DOI: 10.6977/IJoSI.202506_9(3).0003
I. Appaji, P. Raviraj/Int. J. Systematic Innovation, 9(3), 20-30 (2025)

Hybrid intelligence model for traffic management in intelligent transportation systems

Impana Appaji[1,2], Pandian Raviraj[3]*

[1]GSSS Institute of Engineering and Technology for Women, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India

[2]Infosys Limited, Mysuru, Karnataka, India

[3]Department of Computer Science and Engineering, GSSS Institute of Engineering and Technology for Women, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India

*Corresponding author E-mail: impana.appaji@gmail.com

(Received 13 January 2024; Final version received 16 March 2024; Accepted 16 July 2024)

Abstract

A typical traffic environment in an intelligent transportation system (ITS) involves various infrastructural units that generate a vast amount of sophisticated traffic data. Such a form of complex data is challenging to analyze and hence poses a potential issue in designing an effective and responsive traffic management system. Therefore, this paper develops an analytical modeling approach to harness the potential of artificial intelligence and computational intelligence. The scheme presents a simplified predictive approach that is meant to mitigate current issues and promote intelligent traffic management. The simulated outcome of the study showcases that the proposed scheme offers a significant advantage in its predictive performance in ITS.

Keywords: Artificial Intelligence, Computational Intelligence Technologies, Intelligent Transportation System, Traffic Management

1. Introduction

With the rising demands of incorporating modern technologies, the transportation system has been witnessing a new paradigm shift toward revolutionizing itself from a conventional to an intelligent transportation system (ITS) (Shaaban et al., 2021). In contrast to the conventional transportation system, the significance of ITS in the future is considerably high owing to its beneficial features of enhanced safety, smart traffic management, positive impact on the environment, higher efficiency and time-saving, effective infrastructure management, emergency response, and management (Barodi et al., 2023; Chowdhury et al., 2023; Karthikeyan & Usha, 2023; Kumari et al., 2020). However, it is not a simplified process to deploy ITS as there is a heavy infrastructural cost underlying its implementation process (e.g. modern technologies, communication networks, sensors, etc.) (Njoku et al., 2023). Another bigger challenge is to ensure complete traffic management operations, knowing that devices and services from different manufacturers and vendors are included. At present, there are no standard and generalized technologies and protocols for the effective implementation of ITS, which poses a primary concern for smart traffic management. There is an involvement of various intricate systems in conducting the maintenance and updating operation, which is challenging. Automating the entire process that runs heterogeneous forms of services is a heavily challenging task (Sharma et al., 2021). Another important aspect of traffic management in ITS is the need for reliable and effective decision-making (Rajkumar & Deborah, 2021). To do so, there is a need for real-time traffic data with higher accuracy from various sources. Even if all these issues are solved someday, the bigger challenge will still reside in data privacy and data security in ITS (Kołodziej et al., 2022). It is a computationally challenging task to offer security to the massive amount of data collected from infrastructural devices of different designs and operations. Hence, traffic management will always be a potential research challenge when it is related to a highly distributed and large-scale deployment environment of ITS. However, there are some upcoming research studies where traffic management problems have been attempted to be addressed (Zulkarnain & Putri, 2021).

It has been seen that artificial intelligence (AI) and computational intelligence (CI) have been acting as an evolving solution toward addressing various issues related to dynamic problems, which are considered computationally complex. The prime role played by AI and CI-based schemes is in traffic prediction and optimization, adaptive traffic control systems, intelligent routing and navigation, detection and management of an automated event, smart parking solutions, and analysis and management of specific vehicular or driver behavior (Damaj et al., 2022). It is also noted that such schemes also assist data analysis for effective decision-making, optimizing public transportation networks, and integrating with autonomous vehicles (Bıyık & Yigitcanlar, 2020). Hence, the proposed scheme contributes toward developing a novel framework of traffic management by harnessing the problem-solving capabilities of AI and CI-based schemes. The core notion of this model is to develop a generalized model that offers higher coverage to host smart and intelligent predictive operations on large traffic data in the ITS environment. The contribution of the proposed study is as follows:

1. The proposed model introduces a novel traffic management model that can not only monitor the dynamic condition of lanes but also assist in smarter decision-making in complex ITS scenarios
2. The development of the proposed model is conducted considering the practical constraints as well as parameters, such as location, direction, speed, and lane density, which assist in a better form of predictive decision-making
3. The model implements an AI-based scheme where a long short-term memory (LSTM)-based attention network is used along with a reinforcement learning strategy to make intelligent decision-making for vehicles
4. The presented scheme uses CI-based methodology with a definitive objective function applied on an integrated ITS network for optimized service relaying.

The organization of the manuscript is as follows: Section 2 discusses the frequently used methodologies in traffic management in ITS, followed by a briefing of prominent research issues in Section 3. The discussion of the adopted research methodology is carried out in Section 4, while accomplished simulation outcomes are briefed in Section 5. Finally, Section 6 gives a conclusive summary of the complete work and its contribution.

