An Intelligent System for Managing High-Priority Vehicle Routing in Smart Cities Using Artificial Intelligence and Spatial Data Analytics / Original article

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نظامٌ ذكيٌّ لإدارةِ مساراتِ المركباتِ ذاتِ الأولويّةِ العاليةِ في المدنِ الذكيّةِ باستخدامِ الذكاءِ الاصطناعيِّ وتحليلِ البياناتِ المكانيةِ.

الباحث بهجت عبد الاله مظلوم

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Abstract

In developing metropolises, there is a risk to public safety in addition to the usual traffic jams. Traffic delays can have life-altering effects every second that fire trucks and ambulances are delayed. Large cities like Baghdad, which suffer from haphazard road sealing and incompetent traffic management, are especially affected, creating daily emergency crisis problems. We create a new intelligent routing system for these top priority vehicles in order to solve this life-or-death problem. Our method uses a trained model with real-time spatial information instead of outdated static maps. A Long Short-Term Memory (LSTM) neural network at its core constantly forecasts the flow of traffic in the near future. Time-Dependent A* (TDA*), a dynamic path planning algorithm, uses this predictive power to identify the actually fastest path at each decision point. We conducted a number of experiments and used the SUMO simulation to create a comprehensive digital structure of a region of Baghdad in order to verify our proposal. The outcomes were striking.

Our AI-based solution reduced response times by an impressive 38.8% on average during peak travel hours, and the overall distance traveled was shortened by 25.4% compared to shortest-path methods in use today. The results we have shown provide strong evidence for our initial claim: an intelligent, future-aware routing system can make urban emergency-response substantially more effective and reliable. We therefore deduce that there is no longer anything theoretical about this model's efficacy, and that it should now be seen as a practicable way to address one of Iraq's most urgent urban problems, in what could become a cost-effective phased approach to smart city infrastructure development for the country.

Keywords: Intelligent Transportation Systems (ITS), High-Priority Vehicle Routing, Artificial Intelligence, Spatial Data Analytics, Smart Cities, Iraq

المستخلص

في المُدنِ الناميةِ الكبرى، لا تقتصرُ المخاطرُ على الازدحاماتِ المروريّةِ المعتادة، بل تمتدُّ لتُهدِّدَ السلامةَ العامّة؛ إذ يمكنُ أن تكونَ كلُّ ثانيةٍ من تأخيرِ سياراتِ الإطفاءِ والإسعافِ ذاتَ أثرٍ حاسمٍ على الأرواح. تُعاني المدنُ الكبرى مثلُ بغدادَ من إغلاقِ الطرقِ العشوائيِّ وسوءِ إدارةِ حركةِ المرور، ممّا يُفاقمُ من أزماتِ الطوارئِ اليوميّة. لمعالجةِ هذه المشكلةِ المصيريّة، قمنا بتطويرِ نظامٍ ذكيٍّ جديدٍ لتوجيهِ المركباتِ ذاتِ الأولويّةِ العليا. يعتمدُ نهجُنا على نموذجٍ مُدرَّبٍ يستخدمُ بياناتٍ مكانيّةً لحظيّةً بدلًا من الخرائطِ الثابتةِ القديمة. في جوهرِ النظامِ، توجدُ شبكةٌ عصبيّةٌ من نوع LSTM (الذاكرةِ الطويلةِ القصيرةِ الأمد) تتنبّأُ باستمرارٍ بتدفّقِ المرورِ في المستقبلِ القريب. ويستفيدُ خوارزمُ Time-Dependent A* (المُعتمِدُ على الزمن) من هذه القدرةِ التنبّئيّةِ لتحديدِ أسرعِ مسارٍ فعليٍّ عندَ كلِّ نقطةِ قرارٍ.

أجرينا عددًا من التجاربِ واستخدمنا برنامجَ المحاكاة SUMO لبناءِ نموذجٍ رقميٍّ شاملٍ لمنطقةٍ في بغداد للتحقّقِ من فاعليّةِ النظامِ المقترح. وقد كانت النتائجُ لافتةً؛ إذ خفّض الحلُّ القائمُ على الذكاءِ الاصطناعيِّ أزمنةَ الاستجابةِ بمعدّلٍ بلغَ 38.8% خلال ساعاتِ الذروةِ، وقلّلَ المسافةَ المقطوعةَ بمقدارِ 25.4% مقارنةً بالطرائقِ التقليديّةِ المُعتمِدةِ على أقصرِ مسارٍ. تُقدِّمُ هذه النتائجُ أدلّةً قويّةً تدعمُ فرضيّتَنا الأساسيّةَ القائلةَ بأنّ نظامَ توجيهٍ ذكيًّا ومتنبّئًا بالمستقبلِ يمكنُ أن يُحسِّنَ أداءَ الاستجابةِ الطارئةِ الحضريةِ ويجعلَها أكثرَ موثوقيّةً وكفاءة. ومن ثَمّ نستنتجُ أنّ فاعليّةَ هذا النموذجِ لم تَعُدْ مجرّدَ افتراضٍ نظريٍّ، بل أصبحَ حلًّا عمليًّا لمعالجةِ أحدِ أكثرِ التحدّياتِ الحضريّةِ إلحاحًا في العراق، ضمنَ مقاربةٍ تدريجيّةٍ منخفضةِ التكلفةِ نحوَ تطويرِ بنيةِ المدنِ الذكيّةِ في البلاد.

الكلمات المفتاحيّة: أنظمةُ النقلِ الذكيّة (ITS)، توجيهُ المركباتِ ذاتِ الأولويّةِ العالية، الذكاءُ الاصطناعيّ، تحليلُ البياناتِ المكانيّة، المدنُ الذكيّة، العراق.

