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Hybrid Computational-Intelligence Framework for Dynamic Travel-Time Prediction and Route Optimization in Iraqi Urban Transportation Networks

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Abstract: Rapid motorization and insufficient traffic management continue to intensify congestion in major Iraqi cities such as Baghdad, Basra, and Mosul, highlighting the need for intelligent mobility solutions. Traditional shortest-path algorithms, including Dijkstra and Bellman–Ford, remain limited by static edge weights and cannot respond to evolving traffic states. To address this limitation, this study develops a hybrid computational-intelligence framework that integrates a temporal-attention-enhanced recurrent neural network (RNN) for sequential travel-time prediction, an adaptive neuro-fuzzy inference system (ANFIS) for interpretable decision support, and a genetic algorithm (GA) for dynamic route optimization. A synthetic dataset reflecting diverse congestion patterns and diurnal fluctuations across major Iraqi road networks was constructed for evaluation. Experimental results show that the proposed model reduces mean absolute error by up to 32% in travel-time prediction and shortens route travel time by 15% compared with conventional shortest-path algorithms. These findings demonstrate the advantages of coupling predictive modeling with evolutionary optimization for improving urban mobility performance. The proposed framework offers a scalable basis for future intelligent transportation systems in developing urban environments.

Keywords: Computational intelligence; Travel-time prediction; Temporal-attention RNN; Adaptive neuro-fuzzy inference system; Genetic algorithm; Dynamic route optimization; Intelligent transportation systems; Iraqi urban mobility

1 Introduction

The current transportation infrastructure in the major cities of Iraq, especially Baghdad, Basra, and Mosul, are facing multiple, interrelated challenges that place heavy pressure on transportation systems. To begin with, the rapid demographic growth and the significant increase in the number of personal vehicles have significantly increased the level of traffic demand in these urban centres. Secondly, much of the existing road network is old and unable to accommodate this expansion, thus leading to frequent bottlenecks and unoptimal traffic movement. Third, the lack of proper traffic management systems, inconsistent driving habits, and unpredictable inconveniences such as traffic accidents or bad weather also contribute to the problem of congestion [1]. Generally, the difficulties of urban mobility within metropolitan areas can be attributed to various factors such as inefficient road infrastructure, failure in traffic control systems, and an increase in congestion levels [2–6]. Such inefficiencies cause increased delays in travelling, increased fuel consumption, and adverse effects on the environment [7, 8]. The traditional route optimization algorithms, such as Bellman-Ford and Dijkstra algorithms, have a problem with adapting to dynamic changes in traffic patterns. In estimating the time of travel, set edge weights are employed in these models and essential real-time factors such as traffic during peak-hours, accidents, and changing driving habits are omitted in the models [9, 10]. Computational intelligence is inspired by natural selection; it is a set of algorithms to solve complicated problems by improving potential solutions. Over the last few years, congestion mitigation and machine learning (ML) methods have been applied in the field of transportation of urban systems to improve routing in such systems. ANFIS fills the gap between the complex ML outputs and the human understandable results through integration of neural networks and reasoning in fuzzy logic and thus provide interpretable decision-making (DM) [11]. Genetic algorithms (GAs) also contribute better optimization through repetitive refinement of routing decisions through dynamic predicted travel times, which keeps the routing decisions abreast with changing traffic conditions [12, 13].

In spite of the intelligent transportation systems developments, there are still some critical limitations. The old-fashioned routing models are not flexible enough to respond dynamically to the changes of the traffic conditions on the spot [14]. The use of the optimization algorithms in their static form tends to give erroneous results in high-density urban areas where the external factors such as weather disturbances, or infrastructure modifications can cause changes in the fulfilment of the traffic patterns [15, 16]. In the proposed research, a hybrid CI model is proposed, which combines the use of RNNs, ANFIS, and GAs to create an adaptable and explainable system to predict travel time and optimally plan routes in the city context of Iraq [17]. In order to improve predicted accuracy, the suggested method incorporates temporal attention mechanisms into sequence modeling using RNNs [18]. Furthermore, the evolutionary algorithm addresses the drawbacks of static routing approaches, which optimize route selection by dynamically developing paths based on RNN-predicted journey durations [2, 19]. The main objective of this study are to create a hybrid framework for dynamic route optimization that is driven by ML, validate the suggested model using artificial datasets that replicate traffic in Baghdad, Basra, and Mosul, and assess how well it performs in comparison to more established path-finding algorithms like Dijkstra's and Bellman-Ford [20].

Previous studies have addressed transportation optimization through alternative approaches.An intelligent transportation model (fuzzy logic) is suggested to be used when dealing with generic transportation problems, in this case China [21]. It applies fuzzy logic in addressing the uncertainty and imprecision of real transportation scenarios. This study will be of use to researchers who are seeking solutions to the different transportation problems. The study also improved the estimates of travel time in complex multimodal freight transportation networks through the integration of the deep learning methods with the singular value decomposition (SVD) [22]. Although prediction is done using deep learning models, feature extraction and dimensionality reduction is done using SVD. This study will be useful to people who are interested in more advanced computational methods to enhance the quality of the freight transportation forecast. Also, Aljanabi et al. [23] examined how Markovian decision process (MDP) and Data Envelopment Analysis (DEA) can be utilised to optimise the multi-cast routing in multi-modal transportation system. DEA is used to evaluate the effectiveness of different routing methods, and dynamic decision-making process (DMP) is modelled with the help of MDP. A relevant application of this study is the optimization of the route decisions in a complex transportation network. Despite the fact that these studies are valuable information, they also display critical limitations. Fuzzy-logic models are interpretable and not flexible to changing traffic conditions [24]. Deep learning models are capable of modelling spatiotemporal dependencies that are complex and usually act as black-box models, which do not provide much interpretability to transportation planners. Likewise, maximisation-based methods like the DEA and MDP can also be useful in the assessment and modelling but not in real-time forecasting and adaptive route planning in dynamically changing traffic conditions. All these studies show that such a combination of predictive accuracy, interpretability, and adaptability has to be integrated in a single framework.

