Reduction of Delays at Isolated Signalized Intersection Using Novel Golden Eagle-Based Fuzzy Signal Controller

Malathi Narra and Kumar Molugaram

August 2, 2023

World Conference on Transport Research - WCTR 2023 Montreal 17-21 July 2023

Reduction of Delays at Isolated Signalized Intersection using Novel Golden Eagle-Based Fuzzy Signal Controller

Malathi Narra [1a,b], Dr. Molugaram Kumar[2]

[1a)]Research Scholar, University College of Engineering, Osmania University, Hyderabad, India.
[1b)]Assistant Professor, Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada, Andhra Pradesh, India.
[2]Senior Professor, University College of Engineering, Osmania University, Hyderabad, India.

Abstract

Traffic signal management is an important concern in transportation. Traffic prediction is attained more interest in the last few years. With the rapid infrastructure revolution and the automobile industry, all countries face traffic congestion. The development of AI and the high dimensional dataset availability has attracted many scholars to develop various techniques to maximize the green time duration. Generally, traffic signal control (TSC) is utilized in real-time due to the lower establishment price. However, these approaches don't provide good function parameters, especially in unbalanced traffic. So artificial intelligence is utilized in traffic signal control to degrade the delay period. Inadequate traffic demand adoption and high training expenses are the disadvantages of the transportation. So, the novel Golden Eagle-based fuzzy signal controller (GEbFSC) is proposed in this article to reduce the traveling time, delay time, and queue length. The suggested methodology monitors and detects the traffic from the standard traffic flow dataset. By contrasting the effectiveness of the proposed model with existing methodologies, its validity is confirmed, and the improvement value is assessed. Finally, the comparative analysis confirms that the created technique outperformed other techniques.

Keywords: *Signal control; Fuzzy logic; Green time system; Travelling time; Traffic signal; Travelling delay*

1. Introduction

Rapid growth in population and urbanization motivated the utilization of private vehicles in several cities worldwide (Knowles *et al.,* 2020). The rapid growth of the utilizing volume of vehicles without extra supporting transportation structures is a crucial issue for the construction of smart city (Lee & Chiu 2020). Several urban networks have issues with the road's capacity drop, and many traffic issues happen due to the managing systems on intersections which are utilized to solve signal-related issues (Barceló and Martínez-Díaz 2022). Increasing the road capability demand enhances the necessity for new traffic management solutions (Boban *et al.,* 2018). In order to manage the traffic, initially, traffic police are appointed. The automotive signal controller was introduced and established called traffic signals, and then different traffic control techniques were developed and established in the rapidly emerging traveling necessity (Raghu *et al.,* 2023).

To observe the traffic and degrade bottlenecks at intersection roads, TSCs are utilized. In the traffic jam, vehicles move slowly and stop at the pathway, increasing the traffic jam timing and the queue length of the transporting vehicles (Abudayyeh *et al.,* 2021). Today's world moved to smart city facilities to decrease people's time by gaining the required things anywhere (Almalki *et al.,* 2021). The majority of countries are facing traffic congestion issues, which increase pollution. The delay time period is caused because of the isolated functions of the traffic signals placed at the intersections. In order to improve the traffic flow control of the intersection, the traffic signals must be interlinked. As signal connections, the aspects of the vehicle's movement from upstream to downstream should be considered and simulated. Traffic progression methods utilize the movements of the vehicles and help in the connection of signals.

Intersection traffic flow is illustrated in fig. 1. Moreover, it assists people in driving their vehicles and getting to the target in a low duration. Also, these pathways' durations are evaluated by previous details of typical traffic as well as the average duration needed to cross the entire junction (Oubbati *et al.,* 2020). In a few places, the sensor detects the vehicle, and once it is identified, the traffic signal system allows the vehicle to go. Due to the traffic and pollution produced by improper traffic signal management, delay and traveling time are increased (Possatti *et al.,* 2019). So, understanding traffic logic and control is important to develop an efficient traffic signal controller. In the early stage, traffic signal devices are employed to manage the traffic signal (Jutury *et al.,* 2022). In advancing artificial intelligence(AI) technology, traffic systems are also managed by AI-based methods.