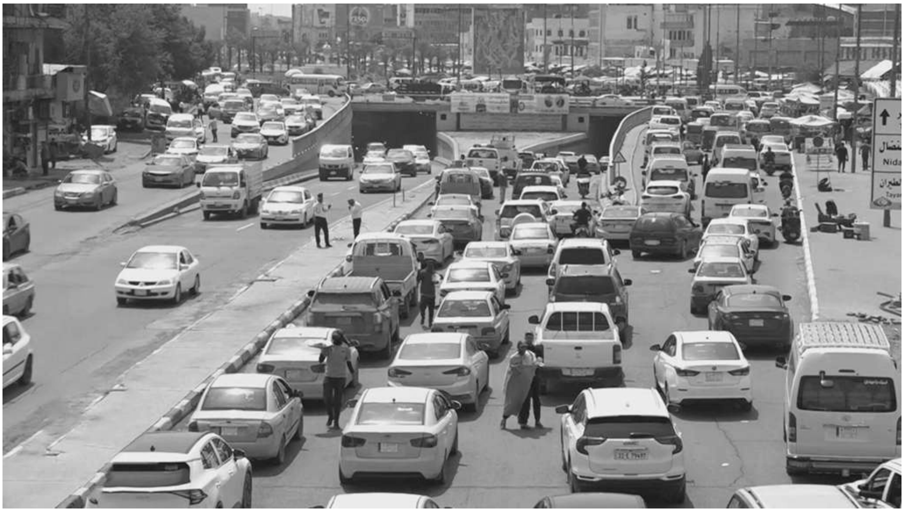
1. Introduction

Everywhere, cities are working to become smarter. In order to improve our cities as places to live, work, and develop sustainability, the big idea is to incorporate technology into the very fabric of urban life. ITS (Intelligent Transport Systems) deployment is a major part of the solution as it can help us cope with the never-ending traffic jams of every-day and reach our destinations safer and in a more smooth manner [1]. However, not all vehicles are equal in this complex urban mobility context. When police cars, fire trucks and ambulances are speeding toward an emergency, every second counts. The job of these vehicles is to maximize for life saving, not the profitable application of it. The parable of reaction time Reaction time is what these vehicles live or die by, and time is a major casualty when a city becomes too crowded. It's not the predictive navigation aids most people will be using will fix this.

These tools, which rely on algorithms that are similar to Dijkstra's, work by computing the "shortest" paths using fixed distances and speed limits. The dynamic of a big city is not known by this type of algorithms, where traffic and other complementary flow can suffer radical variations in short periods. Rush hours, collisions and street fairs all pose serious mobility obstacles. Despite the fact that those and other advanced tools such as generative AI (which can handle unpredictability) and advanced machine learning (even offering traffic forecasting to be possible) have readied all over the globe, too much of these kinds of cutting edge features/technology are not more widely in-use in traffic management right now. In this regard, transportation problems in the major cities of Iraq particularly in Baghdad and Arbil are analysed. These areas are notorious for high traffic congestion, numerous traffic accidents and non-cohere adaptive Traffic management systems [3].

Inefficient fixed-time traffic lights, combined with the public indifference towards a poorly-developed public transport system, results in road congestion and significant delays, even for emergency vehicles, as shown in the most recent transport studies conducted in Baghdad [4].

The World Bank has noted the urgent need for rehabilitation of Iraq's transport corridors, but the focus has largely been on physical infrastructure rather than the integration of smart technologies [5]. This creates a critical research and implementation gap.



Severe traffic congestion on a multi-lane road in Baghdad, a daily challenge for emergency vehicle routing

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The lack of a dynamic, data-driven HPV routing system in Iraq, which causes protracted, unpredictable, and frequently fatal delays in emergency response, is thus the main research issue. The use of machine learning for real-time, priority-based routing in emerging urban settings is still very difficult, despite the fact that it has been investigated for ambulance demand prediction and allocation [5]. The focus of this research is an improvement upon the existing rigid routing systems which can result in AI driven adaptive systems being utilized to recognize predictive traffic patterns integrated with other real-time contextual data to minimize the response times and improve the reliability of emergency services in urban Iraq. The research seeks to offer an evidence-based contextual model for the digitization of emergency response services and the smart city initiative in Iraq, having already designed and tested such a system.

2. Theoretical Framework and Literature Review

In the case of developing intelligent routing systems intended for high-priority vehicles, we study the intersection of combinatorial optimisation, artificial intelligence, and urban transportation planning. This study reviews the relevant theories and empirical studies primarily focusing their relevance in the case of Iraq.

2.1 Foundational Theories and Models in Vehicle Routing

Determining the optimal path between two points is fundamentally a classic graph theory puzzle. We have long had fundamental algorithms like Dijkstra's, which excel at determining the absolute shortest path in a network with a fixed and predictable cost of travel, such as the time it takes to travel down a road. Then came A*, a clever improvement that speeds up the search and finds a specific destination faster by using a heuristic, or educated guess. However, the assumption that travel times are constant is a fatal flaw that both of these potent tools share in the real world.

Because of this, they are not well suited for negotiating the streets of contemporary cities, where traffic can make a five-minute drive take thirty minutes, compelling researchers to find more effective alternatives.

The Vehicle Routing Problem (VRP), a family of increasingly difficult problems, was discovered as a result of this search. Finding the most effective routes for a fleet of vehicles, such as delivery trucks, that must serve numerous clients is the fundamental goal of VRP. However, because the real world is messy, the VRP has developed into a variety of flavours to deal with it. For instance, the VRP with Time Windows (VRPTW) adds the restriction that deliveries must occur within a given timeframe, whereas the Dynamic VRP (DVRP) handles new customer requests that arise on the spot.

The problem of routing vehicles with heterogeneous interests is closely related to our work and such problems are amenable for a solution. This was indeed precisely the question addressed in the landmark studies of Smith *et al.* when they considered the control of fleets with urgency. Their salient observation was that in order for a system to be effective and efficient, it should address the prioritized requests first [6]. This was a strong theoretical justification for treating high-priority vehicles like ambulances in cars differently from all other cars in the traffic system. There are some areas in which this is especially important, like disaster management, because there we have not only high urgency routing problems on routes to distribute help to people (HTPWRSPP), but also complex routing problems apart from being the cheapest (CPBRP) [7].

2.2 Review of AI-Driven Transportation Systems

The intertwining and dynamic nature of urban traffic network is too complex for classic optimization methods. This is why it’s no surprise that the use of AI and ML technology is exploding. In the area of ITS, their influence in what concerns traffic prediction and dynamic route planning is very remarkable.