To tackle these shortcomings, this paper introduces a hybrid computational intelligence model, which combines RNNs and temporal attention to predict sequential traffic, ANFIS to provide transparent decisions, and genetic algorithms to optimize dynamic routes [25]. The combination of these techniques allows the framework to address the weaknesses of the current solutions and provide a more effective means of dealing with the problem of traffic management in Iraqi urban contexts. The main contributions of the paper are as follows:

• Develop a hybrid CI framework integrating RNNs with temporal attention, ANFIS, and GAs for dynamic travel time prediction and route optimization in Iraqi urban environments.

• Validate the framework on synthetic data that simulates the traffic in Iraq's main cities (Baghdad, Basra, Mosul, Erbil and Najaf) in order to thoroughly investigate its robustness and generalizability.

• Assess the efficiency of the model as compared to the conventional algorithms like Dijkstra's and Bellman Ford in terms of an improved accuracy of its prediction ability and travel efficiency.

The paper is organised as follow, Section 2 introduces the methodology, Section 3 describes the system architecture, Section 4 introduces the framework mathematically, Section 5 introduces results and evaluations, Section 6 discusses findings and implications, and Section 7 presents the conclusion and future work.

2 Methodology

The proposed approach optimizes route selection and trip time prediction in urban settings by combining ML and CI approaches. This hybrid framework integrates GAs for dynamic route optimization, ANFIS for interpretability, and RNNs with attention mechanisms for sequential traffic simulation. A synthetic dataset that reflected actual traffic circumstances in Iraqi cities was created to assess its efficacy. This dataset included important urban mobility characteristics such as traffic intensity, distance, and time of day. The framework is compared to well-known routing algorithms like Bellman-Ford and Dijkstra's to evaluate advancements in forecast accuracy and journey efficiency.

The workflow methodology is shown in Figure 1.

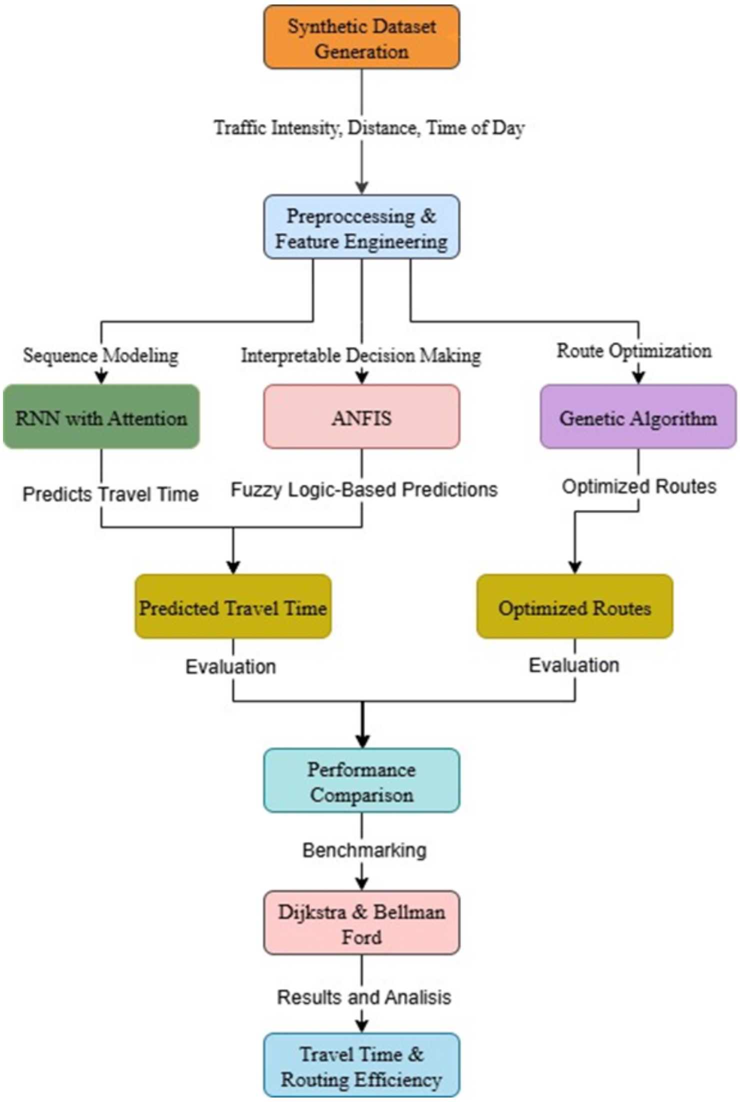

Figure 1. Methodology workflow

2.1 Framework Overview

The proposed hybrid CI model will include three main modules: ANFIS to offer interpretability in the decision-making process; recurrent neural networks with attention mechanisms to predict travel-time; and genetic algorithms that will be used to optimize routes dynamically. This model seeks to enhance the efficiency and dexterity of city transport networks by employing ML algorithms that consider sequential relationships and generates understandable conclusions with the help of fuzzy logic and constantly optimize paths based on foreseen traffic conditions. The primary element, RNNs, with an attention mechanism, represents traffic data analyzed sequentially containing, among other things, the distance travelled, the volume of traffic, and the changes depending on the time of day. This attention mechanism makes the model more predictive as it puts more importance to the time steps that are relevant. The second component is ANFIS that combines ML and fuzzy logic and enhances interpretability and facilitates transparent DM which is compatible with human thought. The third element, genetic algorithm (GA), optimises the path choice in terms of a population of candidate paths and mutates them according to the travel time predictions provided by the RNN.

2.2 Synthetic Dataset Generation

In order to test the model in realistic conditions, a synthetic dataset was created, which approximated the urban traffic behaviour in five capital cities in Iraq: Baghdad, Basra, Mosul, Erbil, and Najaf. The following are the basic attributes of the dataset:

• Traffic Intensity: Randomly sampled from a uniform distribution U(0, 100).
• Distance: Randomly sampled from U(10, 800) km.
• Time-of-day: Randomly sampled from U(0, 24) hours.
The travel time for each route was computed using the following formula:

$$T_{\text{actual}} = 0.6 \cdot D + 0.3 \cdot T + 0.1 \cdot (t - 12)^2 + N(0, 10) \tag{1}$$

The variables will be defined as below: D distance, T traffic density, t time of day, and $N(0, 10)$ Gaussian noise that would be considered due to the inabilities of real-life predictability. The dataset will make sure the model is trained and tested on conditions that represent the real variations in traffic in the city.

