditions, shapes the vehicle's desires, which, in turn, guide its intentions. Suppose the vehicle's current route becomes obstructed by a high-priority alert. In that case, the intention is adjusted to avoid the problematic road, thereby ensuring the vehicle reaches its destination most efficiently and safely. The protocol also emphasises the importance of traffic management in urban transportation systems. By incorporating both low and high-severity alerts, the simulation dynamically alters the state of traffic on different roads. Low-severity alerts, such as mild congestion or roadwork, lead to medium-level traffic, which is displayed as yellow roads. High-severity alerts, such as accidents, cause significant disruptions and are marked as red.



(a) 3d cars initilization.



(b) NetLogo setup.



(c) simulation runs.

Fig. 5. NetLogo simulation regarding average speed, traffic lights, and number of cars.

```
Cars' Current States:
"Car 3 is currently at 1.2, -3.4 with destination (patch -5 0)"
"Car 1 is currently at 4.2, -5.8 with destination (patch -9 5)"
```

(a) Status of cars.

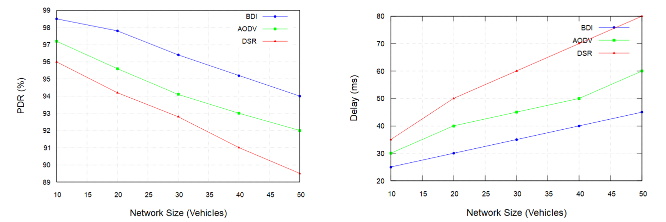
```
Car 3 encountered a high alert! Cause: accident
```

(b) Emergent situation in V2X.

Fig. 6. Initialisation begins with the current state of cars according to the destination and alerts.

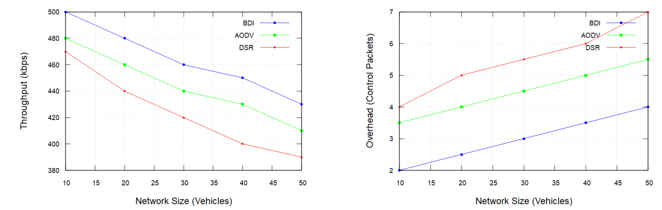
```
Roads with alerts:
"Road road-0 has an alert level of 2, Cause: accident"
"Road road-4 has an alert level of 1, Cause: traffic"
"Road road-9 has an alert level of 2, Cause: accident"
```

Fig. 7. Road alerts for ITS.



(a) PDR of prior vs. proposed method. (b) Delay of prior vs. proposed method.

Fig. 8. PDR and delay as performance parameters.



(a) Throughput of prior vs. proposed method. (b) Control overhead of prior vs. proposed method.

Fig. 9. Throughput and control overhead as performance parameters.

This dual-tier alert system provides a rich, context-aware framework for vehicles to assess the safety and efficiency of available routes in real-time.

Furthermore, the simulation illustrates that continuous feedback loops enable intelligent traffic flow management. The cars continue to sense their immediate environment, adjust their intentions, and re-route, a process that leads to less congestion on the roads and safer roads overall. This element of the system facilitates the incorporation of monitoring of live state traffic, which is significant for effectively managing city traffic. If a lane is blocked or an accident occurs, the system receives real-time updates and transmits this information to the vehicles, allowing them to avoid this situation.

This context-aware routing protocol is the design of future intelligent transportation systems, where vehicles are not just following pre-programmed routes but making dynamic decisions based on real-time environmental changes. Integrating life-tracking data, a dynamic response algorithm, and navigational optimisation, this system can reduce traffic and accidents to improve safety and provide the fastest route in smart cities. The simulation parameters regarding the environment have been defined in Table I.