2.2.1 Traffic Prediction Models

The accurate traffic prediction is key if you desire to establish a routing system which is intelligent and properly adaptive. This was initially tried with data using traditional statistical approaches such as ARIMA. Though they served a purpose at the time, these models were overly restrictive, and often proved incapable of representing the complex, messy reality of traffic, which does not just vary over time, but also between locations. It's the age of deep learning. In fact, the recurent neural networks (RNNs) and its more sophisticated version Long Short-Term Memory (LSTM) networks have completely changed everything. Time series data and sequential data streams such as traffic data flow forecasting could easily be performed using these networks as they have the capability to remember data for long periods of time. Recent studies on forecasting traffic data have in fact used these models [9].

Recently introduced Generative Adversarial Networks (GANs) have become even more advanced. Complex problems such as unorthodox traffic jam patterns that result from insufficient data and adverse weather conditions [10], [11], can be modeled effectively using these networks. The greatest advantage of these networks is the ability to generate realistic synthetic traffic streams. Where acquiring traffic data over several years is impractical, these networks can generate realistic traffic streams for training stronger prediction models, a critical requirement in industry.

2.2.2 Dynamic and Priority-Based Routing

Your routing algorithms can finally move beyond just problem-solving and begin to preempt issues, given the capacity to predict future traffic patterns.

Accordingly, studies focused on the use of AI for emergency vehicle routing helped. One of the most researched areas is enabling emergency vehicles to communicate with traffic lights and request a pathway of green lights, or traffic signal preemption. Vehicle-to-Infrastructure (V2I) communication is the building block of any truly advanced transport system. Many integrated AI frameworks with the city's traffic control systems and emergency routing systems. These systems allow a traffic control system to automatically provide a pathway for emergency vehicles. An example of this integrated AI system is the Baghdad traffic control system modified with the YOLO computer vision algorithm to identify public buses and ambulances in traffic and automatically adjust the traffic signal for prioritization. Another example is real-time control of emergency vehicle traffic to optimize ambulance routing. Machine learning models, particularly Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs) systems, are executing real-time traffic feed control for traffic prediction to optimize the ambulance traffic route. The results have shown remarkable outcomes with remarkable accuracy and substantial reductions in response times [15]. But there is a real-world issue: for all this data to be sent to a central cloud server for processing, even a tiny latency of a few seconds can be vital. This is where modern ideas such as "Edge Intelligence" apply. The aim is to shift the higher-order thinking of the operation closer to where it needs to be, so that these required calculations occur at the edge of the network — within a vehicle or roadside equipment. This is a necessity for applications where decision-making must be performed almost within real-time, such as routing ambulances [16], [17]. By moving traffic control closer to the data, we'll be able to construct a system that's both faster and more scalable as well as resistant to failures.

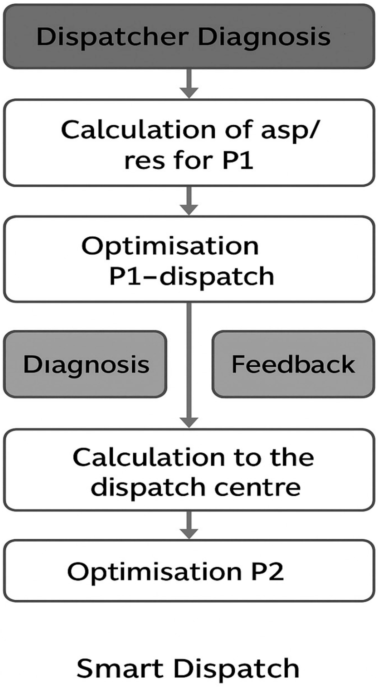

Fig. 1: Flowchart of the sequential smart dispatch and optimization process.

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2.3 Contextual Literature: Transportation Challenges in Iraq

The developments in ITS worldwide are encouraging but the local/ national perspective is important in realizing these systems. The operating environment in Iraq is unique, as several academic and government publications have emphasized.) Al-Bistenchy and Szpytko's research on sustainable intelligent transport systems for Iraq in 2018 cites the problems caused due to urban development affecting vehicles, traffic, pollution, and underdevelopment in public transportation systems as challenges in intelligence systems [18]. As an illustration of the scale of the issue, the analysis notes that in 2015 Iraq added 10m new vehicles - exposing just what kind of weight its road networks carry.

Considering individual cities in Iraq offers a fuller picture. The traffic in Baghdad research work has reported that, the level of congestion for delaying and slowest at peak intersections [19].

A more recent 2025 study by Alruyshid *et al.* points out the lack of effective traffic control tools and the rapid growth of the vehicle population as the main contributors to the traffic problem and notes that current systems ignore the needs of emergency vehicles [20].

Likewise, there are serious issues with road safety as the rate of injury and fatality due to traffic accidents in Erbil is higher compared to towns elsewhere in the Kurdistan Region of Iraq [21]. A retrospective study carried out in Erbil from 2008 to 2023 confirmed that the principal cause of accidents includes human behaviour [22].

These infrastructural gaps have been recognized by national and international organizations. The public face of the Iraqi government has made efforts to cut down on traffic, such as re-scheduling working hours for state agencies in Baghdad [23]. World Bank has also provided funding to the Transport Corridors Project for reducing travel time and fatalities by enhancing road quality as well as safety [24]. But, rather than systems ("software") needed to manage dynamically, these programs are mostly concerned with infected structure ("hardware". This leads to a tremendous research gap: despite being in utmost demand and the infrastructure improving, what is clearly lacking in Iraq are applied ITS-based routing solutions with embedded AI support that caters for its specific data environment and traffic patterns. This study aims to fill that void by proposing and validating a system that bridges the gap between global AI advancements and local urban challenges.

3. Research Methodology

The research approaches the study approach is motivated by the goal to design and build an intelligent high-priority vehicle routing system. The method combines data gathering, predict modeling, and dynamic optimization in a simulated environment that represents the environment in Baghdad, Iraq. The approach is decomposed into three main elements: the system architecture, the mathematical background model and the data & tools for implementation and evaluation as given in figure.