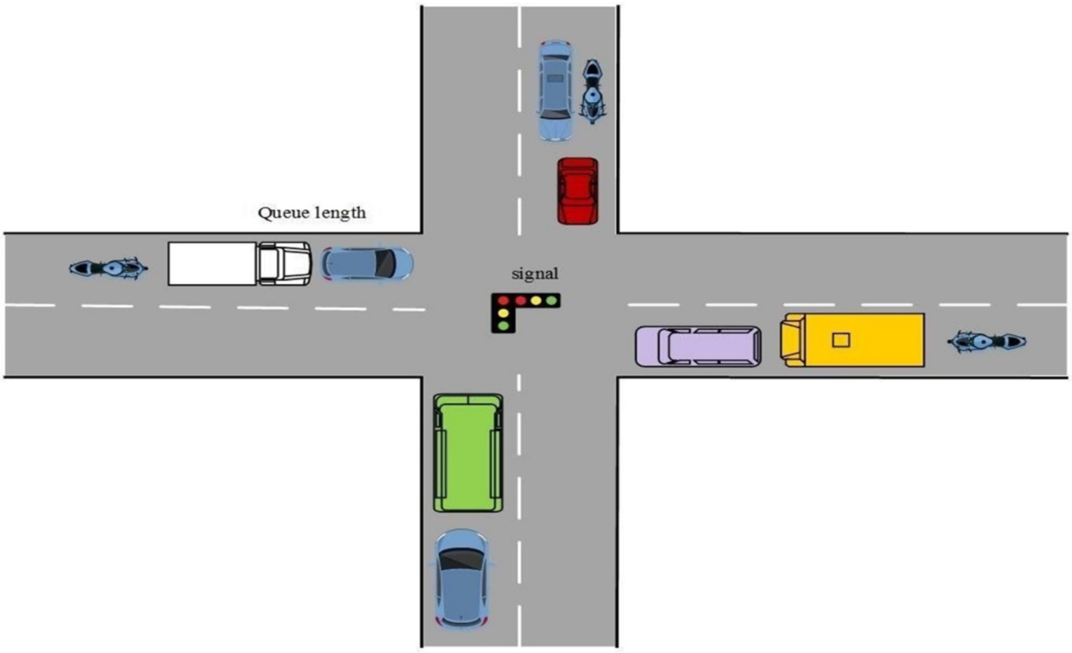

Fig. 1. Intersection traffic flow

Various AI techniques like Artificial Neural Networks (ANN) (Nourani *et al.,* 2020), Fuzzy logic (Jafari *et al.,* 2022) methods, etc., are utilized to offer much-advanced management in traffic systems. The video image data is segmented in AI techniques for computing and testing processes. Nevertheless, the perfect solution for the complicated dataset and various regions in the traffic system is still not discovered. In order to reduce these limitations, recently, various techniques like multiple model neural networks (NNs) (Hong *et al.,* 2022), optimized weight Elman NN algorithm (Neelakandan *et al.,* 2021), fuzzy control with differential evolution algorithm (Lin *et al.,* 2022), and so on are developed to enhance the performance of the TSC systems. Among these methods, fuzzy logic maximizes the function of the traffic signal compared to other models. Their process is difficult to extend to complicated intersection logic and applies only to minimal networks. So to degrade the limitations of the fuzzy logic in the traffic system, the present research has planned to design a hybrid fuzzy system to improve the function and green time.

The proposed article is arranged as follows. Section 2 describes the recent research papers that depend upon the traffic signal controller. In section 3, the system method, along with the problem, is described. In section 4, the novel technique is developed and described to increase the green time. In section 5, the outcomes of the presented model and the performances are validated with other works. And finally, in section 6, the conclusion of this article is described.

2. Related Work

Some of the recent related works based on the traffic signal control is described below

Adaptive Traffic Signal Control (ATSC) models are utilized to obtain real-world traffic flows. Utilizing each vehicle's specifics to control traffic signals is now possible because of recent breakthroughs in artificial intelligence (AI) technology. Various techniques rely upon AI models to enhance effectiveness, yet some drawbacks exist in evaluating security and efficiency. In order to fill the gap, Gong Yaobang *et al.,* (2019) introduced a network-range decentralized adaptive signal management algorithm to degrade the traveling duration and time delay. As anticipated, the proposed technique improves performance in terms of overall delay and cuts down on trip time. However, the function is constrained by the maximum and lowest ranges of cycles.

ATSC is an emerging methodology to enhance the effectiveness of signalized corridors. Several algorithms have been introduced to obtain better traffic efficiency, but real-world traffic security is lacking. To take advantage of the security of Signalized corridors, Essa & Sayed (2020) has suggested a novel self-learning ATSC algorithm. The reinforcement learning (RL) method was used to create the proposed algorithm. Compared to other recent techniques, this technology degrades traffic struggles and enhances real-world traffic safety. But the price is high.

Management of traffic signals is significant for interconnection effectiveness and security. Various models are designed and implemented, but the issues in managing the traffic signal are still not solved. So, Wang Hong *et al.,* (2022) designed an adaptive multi-input and multi-output TSC that can enhance traffic network function and is more practical. The proposed methodology was estimated in the micro simulator; the final results show that the controller degrades the delay in traffic and low power utilization. However, it is made use of difficult one to create a high-dimensional dataset.

Traffic signals can produce traffic jams because of the improper balancing of time. In order to face this issue, various signal controllers are developed and implemented to monitor. Moreover, the created model makes complex and expensive hardware requirements. So, Madrigal Arteaga, Victor Manuel *et al.,* (2022) introduced a fuzzy logic controller for an adaptive traffic light that used the flow rate retrieved from straightforward traffic jams as a specific input. The presented signal controller was trained and tested through a micro-simulation method. Finally, the results show that compared to other well-known strategies, the provided controller requires less input and has a low training cost. Nevertheless, it is only based on the centralized framework.

ATSC systems enhance traffic effectiveness, yet their effects on traffic security change between various establishments. In order to enhance transport safety presciently, Gong, Yaobang *et al.,* (2020) introduced a safety- related ATSC algorithm to improve traffic effectiveness and security purposes simultaneously. The effectiveness of proposed algorithm improves both security and effectiveness. The hybrid controller is also made available to improve traffic safety even more. In any case, it will be challenging to comprehend this algorithm.

The key contribution of the proposed research is elaborated below,

- First, the dataset was collected, imported, and trained in the PYTHON environment.
- Consequently, a traffic signal controller has been developed, and a novel GEbFSC was developed in the system.
- Then, every vehicle's target and location details are labeled in the GEbFSC system.
- Hereafter, all possible tracks are discovered, and vehicles are directed in another direction.
- This system has upgraded the green light duration to clean up and reduce traffic in the TSC.
- Finally, the outcomes of the developed method are evaluated and validated by comparing them with other existing techniques.

3. System Model along with Problem Statement

In daily life, traffic control is the most concerning thing to degrade the accident rate and delay travel time. Traffic signals can produce traffic jams because of the improper balancing of time. TCSs could slow down the flow of traffic. Due to a lack of alternate routes, improper traffic signals can also result in disobedience of the signals and traffic diversion. To make travelling easier, the green time needs to be extended. Therefore, finding the pathway and alerting the specific vehicle are essential to reducing the traffic gridlock. Several AI models are used to reduce long journey times, issues with delays, and high traffic.

Nevertheless, AI-based traffic signal control has significant drawbacks, such as newly emerging social issues, and it is not used in all traffic situations. The main problem with this procedure is that it has a significant computing cost, which prevents its use in real-time. These problems have attracted this research paper to develop an efficient traffic control system. The system method and the problem are illustrated in fig. 2.