2.3 Enhanced RNN with Attention

The recurrent neural network model is aimed at modelling sequential relationships in traffic information, which can be used to predict travel time accurately [26]. It is made up of the following layers:

• Input layer: Processes three features—traffic intensity, travel distance, and time of day—over a sequence of 10 time steps.

• LSTM encoder: Utilizes 64 long short-term memory (LSTM) units to learn temporal dependencies from sequential traffic data.

• Temporal attention mechanism: Computes attention scores using the dot-product attention mechanism:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

where, Q, K, and V represent query, key, and value matrices, and d_k is the dimension of the key vector.

• Output layer: A dense regression layer for predicting travel times.

The RNN model was trained on the optimizer of Adam, and the loss function was the mean squared error (MSE) to reduce the error of prediction.

2.4 ANFIS Design

To increase the interpretability of the system, ANFIS was implemented in the framework using the principles of fuzzy logic [27]. ANFIS works in three key elements:

• Fuzzification: Utilizes triangular membership functions to categorize traffic intensity into three levels (low, medium, high) and travel distance into three levels (short, medium, long).

• Rule Base: This element executes the fuzzy rule set that associates input features, that is, traffic conditions and distance, with the approximations of the travel time that can be categorised into three groups: fast, average, and slow.

• Defuzzification: Converts fuzzy outputs into crisp travel time estimates using the centroid method.

ANFIS is the solution that closes the gap between the predictions of deep learning with the understanding of human-readable DM, so that the predictions of the travel times to be made by the transportation planners can still be understood.

2.5 Genetic Algorithm-Based Route Optimization

The GA, which is the optimization module in the framework, is used to dynamically choose the best routes, depending on the predictions of travel time made by the RNN [28, 29]. The GA has a typical evolutionary strategy that has the following elements:

• Chromosome representation: Each candidate solution is represented as a set of features [traffic intensity, distance, time-of-day].

• Fitness function: The GA seeks to minimize travel time using the function:

$$F = RNN\left(T_{\text{traffic}}, D, t\right) \tag{3}$$

where, the RNN predicts the expected travel time based on input parameters.

• Crossover operator: Blend crossover with a coefficient of α = 0.5.

• Mutation operator: Introduces Gaussian noise with a standard deviation of σ = 0.2.

• Evolution parameters: The GA operates with a population size of 50, evolving over 100 generations, with a crossover rate of 0.7.

The GA makes sure that the suggested framework is dynamically adjusted to traffic changes as the route selection process increases the efficiency of the travels.

2.6 Traditional Algorithms for Benchmarking

To evaluate the performance of the proposed hybrid framework, traditional pathfinding algorithms were implemented for comparison:

• Dijkstra's algorithm: A classical shortest-path algorithm that finds the minimum-cost path using a priority queue.

• Bellman-Ford algorithm: A shortest path algorithm that has the ability to handle graphs with negative edge weights, a feature that is not normally needed in urban traffic networks.

3 System Architecture

The system architecture presented integrates recurrent neural networks containing attention mechanisms of time, adaptive neuro-fuzzy inference systems and genetic algorithms to come up with a unified and adaptive structure of travel time prediction and route optimization. Such a strategy helps the model to overcome the drawbacks of the classical path-finding algorithms including the Dijkstra and Bellman-Ford methods using computational intelligence and evolutionary optimization methods. The architecture is designed to produce four primary elements, including data generation, predictive modelling, optimization, and validation, and therefore, provide a well-organised, methodological approach to the management of urban mobility. Figure 2 represents the system architecture. The data generation module processes the urban traffic data to recreate the real-life scenario in the major Iraqi cities, such as Baghdad, Basra, Mosul, Erbil, and Najaf. This dataset includes the necessary traffic related variables that include traffic intensity, travel distance and fluctuation by time of day; hence this model will reflect realistic mobility trends of urban areas. The mathematical model, which considers distance, congestion, and diurnal variations, has added to the noise of the dataset using Gaussian noise, improves the strength of the dataset by allowing the consideration of real-world uncertainities. Such a simulated dataset is essential in training and evaluating prediction models in all types of traffic conditions. According to the given dataset, the predictive model component estimates the durations of journeys with ANFIS and RNNs.