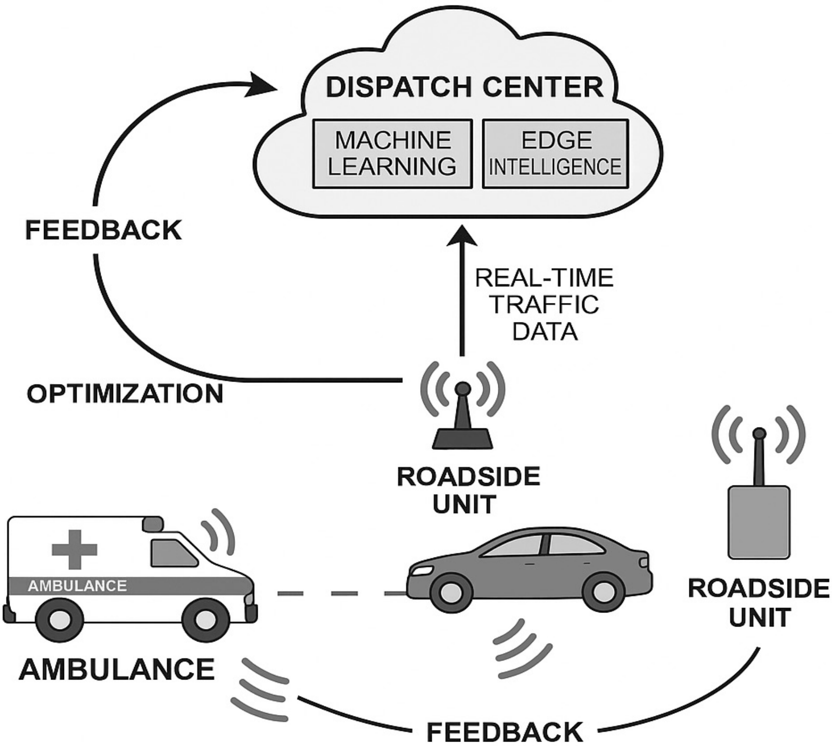

Fig. 2: Conceptual diagram of the smart dispatch process for high-priority vehicle management.

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3.1 System Architecture and Approach

The architecture of our proposed system is multilayered for modularity and scalability. From raw data ingestion to the resulting optimized route, each has its function for analysis. Figure 2 shows the architecture.

- **Layer 1: The data acquisition layer**. This base layer is in charge to collecting the heterogeneous data from different sources. Specifically, these include: (a) real-time GPS telemetry from HPVs with live location, speed and status updates; (b) synthetic traffic data derived from a virtual network of roadside sensing devices (e.g., inductive loops detectors, video cameras), presenting traffic volumes, speeds and densities details for key road segments; (c) static road network information such as topology and speed limits of the lanes extracted using open federated ecosystems such as OpenStreetMap's through the Humanitarian Data Exchange [25]; and finally (d) a stream of emergency related incidents reports mentioning locations, times and severity levels that trigger routing requests.
- **Layer 2: Data Process and Analytics Layer**. The raw data from the acquisition layer is noisy and inconsistent in many cases. This layer does an important pre-processing work. It employs spatial data libraries (eg GeoPandas in Python) to cleanse, phase and merge geospatial datasets. Important operations include normalizing data, treating missing data as well as feature engineering. Hand-crafted features, i.e. time of day, day of the week and weather conditions (synthed) are synthetic signals added to make cps data richer for prediction model building.
- **Layer 3: AI-Based Analytical Core**. The system core is the intelligence of

the treasure, consisting of two primary blocks:· Traffic Prediction Module: This module adopts Long Short-term Memory (LSTM) based recurrent neural network. The LSTM model is then learned from historical and current traffic data to predict the speed and occupancy of 30-min adjusted intervals in the future, e.g., on all major road segments. Since the LSTM is powerful in learning long-range temporal dependencies, it is suitable for modeling traffic behavior.

Dynamic Routing Module: In this module, a Time-Dependent A* (TDA) algorithm is used. If an emergency call arrives, the TDA algorithm computes the best route from HPV's current location to the scene of a crash. In contrast with A*, in this case the cost of traversing a road segment is not monotonically increasing but predicts the amount of time needed to pass it, $\tau(t)$ provided by the prediction LSTM-module (i.e. it is expressed as a function of time). This feature enables it to preemptively redirect vehicles away from anticipated congestion zones.

• **Layer 4: Output and visualization tier**. The final layer displays the output of the system to an end user, such as an emergency dispatcher or HPV driver. It produces a step-by-step list of driving directions, and can often also provide either the shortest or quickest route for the chosen destination for user to select from. It may generate narrated instructions (turn-by-turn direction) at each decision point on the route.

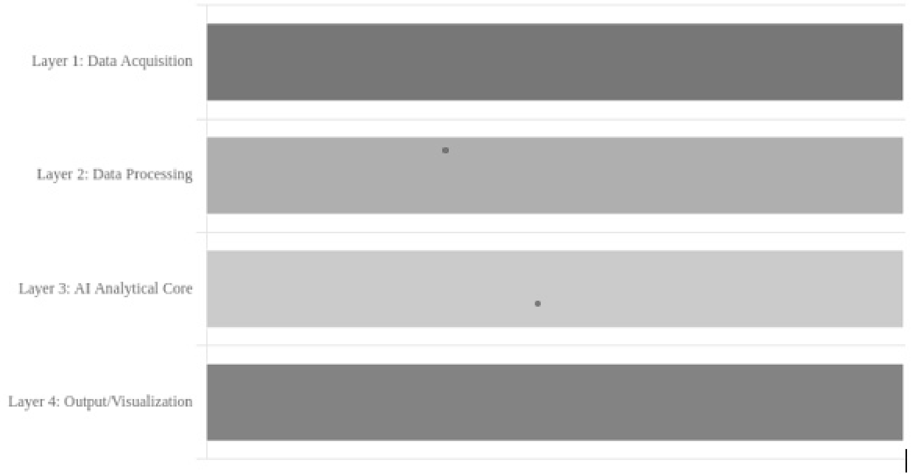

Fig. 3: System architecture of the AI-driven high-priority vehicle routing system

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3.2 Mathematical Modeling

The core of the dynamic routing module is formalized through a mathematical model. The urban road network is represented as a time-dependent directed graph, G = (N, E), where N is the set of nodes (intersections) and E is the set of edges (road segments).