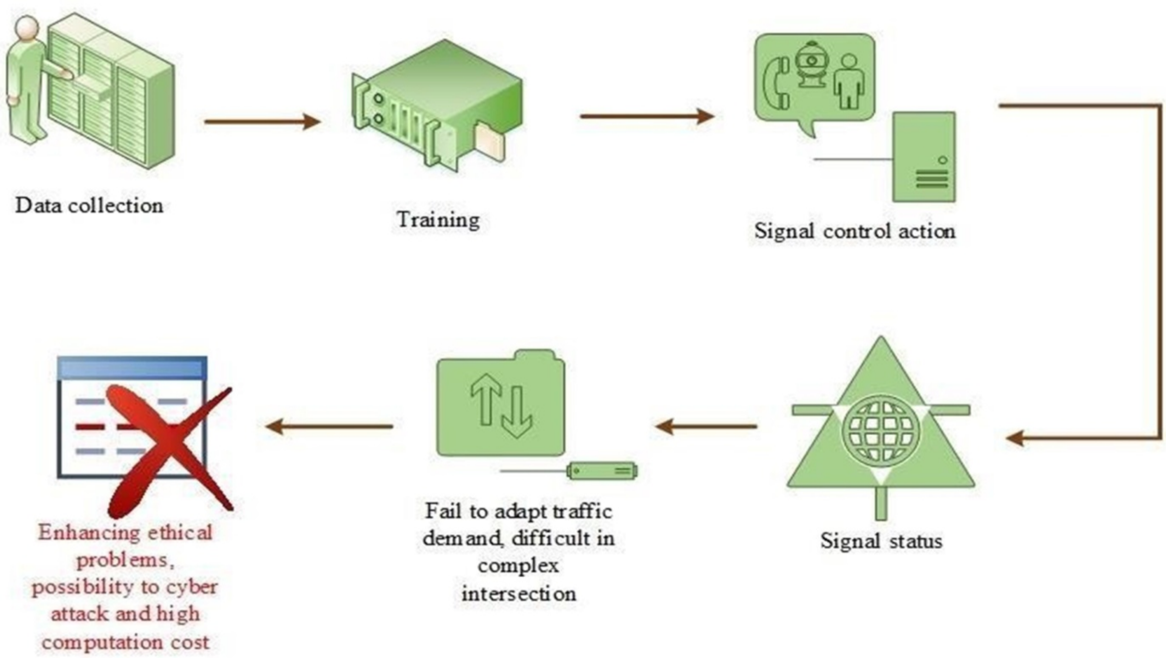

Fig. 2 System model and problem statement

4. Proposed GEbFSC for TSC

One of the significant advantages of the AI-based TSC is that it depends upon the traffic volume, and bottleneck roads can be maximized the green time duration to clear the road and decrease the traffic. In order to effectively decrease the delay and traveling time and upgrade the green time, a new Golden Eagle-based fuzzy signal controller (GEbFSC) has been developed in the PYTHON platform.

At first, the required dataset was gathered for the standard size, and the TSC was designed. Then the presented GEbFSC was developed to upgrade the green light duration in the traffic signal system. The developed technique evaluates every vehicle's destination and possible routes. The presented model's architecture is shown in Fig 3. Additionally, the results are evaluated and validated by comparing them with other existing models.

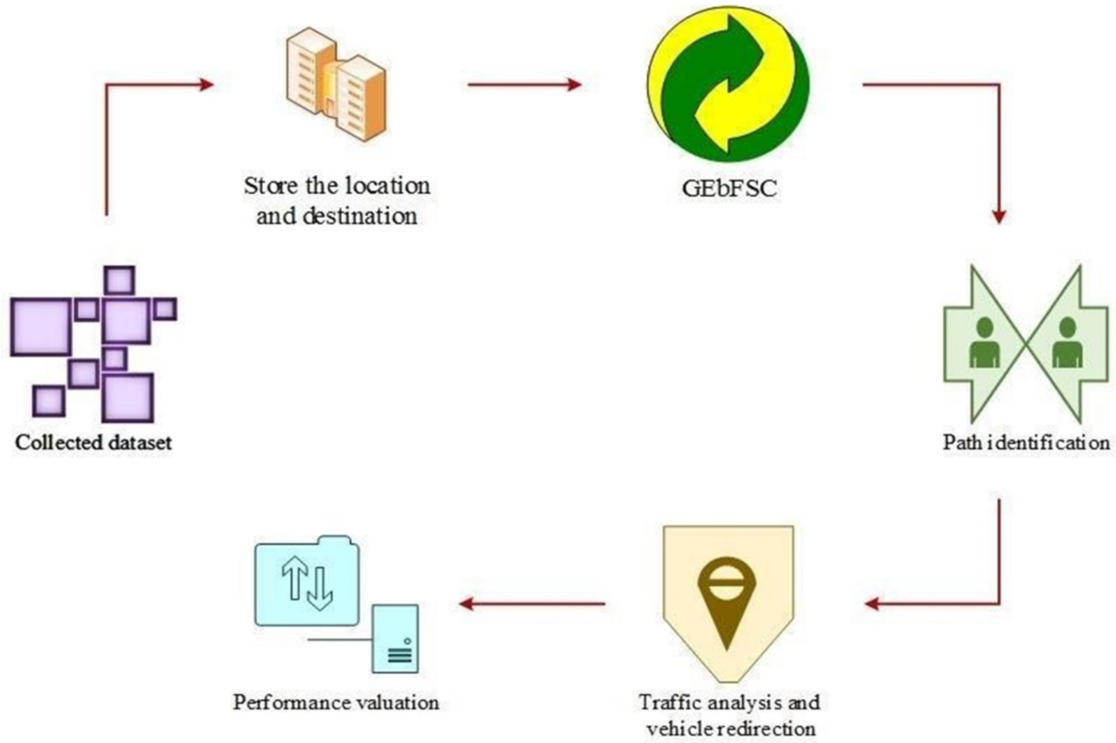

Fig. 3. Proposed GEbFSC for traffic signal control

4.1. Data collection

Table 1. Dataset Description

Time of collection of traffic volume data	1hr at each junction for 3 peak periods of a day
Total stretch length	4.4 km
Length between Pipul road junction and flyover	1.3 km
Length between flyover and Budameru Bridge	1 km
Length between Budameru Bridge and Prabhas College	1 km
Length between Prabhas College and BRTS junction	400 m
Length between BRTS junction and railway station	750 m

4.2. GEbFSC design

A new Golden Eagle-based fuzzy signal controller (GEbFSC) was designed in this paper to manage traffic and degrade delay time. The proposed model integrates Golden Eagle optimization (Mohammadi-Balani *et al.,* 2021) with fuzzy logic system (Jafari *et al.,* 2022). Initially, the traffic flow dataset was gathered from the standard website and imported into the system. And then, the presented method was developed in the system model with monitoring parameters. Additionally, the data is processed to neglect null values. In the proposed technique, fuzzy logic is associated with the fitness of the golden eagle to upgrade the green time duration. The FIS contains five layers, and the first layer is the input layer, called the fuzzification layer, which filters data, then three hidden phases, and finally, the last phase, called the output phase, which provides the Fuzzification layer's output. The variation among the noisy data level and result from the determined result is evaluated using eqn. (1).