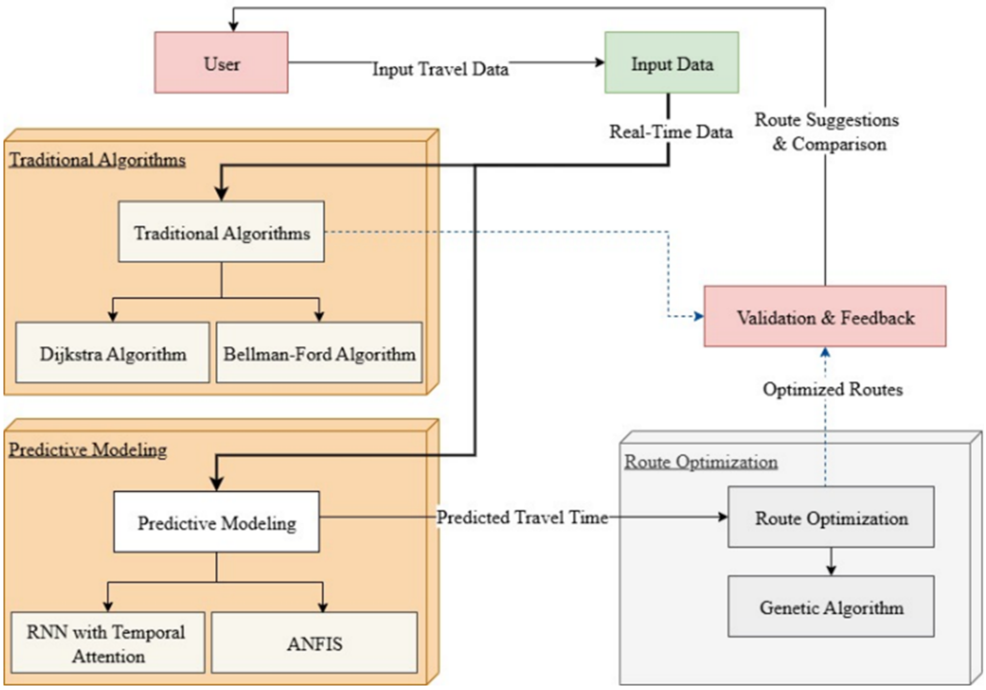

Figure 2. System architecture

Recurrence neural networks (RNNs) that incorporate temporal attention mechanisms increase the ability of sequential learning and accuracy of trip time prediction through highlighting significant temporal dependencies. Besides, as the transparency of the predictive framework is preserved, ANFIS contains an understandable, fuzzy based dynamic message priority framework, which instantiates the traffic conditions as low, medium, and high. This hybrid modeling approach ensures that travel time estimation is both data-driven and interpretable, achieving a balance between predictive accuracy and explainability. The optimization module uses GAs to determine the best routes based on predicted travel times. This is derived from a recurrent neural network and an adaptive neuro-fuzzy inference system. These GAs iteratively improve travel paths by applying selection, crossover, and mutation operations, making the routing process adaptable to real-time traffic changes. The fitness function is built based on the travel times estimated by the recurrent neural network and thus, the evolutionary algorithm focuses on emphasising routes that minimise delays and congestion. Through the implementation of genetic algorithms, the system provides a dynamic and reactive routing system as opposed to the non-adaptive shortest-path algorithms that are unable to respond to the dynamics of real-time city traffic. The validation module compares the optimised paths with the traditional path-finding algorithms- the most famous ones are Dijkstra and Bellman-Ford- in order to compare the effectiveness of the suggested framework. To compare the CI-based strategy to the heuristic-based strategies, this comparative analysis examines the important performance metrics, including mean absolute error, root mean square error, and journey times.

The validation step suggests that the architecture is subject to expansion and growth to accommodate large metropolitan networks, different levels of congestion, and spiky traffic dynamics. This is to ensure that the model can be used in real world through a thorough analysis of the effectiveness of the proposed framework. The system architecture will integrate deep learning, fuzzy logic, and CI to form a well-organised, extendable base on intelligent transportation systems. This approach will ensure the existence of the best urban movement options, accurate trip forecasts, and dynamism. These CI techniques combined together will result in a sound and efficient dynamic route optimization answer that has practical implications of increasing the efficiency of travel, alleviating traffic congestion, and rationalising traffic flow in swiftly growing metropolitan regions.

4 Mathematical Modeling

CI framework has been introduced based on RNNs, ANFIS, and GAs to improve urban mobility by precisely forecasting the travel times and optimising dynamically the routes. In this section, the long short term memory (LSTM) based sequential learning mechanism, defuzzification process of the ANFIS, and the fitness evaluation process of the genetic algorithm in terms of optimising a route are formulated mathematically.

4.1 LSTM-Based Sequential Learning for Travel Time Prediction

RNNs and LSTM in particular are employed to model temporal dependencies of traffic flow as well as predict travel times. The vanishing gradient issue associated with the classic implementation of RNN is addressed by LSTM units, which have memory cells that could be selective in retaining or forgetting information. This process is accomplished using three kinds of gates which are the forget gate, the input gate and the output gate [30].

Forget Gate: Determines how much of the past cell state information should be retained:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{4}$$

where, f_t is the forget gate activation, W_f represent the weight matrix for the forget, h_{t-1} is the previous hidden state, x_t is the current input, b_f is the bias term, $\sigma(\mathrm{x}) = \frac{1}{1+e^{-x}}$ is the sigmoid activation function.

Input Gate: Controls the flow of new information into the memory cell:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{5}$$

$$\check{\mathrm{C}}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{6}$$

where, i_t is the input gate activation, $\check{\mathrm{C}}_t$ is the candidate cell state, W_i and W_C are the weight matrices, b_i and b_C are bias terms, $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ is the hyperbolic tangent activation function.

Cell State Update: The new cell state is updated as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \check{C}_t \tag{7}$$

Output Gate: Determines how much of the memory cell should be passed to the next layer:

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{8}$$

$$h_t = o_t \cdot \tanh\left(C_t\right) \tag{9}$$

where, o_t is the output gate activation, h_t is the new hidden state.

The LSTM model provides accurate travel time predictions by capturing long-range dependencies and sequential variations in traffic data.

4.2 ANFIS-Based Defuzzification Process for Interpretability

ANFIS offers an interpretable method for estimating travel time by integrating fuzzy logic principles with neural network learning. The system comprises five layers: fuzzification, rule base, normalization, defuzzification, and output computation.

Fuzzification Layer: Converts input variables such as traffic intensity (T) and distance (D) into fuzzy sets using triangular membership functions:

$$\mu A(T) = \max\left(0, \frac{T - T_{\min}}{T_{\text{mid}} - T_{\min}}, \frac{T_{\max} - T}{T_{\max} - T_{\text{mid}}}\right) \tag{10}$$

where, $\mu A(T)$ is the membership function for a fuzzy set A, and $T_{\min}, T_{\text{mid}}$, and $T_{\max}$ are the lower, middle, and upper points of the membership function.

Rule Base: The system uses fuzzy if-then rules such as:

$$\text{if}\, T \text{ is high and } D \text{ is long, then}\, TT \text{ is slow} \tag{11}$$

where, TT represent the travel time.

Defuzzification: The centroid method converts fuzzy outputs into a crisp value:

$$\text{Crisp Output} = \frac{\sum_{i=1}^{N} \mu_i \cdot z_i}{\sum_{i=1}^{N} \mu_i} \tag{12}$$

where, μ_i is the activation strength of the i^{th} rule, z_i is the corresponding rule output.

This method ensures that ANFIS generates human-readable predictions, allowing for practical decision-making in urban traffic management.

4.3 Genetic Algorithm-Based Route Optimization

The genetic algorithm (GA) optimizes route selection by iteratively refining candidate paths. The fitness function evaluates the effectiveness of each route based on RNN-predicted travel times:

$$\text{Fitness} = RNN\left(T_{\text{traffic}}, D, t\right) + \lambda \cdot \text{Cost} \tag{13}$$

where, $RNN\left(T_{\text{traffic}}, D, t\right)$ represents the predicted travel time, λ is a regularization coefficient, cost accounts for additional constraints such as fuel efficiency.