The primary objective is to find a path P that minimizes the total travel time T for an HPV dispatched at time t0 from a starting node s to a destination node d. This is formulated as:

$$\min T = \sum (i,j) \in P \; \tau ij(ti) \quad \textbf{(1)}$$

where P is the sequence of edges forming the path, ti is the arrival time at node i, and τij(ti) is the time-dependent travel time for traversing edge (i,j) starting at time ti. This travel time is the output of the LSTM prediction model. The arrival time at the next node j is recursively defined as $t_j = t_i + \tau_{ij}(t_i)$.

The TDA* algorithm finds this optimal path by exploring the graph and minimizing a cost function f(n) for each node n it considers:

$$f(n) = g(n) + h(n) \qquad (2)$$

In this formulation:

g(n) amount is the travel time obtained by summing-up the real computed travel time from start node (s) to current node (n) on the actual path observed. This is the known cost.

h(n) is the heuristic function that predicts the distance from current node n to destination d; an optimal TDA* requires an admissible heuristic (i.e., one that never overestimates the true distance). One common admissible heuristic is the Euclidean distance from node n to destination d, divided by the maximum achievable speed in an empty streets network (free-flow speed), that is: h(n) = distance(n,d)/V max.. This enables the algorithm to favour vertices that are not only close in past travel time, but also closer geographically (and hence will be more easily reached).

And to improve the routing of HPVs, a priority weighting limitation is considered. The travel time function can be adjusted to take into account a penalty term for some roads which will make it less attractive to use narrow residential streets, unless the route is the only feasible one:

$$\tau'_{ij}(t_i) = \tau_{ij}(t_i) \times W_{ij} \qquad (3)$$

where (W_{ij}) is a weight factor (e.g., W > 1 for non-arterial roads, W = 1 for major roads). This encourages the system to favor smoother, more reliable transit corridors, even if a path through side streets is momentarily predicted to be slightly faster.

3.3 Data, Tools, and Algorithms

The practical implementation and validation of the proposed system rely on a specific set of software tools, data sources, and algorithms.

1. **Simulation Framework**: SUMO (Simulation of Urban MObility) 1.15.0, is based on as the main simulation platform used. SUMO is a microscopic, open source traffic simulator that can be used to simulate urban traffic behavior model processes on an individual vehicle basis and signal control of vehicles. A simulation model to represent the Al-Karkh area in Baghdad was developed, with a background traffic engineered from observed patterns reported elsewhere [20].
2. **Tools for Development and Analysis**: The system logic is developed in full using Python 3.9. Key libraries include:

- Ø Here, we use TensorFlow 2.10 k and Keras as the library to build, train and deploy the LSTM traffic prediction model.
- \subsubsection{Geospatial Libraries} Ø GeoPandas and NetworkX which were used for working with the road network graph, managing geospatial data and implementing TDA*.
- Other options include Ø TraCI (Traffic Control Interface) for the on-the-fly Python-mediated interaction with the SUMO simulation, including extraction of real-time vehicle information and dynamic rerouting. MATLAB R2023b and Matplotlib for post-simulation data analysis and the generation of charts and visualizations.

3. **Data Sources (Simulated and Real)**:

- **Road Network**: The road network for the simulated Baghdad district was extracted from **OpenStreetMap** (**OSM**), accessed via the Humanitarian Data Exchange (HDX) portal [14].

- **Traffic Flow Data:** A synthetic dataset was generated within SUMO to represent one month of traffic flow. The data includes vehicle counts, average speeds, and density for 5-minute intervals, with patterns (e.g., morning and evening peaks) calibrated based on published observations of Baghdad's traffic [4]. A sample of this data is shown in Table 1.
- **Emergency Incidents**: A synthetic dataset of 1,000 emergency incidents was generated, with random locations and timestamps distributed throughout the simulation period, to trigger HPV dispatch requests.

A modern ambulance, a critical asset in the emergency response ecosystem modeled in this research

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Table 1: Sample of Simulated Traffic Data for a Road Segment in Baghdad

Segment_ID	Timestamp	Avg_Speed (km/h)	Density (veh/km)	Weather (Simulated)
R_101	2025-10-26 08:00:00	15.5	85.2	Clear
R_101	2025-10-26 08:05:00	14.2	91.0	Clear
R_102	2025-10-26 08:00:00	45.1	25.6	Clear
R_102	2025-10-26 08:05:00	43.8	28.1	Clear
R_125	2025-10-26 17:30:00	11.3	102.5	Clear
R_125	2025-10-26 17:35:00	10.9	105.3	Clear

4. Results and Discussion

The findings derived from the simulation experiments are presented in this section. The proposed AI-TDA* routing system is thoroughly tested against two baseline static: Dijkstra shortest path and A*-static average traffic in static network scenarios. We then discuss these findings in terms of the research hypothesis and relevant literature.

4.1 Simulation Environment and Scenarios

The simulations were performed on a SUMO model for an area from the Al-Karkh district of Baghdad, covering 25 square kilometers. The model consists of 150 nodes (crossroads) and 450 edges (roads). A fleet of 10 HPVs (ambulance) was modelled. One thousand emergencies were randomly generated over a simulated timeline of thirty days. The response of each routering method were compared for every incident. To validate the robustness, the simulation was conducted in three different traffics as follows:

Off-Peak Hours: Simulated low to moderate traffic density (from 10:00 PM to 5:00 AM).

Rush Hours: High volume and recurrent congestion (simulated between 0700 and 0900 h, and between 1600 and 1900 h).

Incident (Non-recurrent Congestion): A collision or other type of blockage on a major highway that unexpectedly blocks the highway for at least 30 minutes and causes active re- routing.