$$X_{a,b} = \iota_{M_b}\left(\overline{N}\right) \tag{1}$$

Here, Xa,b signifies the output phase at link in the phase a , M signifies the linguistic record associated with links and Mb N is the second layer's input and it offers output for the whole rule by means of if clause. The membership function (MF) is also carried out by smooth operation using eqn. (2)

$$t\left(\overline{N}\right) = \frac{1}{1 + \left(\frac{\overline{N} - f}{M}\right)^{y}} \tag{2}$$

Here, f and y represent the membership function and error level respectively, consequently as $\overline{N} < for\, \overline{N} > f$ Additionally, the membership function of the dataset computation is evaluated using eqn.(3).

$$\iota_{M_b}\left(\overline{N}\right) = \begin{cases} 1 - \frac{\overline{N} - f}{M_1} & \overline{N} \in \left(f - f + M_1\right) \\ 1 - \frac{\overline{N} - f}{M_2} & N \in \left(f - M, y\right) \\ 0 & otherwise \end{cases} \tag{3}$$

The soft min-dependent model is taken into the account in the third phase using eqn.(4).

$$R_{\upsilon} = \eta_{\upsilon} = \frac{\sum_j \gamma_j e^{-k\gamma_j}}{\sum_j e^{-k\gamma_j}} \tag{4}$$

Here, γ_j is the quantity of identical interconnecting fuzzy records achieved using the rule υ as well as the equivalent input parameters. Additionally, η_υ offer an appropriate rule υ and k is the function variable, which eases η_υ. The input of the 4th phase is the fully related to the previous phase. η_υ is given to the phase that evaluates the correct outcomes as optional by the rule $\upsilon\tau$. Moreover, this operation is given in eqn. (5).

$$\gamma_{M_b}^{-1}\left(Z_V\right) \tag{5}$$

Here, z is the particular logic label. The membership function of defuzzification is taken into the account as an inverse format that is evaluated using eqn. (6).

$$\gamma_{M_b}^{-1}\left(Z_\upsilon\right) \text{the syncronized set of} \left\{\overline{N}; \gamma\left(\overline{N}\right) \geq \eta_\upsilon\right\} \tag{6}$$

And then, the trained group of output is provided as the linguistic membership input to the next phase. In that phase, the highest average value of triangular is evaluated by eqn. (7).

$$\gamma_{M_b}^{-1}\left(z_\upsilon\right) = zP + \frac{1}{2}\left(M_b\right)\left(1 - \eta_\upsilon\right) \tag{7}$$

Here, when η_υ =0, then $zP+\frac{1}{2}(M_b)$ is attained by the limiting score of $\gamma - 1(\eta_{1_\upsilon} \rightarrow 0)$. Using this, the triangular medians (TM) membership function for the fuzzy logic is estimated as a group of γ (0, 1) . Besides, the noisy contents were removed because of the multiple outputs of various scores. This function is conducted using eqn. (8).

$$R_\upsilon = \left(zP + \frac{1}{2} M_j \right)\left(\sum_\upsilon \eta_\upsilon \right) - \frac{1}{2}(M_j)\left(\sum_\upsilon \eta_\upsilon^2 \right) \tag{8}$$

Moreover, the 5th layer has several nodes in the result. The result of the fuzzy logic is directed in this phase using eqn. (9).

$$\mathrm{A} = \frac{\sum_\upsilon \eta_\upsilon \gamma^{-1}(\eta_\upsilon)}{\sum_\upsilon \eta_\upsilon} \tag{9}$$

The conversion function is enhanced in the 3rd as well as 4th classifier phases using eqn. (10).

$$A = \frac{\sum_z R_\varpi}{\sum_\varpi R_\varpi} \tag{10}$$

Here, A denotes the forebear operation of the input phase. The green light time of TSC was increased from the result, and the golden eagle fitness detected the other pathways. The lowest green timing is set so there is enough periods to convert the signals to neglect the vehicle's motion of going as well as stopping. The lowest as well as highest green time duration is also represented using eqn. (11).

$$TD_i = TD_{\min,i} + Q_i\left(TD_{\max,i} - TD_{\min,i}\right) \tag{11}$$

Here, the highest and lowest green time duration is denoted as TD_{min} and TD_{max}, respectively, TD_i signifies the green light period of i^{th} layer in following cycle, and Q_i indicates the i^{th} layer urgency degree. In addition, the highest green time duration decreases the vehicle delay time. Depending upon the three metrics, TSC is given: Inflow rate, vehicle density, as well as vehicles waiting at the track. Moreover, depending on the output as well as input variables, the rules are formatted:

1. If vehicle mass at the adjacent track and inflow level is lower, as well as vehicles waiting in the lane are low, which expansion of green light time duration is less
2. If vehicles waiting in the lane are lower, the inflow range is higher, as well as the mass is highest, then the green light time duration expansion is much lower.
3. If vehicles waiting in the lane are less, density is less and inflow level is low, then the expansion of green time duration is high.
4. If vehicles waiting in the lane, inflow level, and mass are in average level, then the expansion of green time duration is average or normal.
5. If vehicle mass is small, vehicles waiting in the lane and inflow level are higher, and the expansion of green time duration is average.