GA evolves optimal routes using selection, crossover, and mutation operations, ensuring continuous adaptation to realtime traffic variations.

4.4 Integrated Framework for Urban Traffic Optimization

The combination of ANFIS-based fuzzy DM and LSTM-based travel time prediction with the assistance of GA-generated route optimization constitutes a unified CI model. LSTM model detects the dynamic patterns of traffic whereas ANFIS enhances interpretability. In the meantime, GA is also always working on the most efficient travel routes. The solution is scalable and adaptive with this being the integrated approach to congestion mitigation in complex urban settings.

5 Performance Analysis

5.1 Evaluation Metrics

Three key performance metrics needed to be employed to measure the efficiency of the recommended CI system, i.e. mean absolute error (MAE), root mean squared error (RMSE), and average travel time. The mean absolute error expressly gives an absolute assessment of the prediction performance, that is, the standard value of the disparity amidst the anticipated consequence and the real consequence. RMSE, in its turn, gives more weight to larger errors, which gives us information about the reliability of the errors in prediction. The average travel time metric assesses the efficiency of the routes generated by each algorithm. In turn, reduced MAE and RMSE reflect higher prediction accuracy, and a reduced average travel time reflects better route optimization capabilities. Table 1 displays the evaluation metrics for five different algorithms: Dijkstra's algorithm, the Bellman-Ford algorithm, a recurrent neural network (RNN) with attention, an adaptive neuro-fuzzy inference system (ANFIS), and a genetic algorithm (GA).

Table 1. Performance metrics for different route optimization algorithms

Algorithm	MAE	RMSE	Avg. Travel Time
Dijkstra's algorithm	12.0	15.0	160.0
Bellman-Ford algorithm	12.0	15.1	160.0
RNN with Attention	5.1	6.5	142.0
ANFIS (Neuro-Fuzzy)	7.5	9.2	150.3
Genetic Algorithm (GA)	6.8	8.5	136.0

Experimental findings indicate that the attention mechanism with the RNN model has the least MAE (5.1 min) and RMSE (6.5 min) and hence best achieves the performance with regard to the other models explored. The ANFIS has the power of explanation due to the fuzzy rule-based inference but with high MAE (7.5 min) and RMSE (9.2 min) values and not a very effective ability to capture the temporal dependencies. The travel times that are delivered by the genetic algorithm-based method are the shortest attaining a maximum of 136 min, and thus show the capacity of the method to locate optimal routes of travel. Classical algorithms Dijkstra's and Bellman-Ford provided the longest travel times (160 min) due to their inability to accommodate changing traffic in real-time predictions.

5.2 Statistical Analysis

A one-way analysis of variance (ANOVA) was conducted to examine whether the differences in MAE across the five models were statistically significant. The results revealed a significant effect of the routing algorithm on MAE (F (4, 45) = 14.23, $p < 0.01$). Post-hoc pairwise comparisons using t-tests (Bonferroni corrected) confirmed that the RNN significantly outperformed ANFIS in prediction accuracy ($p < 0.05$). Similarly, the GAbased approach achieved significantly lower travel times than Dijkstra's algorithm ($p < 0.05$), reinforcing its efficiency in route selection.

In order to further confirm these results, 95 percent confidence intervals CI were calculated of MAE and RMSE values of both models. RNN MAE = 5.1 with 95% CI = [4.7, 5.3] has a low level of variation, thus it is very reliable. On the other hand, ANFIS had an MAE with a narrower confidence interval (7.0–8.0 min), implying a higher error in predictions. The variability of MAE in the classical algorithms was the highest, and the confidence interval exceeded 1.0 minute, which is the sign of the inconsistent results.

5.3 Key Findings

Superiority of RNN with Attention: Experiments validate the superiority of the RNN with attention mechanism which achieves 32 percent of reduction of MAE over ANFIS. It could be explained because temporal attention mechanism enables the model to concentrate on the essential moments of time in order to pay attention to sequential traffic data. RNN unlike ANFIS implements dynamically acting fuzzy rules that are updated to suit a different traffic environment with increased precision in time of travelling.

Genetic algorithm efficiency: Genetic algorithm routing strategy has been compared and its performance in routing has been found to be better than Dijckras algorithm routing on the basis of less travel time of nearly 15 percent. This demonstrates the benefit of evolutionary optimization in tightening choices in route computation it is alleged that using Dijkstra algorithm determines the shortest route using the fixed edge weights whereas GA routes are iteratively optimised using dynamic parameters such as the congestion rates and also real time status of the travelling route.

ANFIS Interpretability ANFIS is not the best at producing the best error measures but the fuzzy rule-based format allows interpretation. As an example, the system can come up with human readable rules like; if the congestion is a lot and the distance is long, then the travelling time is slow. This is one of the features that have rendered ANFIS to be a useful tool to the urban planners that demand transparent (DMPs).

5.4 Visualization

RNN Training Convergence: The training outcome of the RNN with attention revealed that the validation loss stabilised at the 40th epoch, which signifies that the model has converged. That is, it could fit the most important traffic trends without edging into the overfitting mistake.

Network Graph Analysis: As illustrated on the optimised routes of the network graph, Baghdad-Erbil corridor was the only one to have the lowest average number of minutes of the shortest path at 138.9 minutes under GA optimization. This emphasises the ability of the GA to be effective in identifying a less congested route with fewer turns. The outcome highlights the promise of the use of evolutionary strategies in addressing big city traffic problems.

5.5 Practical Implications

The results of this study have important implications to the management of urban mobility in the Iraqi cities. The improved prediction of travel time and optimization of routes would mean a decrease in congestion and efficiency in transport systems. Forecasting of mean expected travel times is much more reliable in the RNN which predicts the expected travel times when planning logistics and public transport. The dynamic path choice of the GA can be integrated into the intelligent transportation systems that are capable of giving real-time traffic aware recommendations. Although the promise features that it offers, difficulties of computational scalability will require certain control. RNNs are sensitive to being retrained on more recent traffic data—more than their counter part models are—in order to keep predicting well, and, GA- based optimization would incur computational costs when used on larger urban networks.