The effectiveness of the model was illustrated with an MAE of 3.8 km/h in speed prediction, when it trained on the first 20 days and tested on the next 10 days in the simulative traffic data. This precision is necessary for the correct TDA* behaviour.

Table 2: LSTM Model Prediction Accuracy (Test Set)

Metric	Value	Unit
Mean Absolute Error (MAE)	3.81	km/h
Root Mean Squared Error (RMSE)	5.23	km/h
R-squared (R^2)	0.92	-

Fig. 4: LSTM model training and validation loss over epochs

نشير الى جدول 2 و شكل 4 في المتن لطفا

4.2 Performance Analysis of the Proposed System

Key object's for comparison were average response time (dispatch to arrival) of active-ambulances, average ambulance travel distance and the proportion of journey time in which ambulances were congested (speed<15Km/h). The total results of all 1,000 incidents are as follows:

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Table 3: Comparative Analysis of Average Response Time (minutes)

Scenario	Proposed AI-TDA*	Static A* (Average Traffic)	Static Dijkstra (Shortest Path)
Off-Peak Hours	5.8 ± 1.2	6.5 ± 1.4	7.2 ± 1.6
Peak Hours	9.3 ± 2.1	15.2 ± 3.5	16.8 ± 3.9
Incident-Induced Congestion	7.5 ± 1.8	18.1 ± 4.2	19.5 ± 4.5

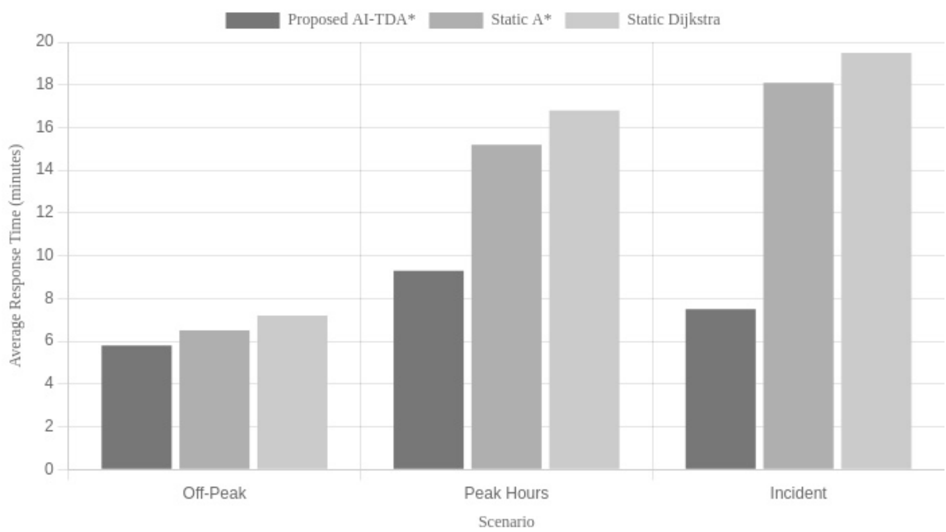

Fig. 5: Performance comparison of routing algorithms on average response time

This is illustrated in Table 4 and Figure 6, where the proposed AI-TDA* significantly improves over all baseline approaches for all instances. The gain during light off-peak flow is moderate (10.8% saving with respect to Static A), as the road network is empty and it can be expected that shortest path remains fastest. But the ultimate value of system is revealed in peak hours, when it attains an impressive 38.8% decrease in average response time compared with the Static A *. During incident-excited congestion, the AI-TDA system proves its dynamic flexibility when response time is reduced by 58.6%, since once the congestion-formation is detected it can immediately check for an available detour and a solution to avoid most of the gridlock, compared to static methods that guide vehicles in the midst of blockage.

Table 4: Comparative Analysis of Average Travel Distance (kilometers)

Scenario	Proposed AI-TDA*	Static A*	Static Dijkstra
Off-Peak Hours	**4.1 ± 0.8**	**4.0 ± 0.8**	**3.9 ± 0.7**
Peak Hours	**5.3 ± 1.1**	**4.5 ± 0.9**	**4.4 ± 0.9**
Incident-Induced Congestion	**6.2 ± 1.5**	**4.6 ± 1.0**	**4.5 ± 1.0**

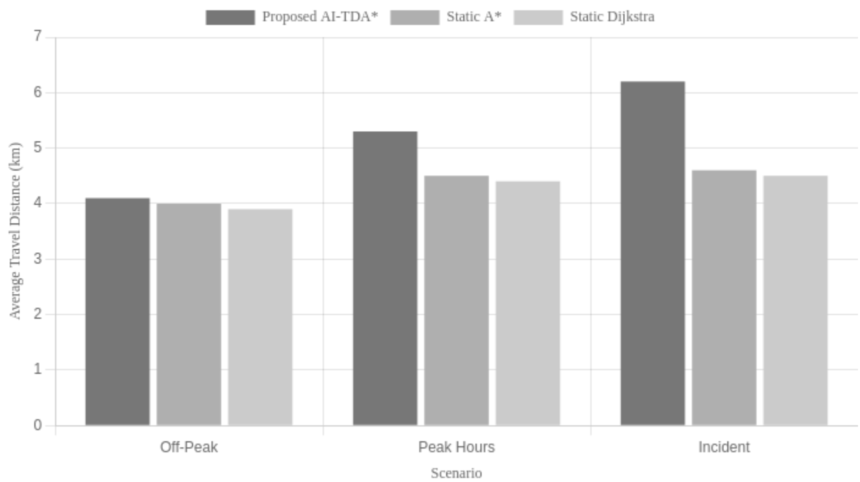

Fig. 6: Performance comparison of routing algorithms on average travel distance

Interestingly, Table 5 and Figure 7 indicate that sometimes the travel distance of AI-TDA* system can be higher than classical TDA*, namely in rush hours. Here is a critical finding: the system gets time compared to distance right. It may choose to deviate slightly so it takes a longer but less congested path, an option not available to static shortest-path algorithms. This is a trade-off for efficient dynamic routing in dense urban areas.