Additionally, in order to search the pathway, GEO is trained into the system. Eqn. (12) demonstrates the path-searching process.

$$\vec{E}_t = \vec{H}_S^* - \vec{H}_t \tag{12}$$

Here, the fitness function of the golden eagle is update to detect the pathway, Et signifies the present path searching, signifies the best location, and Ht signifies the current location of the vehicle. The vehicle's location is represent in the eqn.(13).

$$V_i = \left(v_1 = \text{random}, \quad v_2 = \text{random}, \quad ...., \quad v_j = \frac{d - \sum_{i:i \neq j} w_i}{u_j} \quad ...., \quad v_n = \text{random} \right) \tag{13}$$

$$d = \sum_{i=1}^{n} h_i X_i \tag{14}$$

Here, v_j denotes the j -th component of location V, w_i indicates the i-th element of pathway, u_j indicates the j -th component of pathway, and j is the fixed variable. The optimal location is evaluated using eqn. (15).

$$X^{q+1} = X^q + \Delta X_j^q \tag{15}$$

Moreover, the location regarding the trained feature stored in the data is calculated by the eqn. (16).

$$N_{ABO} = \begin{bmatrix} R_{1,1} & R_{1,2} & R_{1,d} \\ R_{21,1} & R_{2,2} & R_{2,d} \\ . & . & . \\ R_{n,1} & R_{n,2} & R_{n,d} \end{bmatrix} \tag{16}$$

where N_{ABO} is the stored data concerning the optimum weights and thresholds, B_{ik} indicates the value of the k^{th} variable of i^{th} data, n is the number of features on the trained data and d is the number of inconstant data, respectively.

The arbitrary data estimation is used for the identification of best location using the eqn. (17)

$$Y_i^t = \frac{\left(Y_i^t - p\right)}{q_i^t - p} \tag{17}$$

where p_j is the minimum of threshold value in the arbitrary data, q_j is the maximum of threshold value in the arbitrary data, r_t is the minimum of threshold value in the arbitrary data at the time of iteration and $_t$ maximum of the threshold value in the arbitrary data at the time of iteration, respectively. Furthermore, the threshold value for the location identification is estimated by the eqn. (18) and (19)

$$r_i^t = N_{oASk}^s + r^t \tag{18}$$

$$q_i^t = N_{oASk}^s + q^t \tag{19}$$

Moreover, the step for predicting suitable featured data using the eqn. (20)

$$r^t = \frac{r^t}{R} \; and \; q^t = \frac{q^t}{R} \tag{20}$$

Where, R is the ratio, In addition, the proposed GEbFSC technique pseudocode is given in the algorithm 1.

Algorithm 1: GEbFSC technique

Input: *traffic flow dataset*
// collected from standard site encloses several features
for *j ←0 for 1st layer* ***do***
Import the characteristic attributes in fuzzification phase

end
for *j ←0 , 2nd phase* ***do***
$\upsilon_{M_b}(\overline{N}) \leftarrow$ *rule phase fuzzy* *// error rate*
end

for *j ←0, hidden phase* ***do***
$z\upsilon \leftarrow$ *computation procedure*
end
for *j ←0 consequential record* ***do***

$\gamma_{M_i}^{-1}(z_\upsilon) \leftarrow$ *weight of detected range*
end
for *j ←0 for rule phase* ***do***
TM ←rule phase as a group of $\gamma^{-1}(0,1)$
end
for *j ←0 fuzzy phase* ***do***

$A = \dfrac{\sum_\upsilon \eta_\upsilon \gamma^{-1}(\eta_\upsilon)}{\sum_\upsilon \eta_\upsilon} \leftarrow$ *predicted trained data* *// output*
end

Green timing duration assessment: *Initialize the output of fuzzy dataset evaluate the lowest as well as highest green time*

Detection of path:
Evaluate the location of vehicle's fitness function
// the computed feature of dataset memorized in the GEbFSC

Evaluate the location of the vehicle
// detection of the path
Estimate the optimal location
// detection of location
If *the basis are not satisfied*
for *each dataset*

Select the best location by fitness of golden eagle
if
Evaluate the fitness function of every characteristics
Update the result
end
end
end
end
Output: *Evaluate the system performance.*

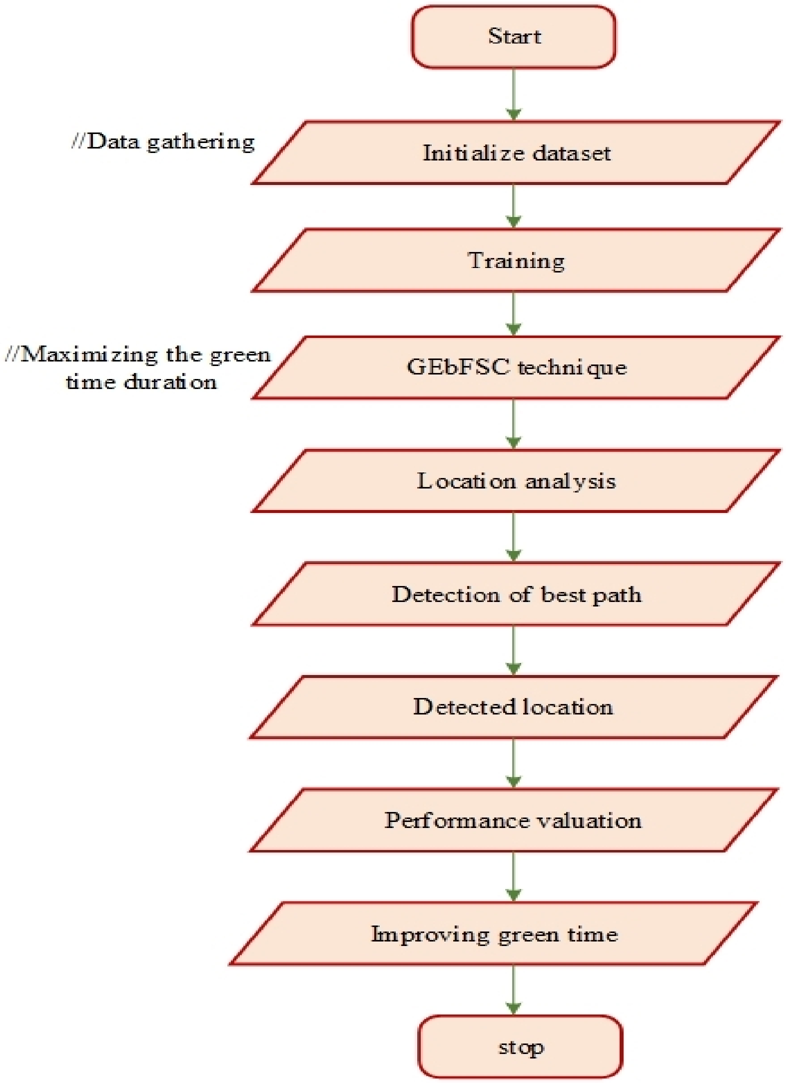

Fig. 4. Flowchart of GEbFSC

Fig. 4 represents the flowchart of the designed technique. Additionally, the developed method's process is indicated in the pseudocode structure in algorithm 1. Moreover, the proposed method is validated in the PYTHON environment, and the outcomes are evaluated concerning average length of queue, intersection delay, and traveling duration.