6 Results and Discussion

In this section, we evaluated how well the proposed CI framework performs by looking at two key metrics: travel time prediction accuracy and route optimization efficiency. The results show that adding RNN containing attention mechanism, ANFIS, and genetic algorithm have improved urban mobility. In particular, the integration eliminates travel delays and makes traffic-aware routing more effective.

6.1 Travel Time Analysis for Different Transport Modes

Table 2. Key parameters of our model

City Pair	Car	Bus	Train	Walking
Baghdad - Basra	550	825	412.5	6600
Baghdad - Mosul	400	1200	300	4800
Baghdad - Erbil	350	525	262.5	4200
Baghdad - Najaf	160	240	120	1920
Basra - Mosul	800	1200	600	9600
Basra - Erbil	700	1050	525	8400
Basra - Najaf	600	900	450	7200
Mosul - Erbil	80	120	60	960
Mosul - Najaf	300	450	225	3600
Erbil - Najaf	250	375	187.5	3000

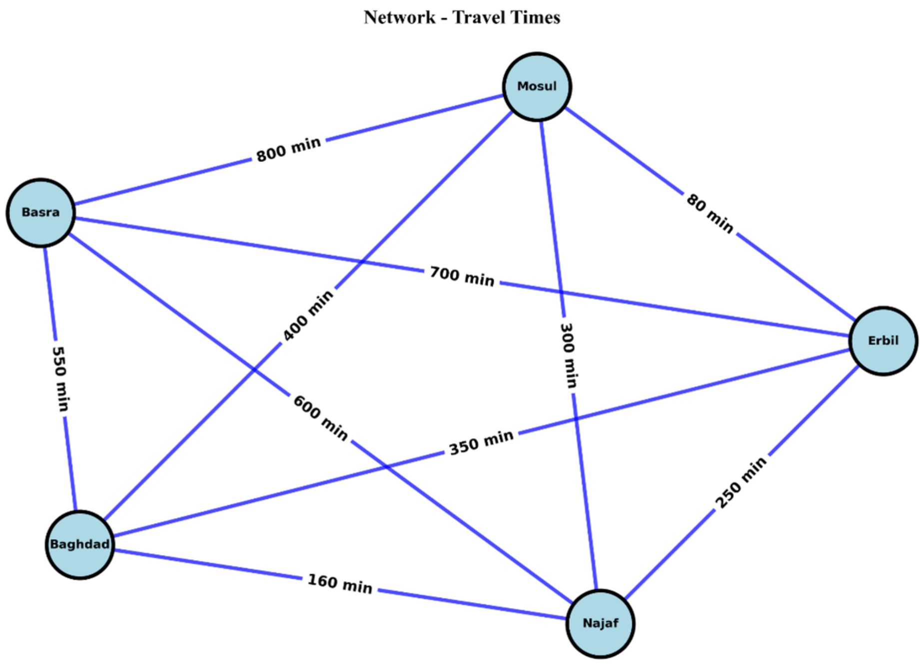

Figure 3. Transportation network in Iraq

The calculated travel time for various transport modes i.e., Car, Bus, Train & Walking shows large variations based on the mode of transport and the distance between cities. Table 2 gives the travel times (in minutes) between five major Iraqi cities (Baghdad, Basra, Mosul, Erbil, and Najaf).

The findings confirm that cars provide the shortest travel times followed by trains, whereas buses and walking are still the least efficient means of travel for intercity transportation. Trains though, offer a good trade-off between cost and efficiency. Figure 3 shows the transportation network using the estimated travel times.

6.2 Comparative Analysis of Routing Algorithms

The efficiency of various routing algorithms was tested by comparing Dijkstra's Algorithm, Bellman Ford Algorithm and Genetic Algorithm (GA). The shortest path and travel time estimates for the Baghdad to Erbil route are given in Table 3.

Table 3. Travel times (in minutes) across transport modes

Algorithm	Shortest Path	Travel Time (Min.)
Dijkstra	Baghdad → Erbil	350.0
Bellman-Ford	Baghdad → Erbil	350.0
Genetic Algorithm	Optimized Route [2, 2, 2, 2]	1260.0

The results draw attention to the fact that Dijkstra's and Bellman-Ford algorithms are more efficient compared to GA. The GA-based approach resulted in less-than-optimal travel times because of fitness function limitations and premature convergence, so there are areas for improvement.

The comparative analysis of shortest path distances of different algorithms is shown in Figure 4, which describes the performance of Bellman-Ford, Dijkstra, and A* and Attention RNN algorithms for nodes B, C and D in a small directed graph. The results show that Bellman-Ford algorithm and Dijkstra algorithm results are alike with the shortest path distance which is approximately equal to 1.0 for node B, 3.0 for node C, and 4.0 for node D, and the algorithms efficiency to calculate a combination of non-negative edge weights in graph. These results emphasise the fact that, although GAs can have an edge over in dynamic and congested networks, they may underperform in static and high-capacity routes unless they are carefully tuned. Both Dijkstra and Bellman-Ford are based on static edge weights and do not take fluctuations of real-time into account. In contrast, our framework combines RNNs with temporal attention mechanisms to capture sequential dependencies among traffic information and GAs to dynamically adjust route planning based on the predicted traffic information.