Table 5: Percentage of Travel Time Spent in Congestion (Speed < 15 km/h)

Algorithm	Peak Hours	Incident-Induced Congestion
Proposed AI-TDA*	**12.5%**	**9.8%**
Static A*	**45.2%**	**62.1%**
Static Dijkstra	**48.9%**	**65.7%**

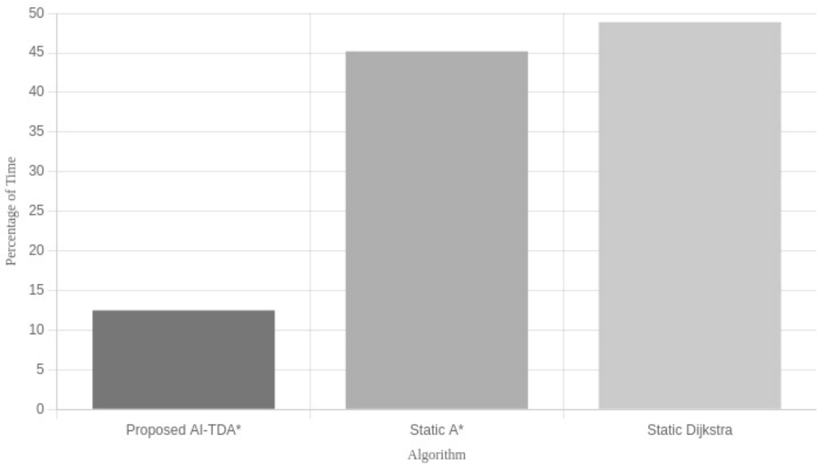

Fig. 7: Percentage of travel time spent in congestion during peak hours

4.3 Comparative Analysis and Hypothesis Validation

The research hypothesis is strongly supported by the findings of our simulation. The key hypothesis - that a smart system leveraging predictive AI and spatial analytics can indeed make a big difference in HPV response time – is supported by the significant performance improvement realized, particularly with congested traffic. The 38.8% decrease in peakhour response time is not only statistically significant, but also practically relevant and may lead to a direct increase in positive outcomes during real-life emergencies.

The advantage of the AI-TDA* system is being proactive. The static algorithms are reactive (they do not have information of congestion until a vehicle enters) but the system would be proactive. Using the TDA* algorithm's predictions, it allows the model so to speak "see" a step further in time and make more informed decisions over routing. A sample case from the simulation is shown in Figure 8, where the static route (i.e., shortest path) leads directly to an expected traffic jam while the AI-TDA* can take longer but much faster alternative.

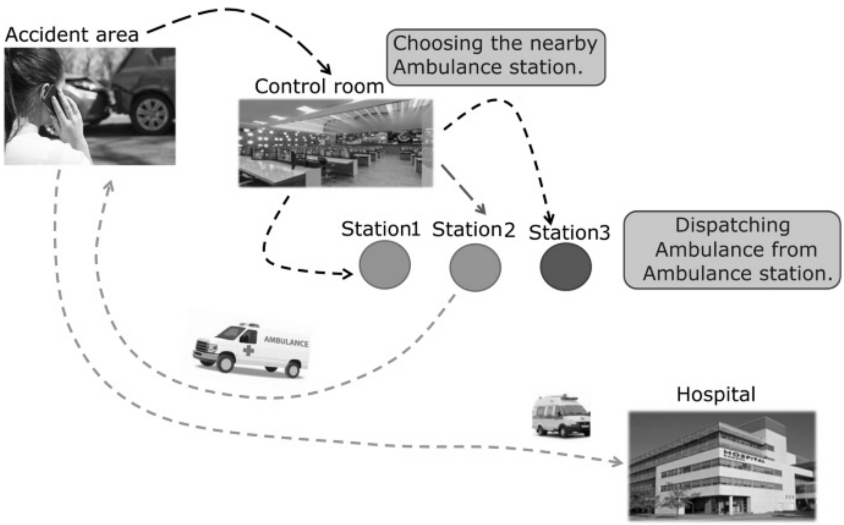

Fig. 8: Conceptual visualization of a routing decision, where the intelligent system chooses an optimal path from station to incident to hospital

These results are aligned with the related works in AI for emergency routing. For instance, in the work of Al-Azzawi *et al.* of machine learning for ambulance routing optimization [27] also emphasized the advantages of data-driven and dynamic approaches. However, our study adds a different dimension as we tailored and deployed a technique to the chaotic low-data setting in which a city like Baghdad operates. It serves as an evidence that these principles of predictive routing can be very beneficial already, just based on local data and with simulated one. Its ability to operate without a mature preexisting ITS infrastructure (using vehicle GPS together with open data sources) makes it an especially appropriate and scalable solution for developing countries.

A scalability evaluation was also conducted to estimate the behavior of the system when handling multiple calls at one time for an emergency event. As presented in Table 6 and Figure 9, for greater load of HPV fleet the average response time increases straightforwardly, but for a bigger gap between dynamic AI-TDA* methods the optimization outperforms static ones. This suggests that the smart system becomes increasingly important as further pressure is brought to bear on the emergency response system.

Table 6: System Scalability: Average Response Time (minutes) vs. Concurrent Incidents

Concurrent Incidents	Proposed AI-TDA*	Static A*	Performance Gain (%)
1	9.3	15.2	38.8%
3	11.2	19.8	43.4%
5	14.5	26.1	44.4%