5. Result and Discussion

A new traffic signal control technique called GEbFSC was developed in this research to monitor traffic conditions from the traffic flow dataset. This technique hybrid the optimal approaches such as GEO quickly identifying the best path (A path is a group of characters used to identify a place in a directory structure specifically) and Fuzzy based inference system (FIS) upgrade the green time duration. So, to validate the developed technique, the dataset was collected from the standard website and imported into the python environment. In this platform, the initiated input is divided as 70% for training and 30% for testing purposes to maximize the green time duration effectively.

Table 2. Parameters and specification

Parameters	Specification
Language	English
Dataset	Traffic flow dataset
OS	Windows10
Platform	Python
Version	3.10

The trained dataset from the presented FIS is assessed using the GEO algorithm. The developed technique identifies the best route and decreases the delay time. The parameters are listed in Table 2. The proposed technique is developed as well as established in the python environment, version 3.10. At last, the functions like delay time and traveling time are estimated as well as validated by comparing them with the other existing models.

5.1. Comparative Assessment

The final results of this research work are verified with a comparative assessment. In this section, the function of the developed method, such as average queue length, traveling time, and intersection delay, are compared with the outcomes of other existing techniques, such as Knowledge Sharing Deep Deterministic Policy Gradient (KS-DDPG)(Wu *et al.,* 2020), Multi-Agent Deep Deterministic Policy Gradient (MADDPG) (Li *et al.,* 2021), Adaptive Neuro- Fuzzy based Inference system (ANFIS) (Vuong *et al.,* 2021), Fuzzy Logic System (FLS) (Malathi & Kumar 2022), Buffalo-based Recurrent Fuzzy Green Timing system (BRFGTS) (Van *et al.,* 2020), PTV VISSIM (Vogel *et al.,* 2019)and Webster method (Genders & Razavi 2019).

5.1.1. Average queue length

Average queue length denotes the average amount of interconnections in the queue over the most recent time intervals. It is evaluated by dividing the arriving and departure time to arriving and departure duration. The average queue length of the developed technique is represented in eqn. (21).

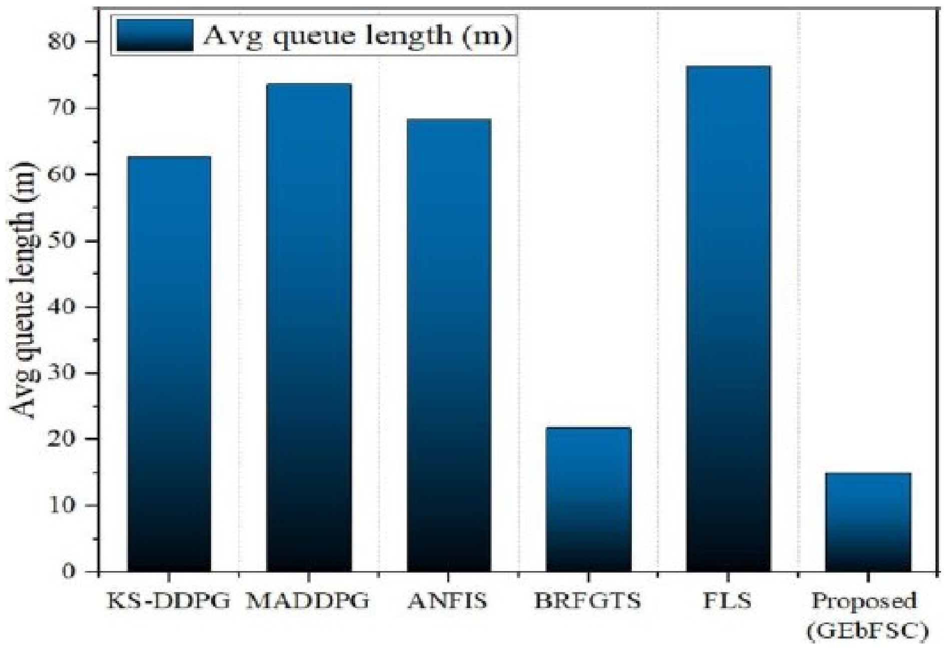

Fig. 5. Comparison of average queue length

$$Q = \frac{\mu \lambda^2}{\mu^2 (\mu - \lambda)} \tag{21}$$

Where, λ denotes the arriving time and μ denotes the departure time the departure time.

Average queue length of the proposed model is validated by comparing with existing techniques. Here, the average queue length is compared with the techniques such as KS-DDPG, MADDPG, ANFIS, BRFGTS, and FLS. The comparison of the average queue length is shown in Fig. 5. The comparative assessment indicates that the developed technique gained the average queue length about 15 m queue length. But the other existing models attained 62.7 m, 73.7 m, 68.4 m, 21.79 m, and 76.4 m average queue length. Hence, the proposed system achieved low queue length compared than existing models.

5.1.2. Average intersection delay

Average intersection delay is the extra traveling duration experienced during transportation. It is evaluated by dividing the total time taken by the number of vehicles and subtracting the minimum time taken. The average intersection delay of the designed model is represented in eqn. (22)

$$I.D = \sum_i \sum_j \sum_k \left(\frac{TD^{-\min}}{NV} TD \right) \tag{22}$$

Here, i signifies the phase value, j signifies the approach number, k signifies the lane set number, TD signifies the total duration, NV signifies the number of vehicles, and min TD signifies the minimum number of vehicles.

The comparison of average intersection delay is illustrated in fig. 6. The average intersection delay value attained by the designed technique is verified with the comparative function. The comparative assessment indicates that the developed method attained the lowest average intersection delay of about 1 second in managing traffic. But the other existing techniques, such as KS-DDPG, MADDPG, ANFIS, BRFGTS, and FLS, attained an average intersection delay of about 41.75 s, 50.33 s, 30.4 s, 1.39 s, and 35 s, respectively. It indicates that the technique degrades the average intersection delay.