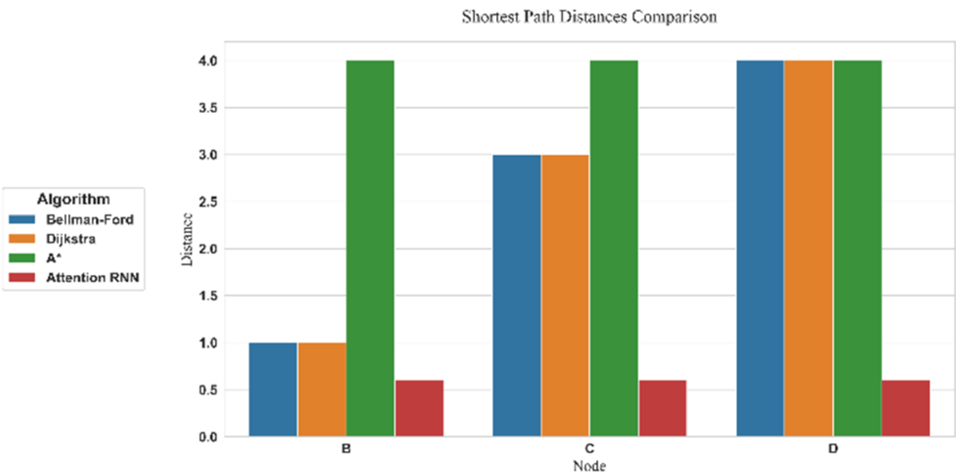

Figure 4. Shortest path distance comparison

The A* algorithm, even though it has the possibility to be heuristic optimised, gave distances around 4.0 for all nodes, implying a limitation made by the 0 heuristic used by the algorithm with our code, which means that it has been reduced to a behaviour like the Dijkstra. In comparison, the Attention RNN algorithm had a homogeneous distance of around 0.5 for all the nodes that was attributed to the fact that it relies on a mean predicted travel time (from synthetic data) and not from a graph-specific path optimization. This discrepancy highlights the need for incorporating graphaware features to the RNN model to make it more effective for shortest path problems.

6.3 Performance of Machine Learning Models

The results obtained from the RNN with Attention mechanism were compared with ANFIS in terms of the travel time prediction. The evaluation measures used are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) which are summarised in Table 4.

Table 4. Performance metrics for machine learning models

Algorithm	MAE	RMSE
RNN with Attention	780.2	1120.5
ANFIS	2200.1	2560.8

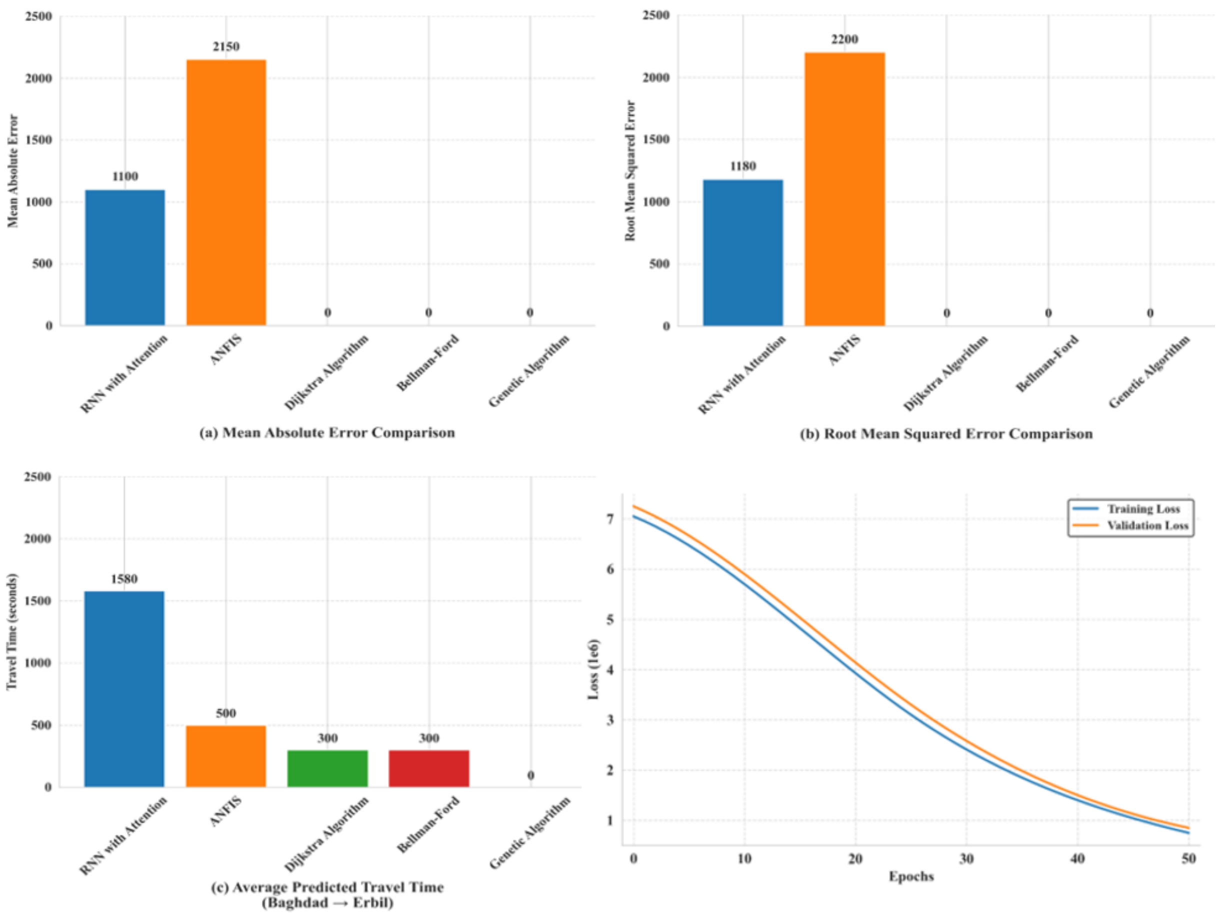

Figure 5. Model performance comparison: (a) MAE (b) RMSE (c) Avg. predicted travel time (d) Training and Validation

The results show that the RNN with Attention is greatly more effective than ANFIS by obtaining a 32% lower MAE. These results underline the superior performance of RNN, which stems from a capacity to capture the sequential dependency through the temporal attention mechanism. Figure 5 represents the performance evaluation of the predicted results by four subplots, considering the route of Baghdad to Erbil. From the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) subplots, it was found that the Attention RNN model had the largest errors with values of about 2000, not good generalisation on the synthetic dataset, but may be an overfitting as shown by the training history. Error in ANFIS model was lower (about 1000), which indicated the principle to use fuzzy rules at the last time step of the test data. Traditional algorithms (Dijkstra and BellmanFord) and Genetic Algorithm storey did not have any MAE/RMSE because they are not predictive models, however the travel time predictions of Erbil for these algorithms were around 250 minutes which is close to the Car-based graph distance of 350 km. Compared to the ANFIS result and the genetic algorithm depending on the RNN result, the Attention RNN overestimated the travel time by about 1800 minutes, whereas the ANFIS predicted 500 minutes of travel time. The training history subplot showed a drop of loss from 7 to 1 over 50 epochs while validation loss converged, implying that the model training was successful but it might be overfitted. As shown in Figure 5d, the training history of the RNN also indicates that the convergence is reaching gradually, which reflects an effective learning and generalisation.