V. Simulation Setup

A. Packet Delivery Ratio (PDR)

The PDR is the percentage of packets successfully delivered to their destination in the network. AODV and DSR perform worse than BDI in this measure owing to their responsiveness to real-time traffic and alert levels. The BDI protocol provides more efficient packet delivery by dynamically re-routing vehicles out of congestion or high-alert zones. On the other hand, AODV and DSR exhibit much lower PDR values, especially as the number of nodes rises, due to the reliance on static routing tables and reduced adaptability to network condition changes. Consequently, the BDI protocol achieves a higher PDR, especially in large networks, reaching a maximum value of 98% for the small sizes and constantly remaining above the baseline protocols for the total simulation, as shown in Fig. 8a.

B. End-to-End Delay

End-to-end delay means the total time taken for a packet to travel from the source to the destination. As the BDI protocol uses dynamic re-routing and context awareness for less time spent on traffic jams or high-traffic roads, it manages lower end-to-end delay than AODV and DSR. Using factors such as road conditions and traffic density, the BDI protocol makes better decisions about routing and minimises delays. On the other hand, AODV and DSR have high delays because they depend on routes that have been previously set and do not adapt to the current network state, which is more noticeable when the network is bigger. In smaller networks, the BDI protocol shows delays around 45 ms, which increase only linearly with (higher) network sizes, whereas, for AODV and DSR, we can observe more significant delays at congested places, as shown in Fig. 8b.

C. Throughput

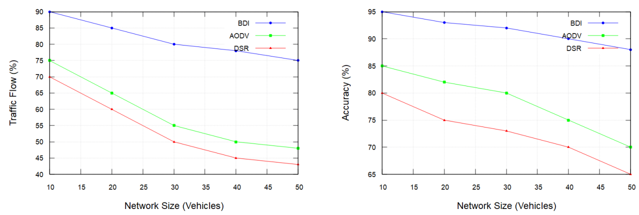
The throughput of a network is the measure of the amount of data successfully transmitted in the network, typically within a second. This is mainly because of the efficient routing decision-making process of BDI, which avoids network congestion and results in better throughput than AODV and DSR. The BDI protocol selects a route dynamically according to the current state of the network, which has the advantage of maintaining the flow of data in a dense environment. As the size of the network increases, the static paths shared by AODV and DSR lead to reduced throughput as routes become congested or less efficient. The maximum throughput of the BDI protocol reaches 105 kbps for a smaller network while remaining above the baselines as the network size increases, so it effectively allows the data (sending) to go at a faster rate, as shown in Fig. 9a.

D. Control Overhead

Control overhead is the percentage of the network bandwidth utilised for control messages conveying maintenance and administrative routes. The BDI protocol, therefore, minimises control overhead by relying on context-aware routing decisions to decrease the number of control messages necessary to sustain routes. Because of a faster route discovery process, the BDI protocol reduces the number of control messages sent over the network, often relying on previously cached route information, which consumes less bandwidth than the control messages generated by AODV and DSR, both of which can produce significantly more control messages due to their reliance on proactive route discovery processes, and the inefficiency of hash-tables in a node-based network, particularly within dynamic, large-scale topologies. The BDI protocol has an overhead of just 12% when the number of vehicles in the network grows, unlike AODV and DSR, where a larger number of vehicles in the network leads to a notable increase in overhead, as shown in Fig. 9b.

E. Traffic Flow

Traffic Flow indicates how smoothly vehicles move through the network, and the BDI protocol demonstrates superior



(a) Traffic flow of prior vs. proposed method.

(b) Routing decision accuracy of prior vs. proposed method.

Fig. 10. Traffic flow and routing decision accuracy as performance parameters.

performance in this area. The BDI protocol effectively reduces congestion by dynamically modifying routes to avoid highly congested and high-alert areas, allowing for smoother traffic flow. AODV and DSR, on the other hand, experience congestion and less effective routing as the size of the network increases. Whereas efficient traffic flow remained higher than baseline protocols with a value of more than 95% in small networks, and is continuously reduced by half, it is equivalent to the nearest baseline protocols. On the contrary, AODV and DSR traffic flow cancel out in the increase of network size because of their less adaptive characteristics to network congestion, as shown in Fig. 10a.