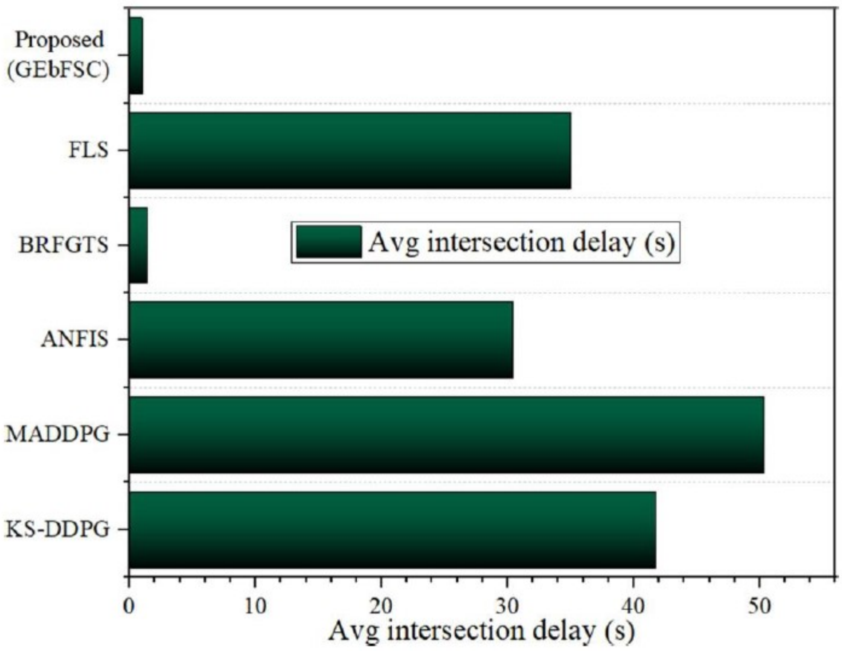

Fig. 6. Comparison of average intersection delay

5.1.3. Average travelling time

Average traveling time is a measure of the time duration of the movement from one place to another. The average traveling time is estimated by dividing the total distance by speed. The average traveling time of the designed model is represented in eqn. (23).

$$T.T = \frac{TD}{S} \tag{23}$$

Where $T.T$ signifies the travelling time, and S signifies the speed.

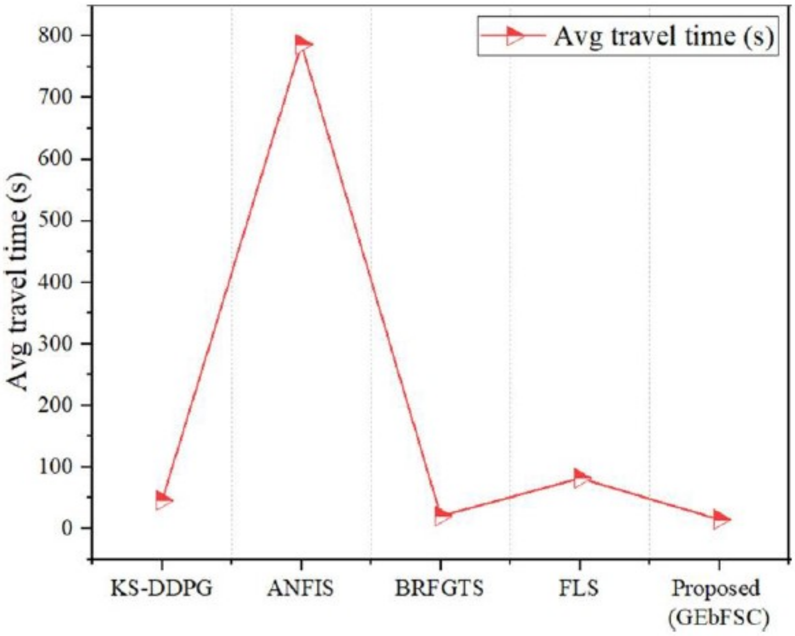

Fig. 7. Comparison of average travelling time

The average traveling time of the presented method is validated with a comparative analysis. The comparative performance of average traveling time is illustrated in Fig. 7. Here, the outcomes are compared with the existing models like KS-DDPG, ANFIS, BRFGTS, and FLS. The average traveling time attained by the designed technique is15 seconds. But the different existing strategies achieved an average traveling time of about 46.08 s, 786.6 s, 20.5 s, and 82 s, respectively. So, it validated that the designed strategy attained a lower average traveling time than other strategies.

5.2. Discussion

A novel AI-based method was developed to monitor the traffic by a traffic signal. At first, the traffic flow dataset is gathered from the standard website and imported into the python system. As expected, the developed technique trained the dataset and reduced the delay time, traveling duration, and queue length. The results show that the proposed architecture has achieved better outcomes and validated the proposed GEbFSC method's efficiency in maximizing green time duration.

Table 3. Performance assessment

Parameters	Performance
Average queue length (m)	15
Average intersection delay (s)	1
Average travelling time (s)	15
Execution time (min)	6

Additionally, traffic is forecasted depending on the trained dataset. At last, the results of the developed model are evaluated and verified with comparative analysis. The statistical assessment of the designed method is elaborated in the Table 3. The performance assessment indicates that the developed technique decreased the average queue length by about 15 m, the average intersection delay by about 1 second, the average traveling time by about 15 seconds, and execution duration by 6 minutes.

6. Conclusion

A GEbFSC technique was proposed in this research work, which enhances the green time and reduces the delay and traveling time. The designed technique is validated with the standard dataset. The gathered data consists of raw data on traffic flow. Additionally, a golden eagle method is integrated with the fuzzy logic in this designed method. Here, the fuzzy logic is utilized to fix the unpredictable dataset for controlling traffic signal timing and the golden eagle optimizer effectively finds the best path location. Hence, the presented model gained a better performance. The designed method is developed and established in a python environment, and the outcomes are estimated with respect to delay time, length of queue, and traveling duration. In addition, the evaluated results are verified with a comparison analysis, and the parameters are estimated. The comparative analysis indicates that in the designed technique, the average queue length is decreased by 6.79%, the average intersection delay is reduced by 0.39%, and the average traveling time is degraded by 5.5%. So, the designed method offers lower delay and queue length in traffic signal management. Additionally, our proposed model efficiently improved the green time about 5s.