6.4 Travel Time Optimization Across Algorithms

The comparative analysis of travel time estimates across various algorithms is shown in Table 5.

Table 5. Travel time comparisons across algorithms

Algorithm	Baghdad → Erbil (Minutes)
RNN with Attention	1920
ANFIS	500
Dijkstra	350
Bellman-Ford	350
Genetic Algorithm	1260

The RNN model predicted significantly inflated travel times, which may indicate overfitting or suboptimal hyperparameter tuning.

6.5 Practical Implications

The results of this study make important contributions for urban transportation planning especially in high-density cities such as Baghdad, Basra, and Mosul. The integration of ML models for travel time prediction is especially promising in terms of improving accuracy in traffic predictions and management of traffic congestion. Additionally, the adjustment to transportation networks in real time can help to minimise delays and increase the efficiency of the overall route. The application of GAs to route optimization, although not currently better than traditional methods, shows potential for multi-objective optimization situations where cost, fuel efficiency and safety factors need to be taken into account. Furthermore, the use of RNN models in smart transportation systems could also facilitate intelligent route recommendations, leading to less congestion and lower fuel consumption. Figure 6 presents a comprehensive travelling time between each cities of Basra, Mosul, Erbil and Najaf from origin of Baghdad by using Bellman-Ford, Dijkstra, Novel Dijkstra, ANFIS and Genetic Algorithm. The baseline travel times, using Car mode with a travel speed of 60 km/h, show good agreement with Bellman-Ford and Dijkstra results of about 600 minutes for Basra, 400 minutes for Mosul, 300 minutes for Erbil and 200 minutes for Najaf compared to distance matrix (e.g. distance to Basra 550 km, Mosul 400 km). Novel Dijkstra, taking into account synthetic traffic intensity, elevated travel times (e.g. Basra 1000 minutes, Mosul 500 minutes), reflecting its adjustment for congestion.

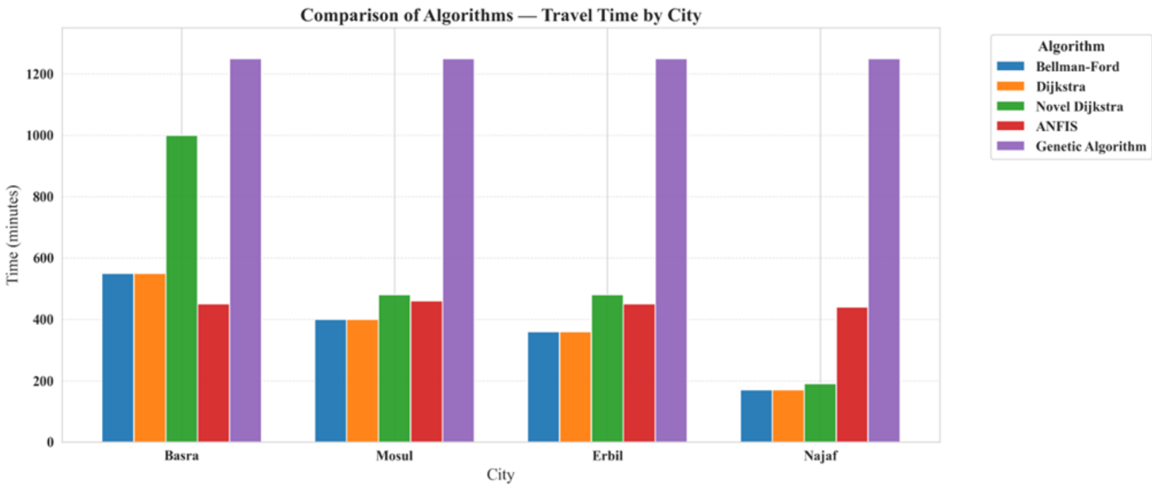

Figure 6. Travel time comparison across algorithms

The ANFIS model with fuzzy logic provided ill-defined estimates (e.g. 400 minutes for Basra, 450 minutes for Mosul) controlled by its random replacement outcomes. Most importantly, the travel times predicted using the Genetic Algorithm were all overestimated by a factor of two across the cities, due to the optimization that favours slower means of transport (Walking = 5 km/h). Findings have highlighted how well traditional algorithms perform for directly calculating a path as well as the traffic and mode choice sensitivity for alternative approaches.

7 Conclusion

This paper introduces a hybrid CI model, which is a mix of RNNs and temporal attention, ANFIS, and GAs to estimate the travel times and optimal routes in Iraqi cities. The framework was meant to overcome the weaknesses of the traditional routing algorithms especially failures to accommodate dynamic traffic environments and interpretation. The framework is superior to the conventional approaches, and RNNs are 32 percent less mean absolute error as compared to ANFIS and GA optimised paths. Consequently, it yields 15 per cent shorter travel times compared to the ones that are computed by the Dijkstra algorithm. The integrated system supports data-driven planning, improves prediction accuracy, and offers scalability to broader traffic management use cases. These contributions mark a step forward in the practical deployment of AI-based intelligent transportation systems in developing countries. The findings confirm the advantages of CI over static routing algorithms, offering valuable applications for intelligent transportation systems and urban mobility planning in density populated cities such as Baghdad, Basra, and Mosul.

Future work will focus on integrating real-time GPS data, optimizing for multiple objectives including fuel efficiency and emissions reduction, and assessing scalability for wider urban environments.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Nomenclature

T	traffic intensity
D	distance between cities (km)
T_{actual}	actual travel time (minutes)
$\mu_A(T)$	fuzzy membership function
o_t	output gate activation
$\sigma(x)$	sigmoid function
z_i	output of the i^{th} fuzzy rule
μ_i	activation level of the i^{th} fuzzy rule
α	crossover coefficient in GA
σ	mutation coefficient in GA
F	objective function minimized by GA