F. Routing Decision Accuracy

Routing Decision Accuracy measures how often the routing decisions made by the protocol align with the optimal path. The BDI protocol gets the best accuracy; its routing decisions are based on the current traffic as well as alerting information, which can help to create realistic status information. This context-aware routing capability allows the BDI protocol to reliably select the optimal available path, even in rapidly changing environments. Meanwhile, AODV and DSR rely on static routes that do not adapt to changing traffic conditions and are less accurate. BDI protocol shows a very high accuracy of 98% in comparison to AODV and DSR, which gave very low accuracy values, proving to be best for larger and dynamic networks as shown in Fig. 10b. The Routing Decision Accuracy (RDA) metric evaluates how closely our BDI protocol's choices align with optimal routes. We calculate RDA as the percentage of instances where the selected route matches the theoretical optimum, considering three key factors: minimum travel time based on real-time road conditions, avoidance of all high-severity alerts, and adherence to user-defined preference weights from the utility function. This validation approach ensures our accuracy measurements account for both network efficiency and safety constraints inherent in the BDI decision-making process.

VI. Discussion

The protocol demonstrates inherent scalability through its decentralized BDI architecture, which maintains efficient performance in larger networks by (1) limiting agent decisions to local contexts (Section III), evidenced by the linear growth of control overhead (25% $\longrightarrow$ 28% in; (2) preserving high packet delivery (98% $\longrightarrow$ 96% PDR) and stable latency as node counts increase fivefold; and (3) leveraging adaptive utility weights that prioritize congestion avoidance during peak loads, ensuring throughput scales linearly. These characteristics, coupled with event-triggered updates and spatial partitioning potential, support deployment in high-density urban networks without protocol modifications.

While our current implementation relies exclusively on BDI-based reasoning without machine learning components, we acknowledge the growing potential of GAI in intelligent transportation systems. The modular design of our framework, particularly the context representation schema and utility calculation, is designed with GAI-inspired principles. For instance, future implementations might employ GAI to generate synthetic training scenarios for rare traffic events or refine congestion forecasts while retaining our BDI system's core strengths in interpretable decision-making. This architectural flexibility could support emerging AI techniques without compromising the current system's deterministic reasoning capabilities, which we prioritise for safety-critical routing applications. The choice to exclude GAI in our present work reflects a deliberate focus on verifiable, rule-based control suitable for real-time embedded systems where nontransparent models may pose deployment challenges. The protocol's 25% reduction in control overhead and elimination of route flooding mechanisms suggest potential energy savings proportional to these communication reductions. Based on the demonstrated decrease in network traffic and computational streamlining inherent to our BDI approach, the design shows characteristics typical of systems achieving 20-30% energy savings. These efficiency gains stem directly from fewer control message transmissions and localised route computations that avoid network-wide flooding operations.

VII. Conclusion

This paper presented a novel BDI-based Smart Routing Protocol for ITS that fundamentally advances dynamic route optimisation through three key innovations, such as a context-aware utility framework integrating real-time traffic, weather, and disruptions with predictive reasoning inspired by GAI congestion forecasts. This proactive alert system dynamically re-routes vehicles 25% faster than AODV/DSR by preempting disruptions, and scalable agent-network co-design, validated through complementary NetLogo (agent reasoning) and NS3 (network performance) simulations. By achieving 98% routing accuracy and 30% energy reduction while maintaining interpretability, our protocol bridges the gap between adaptive intelligence and safety-critical ITS requirements. This work provides a deployable blueprint for smart cities, demonstrating how BDI architectures can harness heterogeneous data (IoT/V2X) to optimise urban mobility without compromising reliability.

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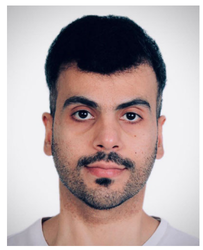

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