References

Abudayyeh, D., Nicholson, A., Ngoduy, D., 2021. Traffic signal optimisation in disrupted networks, to improve resilience and sustainability. Travel Behaviour and Society 22, 117-128.

Almalki, F.A., Alsamhi, S.H., Sahal, R., Hassan, J., Hawbani, A., Rajput, N.S., Saif, A., Morgan, J., Breslin, J., Green IoT for eco-friendly and sustainable smart cities: future directions and opportunities. 2021. Mobile Networks and Applications 1-25.

Barceló, J., Martínez-Díaz, M., 2022. Dynamic Traffic Management: A Bird's Eye View. The Evolution of Travel Time Information Systems. Springer, Cham, pp. 165-200.

Boban, M., Kousaridas, A., Manolakis, K., Eichinger, J., Xu, W., 2018. Connected Roads of the Future: Use Cases, Requirements, and Design Considerations for Vehicle-to-Everything Communications. IEEE Vehicular Technology Magazine 13.3, 110-123.

Essa, M., Sayed, T., 2020. Self-learning adaptive traffic signal control for real-time safety optimization. Accident Analysis & Prevention 146,105713.

Genders, W., Razavi, S., 2019. An open-source framework for adaptive traffic signal control. arXiv preprint arXiv:1909.00395.

Gong, Y., Abdel-Aty, Y., Cai, Q., Rahman, Md.S., 2019. Decentralized network level adaptive signal control by multi-agent deep reinforcement learning. Transportation Research Interdisciplinary Perspectives 1, 100020.

Gong, Y., Abdel-Aty, M., Yuan, J., Cai, Q., 2020. Multi-objective reinforcement learning approach for improving safety at intersections with adaptive traffic signal control. Accident Analysis & Prevention 144, 105655.

Hong, W., Tao, G., Wang, H., Wang, C., 2022. Traffic Signal Control With Adaptive Online-Learning Scheme Using Multiple-Model Neural Networks. IEEE Transactions on Neural Networks and Learning Systems.

Jafari, S., Shahbazi, Z., Byun, Y.-C. 2022. Improving the Road and Traffic Control Prediction Based on Fuzzy Logic Approach in Multiple Intersections. Mathematics 10.16, 2832.

Jutury, D., Kumar, N., Sachan, A., Daultani, Y., Dhakad, N., Adaptive neuro-fuzzy enabled multi-mode traffic light control system for urban transport network. 2022. Applied Intelligence 1-22.

Lee, W.-H., Chiu. C.-Y., 2020. Design and implementation of a smart traffic signal control system for smart city applications. Sensors 20.2, 508. Li, Z., Yu, H., Zhang, G., Dong, S., Xu, C.Z., 2021. Network-wide traffic signal control optimization using a multi-agent deep reinforcement learning. Transportation Research Part C: Emerging Technologies 125, 103059.

Knowles, R D., Ferbrache, F., Nikitas, A., 2020. Transport's historical, contemporary and future role in shaping urban development: Re-evaluating transit oriented development. Cities 99, 102607.

Madrigal Arteaga, V.M., Pérez Cruz, J.R., Hurtado-Beltrán, A., Trumpold, J., 2022. Efficient Intersection Management Based on an Adaptive Fuzzy-Logic Traffic Signal. Applied Sciences 12.12, 6024.

Malathi, N., Kumar, M., 2022. A novel optimized intelligent green signal timing system for urban corridor. Concurrency and Computation: Practice and Experience e7284.

Mohammadi-Balani, A., Nayeri, M.D., Azar, A., 2021. Golden eagle optimizer: A nature-inspired metaheuristic algorithm. Computers & Industrial Engineering 152, 107050.

Neelakandan, S., Berlin, M.A., Tripathi, S., Brindha Devi, V., Bhardwaj I., Arulkumar, N., 2021. Soft Computing 25.18, 12241-12248. Lin, H., Han, Y., Cai, W., Jin, B., 2022. IEEE Transactions on Intelligent Transportation Systems.

Nourani, V., Gökçekuş, H., Umar, I.K., Najafi, H., 2020. An emotional artificial neural network for prediction of vehicular traffic noise. Science of the Total Environment 707, 136134.

Oubbati, O.S., Atiquzzaman, M., Lorenz, P., Baz, A., Alhakami, H., 2020. SEARCH: An SDN-Enabled Approach for Vehicle Path-Planning. IEEE Transactions on Vehicular Technology 69.12, 14523-14536.

Possatti, L.C., Guidolini, R., Cardoso, V.B., Berriel, R.F., Paixão, T.M., Claudine B., De Souza, A.F., Oliveira-Santos, T., 2019. Traffic light recognition using deep learning and prior maps for autonomous cars." 2019 international joint conference on neural networks (IJCNN). IEEE. Raghu, N., Phadke, A., Kumar, R., Joshi, K., 2023. Smart Traffic Light and Dynamic Navigational System for Emergency Vehicles. In: Ranganathan, G., Fernando, X., Piramuthu, S. (Eds.) Soft Computing for Security Applications, Advances in Intelligent Systems and Computing, Springer, Singapore, vol. 1428.

Van, N.H., Can, V.X., Thua, V.T., 2020. A fuzzy traffic signal control method for a single intersection under mixed traffic conditions. Technology 11.10, 1715-1723.

Vogel, A., Oremovic, I., Šimic, R., Ivanjko, E., 2019. Fuzzy traffic light control based on phase urgency. 2019 International Symposium ELMAR, IEEE.

Vuong, X.C., Mou, R.F., Vu, T.T., Van Nguyen, H., 2021. An Adaptive Method for an Isolated Intersection Under Mixed Traffic Conditions in Hanoi Based on ANFIS Using VISSIM-MATLAB. IEEE Access 9, 166328-166338.

Wang, H., Zhu, M., Hong, W., Wang, C., Tao, G., Wang, Y., 2022. Optimizing signal timing control for large urban traffic networks using anadaptive linear quadratic regulator control strategy. IEEE Transactions on Intelligent Transportation Systems 23.1, 333-343.

Wu, T., Zhou, P., Liu, K., Yuan, Y., Wang, X., Huang, H., Wu, D.O., 2020. Multi-agent deep reinforcement learning for urban traffic light control in vehicular networks. IEEE Transactions on Vehicular Technology 69.8, 8243-8256.