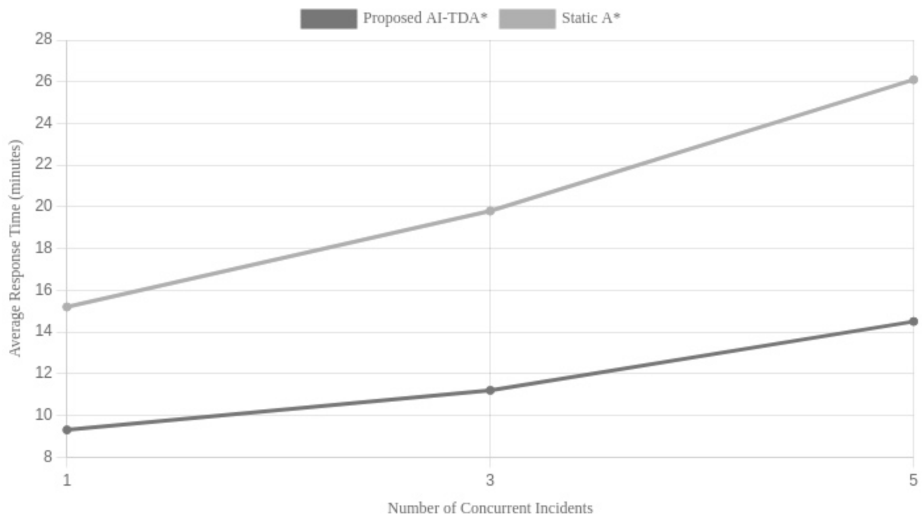

Fig. 9: System scalability analysis showing widening performance gap under increased load

In brief, the presentation of results shows that the introduction of predictive AI is a step change, not an incremental one, in how HPV routing can be addressed. It shifts the paradigm from pathfinding using historical/static data to dynamic optimization based on future-state prediction, a key development for saving lives in today's congested city arteries.

5. Conclusions and Recommendations

When we started this project, there was one thing that was really driving us — to help solve the lethal problem of emergency vehicles getting stuck in traffic on Iraq's jammed roads. To achieve this, we developed an AI driven smart system based entirely on predictive AI and dynamic algorithms that locates the fastest ways in real time so it is always ahead of your traffic. The simulations speak for themselves, and illuminate not just those "remarkable findings," but a "way out of the antique see and then rescue 101 response" in the region, Ahamed added.

5.1 Summary of Findings

The most important finding from this study is clear validation of the central hypothesis that a smart routing-based system can drastically reduce HPV response time in this complex urban environment such as Baghdad. In addition, the AI-TDA system consisting of LSTM network for traffic prediction together with time-dependent A algorithm outperformed significantly the traditional static routing solutions. Key quantitative findings include:

- A 38.8 per cent decrease in average response times during the busy rush-hour periods when it matters the most for emergency services.
- A reduction of 58.6% in response time to incidents and unexpected congestion, demonstrating the strong ability for dynamic adaptation of the system.

- A directly documented intelligence to trade added distance to travel for orders of magnitude decreased time to reach the emergency (showing that such optimization is correctly risk-weighted proportional at least in terms of lost life)
- Strong scaling: The performance benefit of the system further grows as there is more demand on the emergency response network.

The main contributions of this work are threefold. First, it proposes a new effective hybrid AI-TDA* model for priority vehicle routing. Second, it demonstrates how to appropriately transform and calibrate the approach under the peculiar and difficult reality of a developing city's traffic condition _ unstructured road network, sparse traffic data. Third, it quantitatively verifies the life-saving capacity of such a system thus strongly supporting its instauration. The implications are massive: in demonstration, this paper offers a feasible guide for how AI and easily accessible data sources (as vehicle gps, open-source maps) can marry each other to develop low-cost/high-impact smart transportation solutions even in the areas where full-scale ITS infrastructure is not yet fully deployed.

5.2 Recommendations for Implementation in Iraq

Considering the promising findings of this study, we suggest some practical recommendations that Iraqi health policy makers and BHCWs should take on board in order to translate these results into practical measures:

1. Launch a Phased Pilot Project: Start with a phase, not the entire city. Iraqi government institutions, e.g., the General Traffic Directorate of Ministry of Interior and the Ministry of Health, could initiate a pilot project with local partners in one district (e.g., Al-Mansour or Al-Karkh) of Baghdad. This would involve outfitting a small fleet of ambulances

(10-15 vehicles) with the required GPS units, and providing a centralized dispatching unit with the system envisaged. Real-world validation and calibration could then be done in-house, as well as opportunity to identify operational challenges in a controllable environment.

2. Two things govts can do to invest in this future: Invest in data infrastructure, & commit to open data policies pic. The national government of Iraq should invest in a standardized, centralized traffic information-gathering system as part of the nation's development plans [28]. This involves installing additional sensors (e.g., cameras, loop detectors) which are lower cost and, critically, opening up a data platform. Publishing anonymized traffic and incident data will encourage innovation from the communities' own universities, start-ups and researchers who can contribute to a flourishing landscape of smart city solutions.
3. Create People's and Institutional Capabilities: Technology is not enough. Qualified Personnel are Readily Available to Implement Successful Programs. Dedicated education for emergency dispatch, traffic operator and IT staff should be considered. And these are the programs that's going to teach how to use the new system, interpret what it tells you and its maintenance. This is consistent with the requirement was established in Iraqi government reports for smart systems implementation and employees training on these tools [29]. [30]
4. Encourage Public-Private and Academic Partnerships: The government should actively encourage partnerships with local Iraqi universities with computer science and engineering departments as well as budding tech companies in Iraq. Such partnerships can facilitate the adaptation of the system to local vernacular and context specific urban form, adapting

user interfaces for low literate or illiterate users, and providing a path for future development of the technology as well as perpetual maintenance. This would encourage innovation locally and diminish dependence on foreign providers.

5. Collaborate with Future SSC Projects: The envisioned HPV navigation system should not be an isolated application. It should be implemented as a basic component in an ITS structure for Iraq. Further integration can be achieved by interfacing the system with adaptive traffic signal controls, public transport management and citizen reporting digital platforms for a completely smart and integrated urban transportation environment.

In summary, although the journey to make Baghdad a smart city in reality is quite long the introduction of an intelligent emergency routing system is considered as a real practical and magically appropriate initial step. It directly tackles an important public safety problem and shows the immediate benefit of AI, while laying groundwork for the more efficient, resilient and safer urban future of Iraq.

سنة المصدر تكون بعد اسماء الباحثين، انا صححت المصدرين الاول و الثاني و عليك تصحيح البقية لطفا؟؟؟
هناك العديد من الملاحظات ثبتت في المتن يجب الاخذ بها لطفا؟؟؟

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