2. Related Work

The discussion of the related work is restricted only to the state-of-the-art methods witnessed in the current era using CI-based, analytical approaches, and AI-based approaches in traffic management.

- CI-based schemes: This scheme is mainly adopted to enhance the overall transportation system in terms of congestion reduction and improving the flow of traffic. The work carried out by Zhou et al. (2021), Ojala et al. (2020), and Haghighat et al. (2020) has used neural networks as a CI scheme. The majority of the CI schemes have reportedly used fuzzy logic systems to formulate a unique traffic management scheme. The adoption of fuzzy logic has also been witnessed in the work of Tang et al. (2021), where a neural network is used alongside a fuzzy inference system for traffic management. Standalone adoption of fuzzy logic as a CI scheme is reported in the work of Simić et al. (2021), Shi et al. (2020), Lu et al. (2020), Liu et al. (2022), Servizi et al. (2021), and Li et al. (2021), considering various aspects of the urban transportation system. Li et al. (2021) have also used a fuzzy scheme to design a controller system in ITS. Optimization using bio-inspired approaches in clustering the ITS is reported in the work of Jain et al. (2022), Husnain et al. (2023), and Mohammadi & Farahai (2020). The work carried out by Chen et al. (2022) used an evolutionary computing scheme to manage the collaborative traffic framework over the cloud and edge.
- Analytical-based schemes: There are various analytical-based schemes in traffic management in ITS that emphasizes modeling capable of handling various issues. The work of Lee et al. (2021) used a clustering approach where multi-tasking is performed during sequential learning operations to mitigate positioning problems of vehicles. Qadri et al. (2020) emphasized the importance of traffic signals.

Eom & Kim (2020) have a solution for traffic congestion associated with the intersection point. Iliopoulou & Kepaptsoglou (2019) have discussed the likelihood of joint operation of various approaches in mitigating coordination issues in the public transport system. An emergent intelligence scheme is implemented by Chavhan et al. (2021), where the solution is focused on mitigating allocation issues for public transport vehicles in the ITS.

- AI-based schemes: Different variants of AI-based schemes have proven beneficial in making predictive decisions for traffic management in ITS. Adoption of the deep learning approach was witnessed in the work of Malek et al.

(2021), where the prediction of vehicular velocity was carried out using LSTM. The work of Tak et al. (2021) used deep learning for the detection and tracking of vehicular nodes in a traffic scene. Severino et al. (2021) and Sayed et al. (2023) have analyzed the traffic flow and studied its impact on autonomous vehicles using predictive methods. Lytras et al. (2020) used AI to investigate the indicators for catering to dynamic demands in ITS. The model presented by Benterki et al. (2020) uses neural networks and LSTM to perform trajectory prediction by considering the driving behavior of a vehicle for facilitating autonomous maneuvering. Discussion on the importance of the adoption of AI is also seen in the work carried out by Akhtar & Moridpour (2021).

3. Research Problem

After reviewing the existing approaches in traffic management, it is noted that different variants of approaches have been developed. Although such approaches are witnessed with some significant contribution, they are also witnessed with certain impending issues as follows:

- It has been noted that the majority of existing approaches toward ITS have been carried out considering a specific form of research environment and application that restricts the generalized application in practical utilization
- The frequent adoption of approaches in mitigating traffic issues in ITS is carried out using AI-based approaches, which are found to be adopted slightly more often than CI-based approaches. Unfortunately, all these approaches are highly focused on accomplishing their objective function rather than proving their computational efficiency in the presence of a dynamic traffic scenario of ITS
- The adoption of intelligent schemes in ITS is mainly focused on vehicle-to-vehicle communication and not much on the embedded wireless units. This is a prime obstacle to constructing a novel controller and testing it on a large-scale ITS infrastructure
- The majority of existing studies using AI use deep learning approaches where predictive decision-making demands a higher training operation with the inclusion of extensive computational resources. Such schemes, although proven with higher predictive accuracies, could not be used for emergency applications on vehicles in ITS
- Not many existing learning-based approaches are found to emphasize the data quality perspective. It is quite evident that data collected from traffic scenes is highly complex and continuous in form, which imposes another bigger problem in understanding its pattern. Hence, mining proper knowledge from such complex forms of traffic data is a computationally complex process with a lack of studies on optimization approaches.

Therefore, all the above-mentioned statements are prime research problems in carrying out a smart and intelligent traffic management system in ITS. The next section presents a discussion about the problem, solution, and methodologies in the proposed model.

4. Research Methodology

The prime aim of the proposed study is to design a simplified, intelligent, and robust computational framework for traffic management associated with the ITS environment. To facilitate effective decision-making toward modeling highly dynamic traffic management, the proposed scheme places more importance on realizing the importance of traffic data analysis, as well as evolving with a scheme for mitigating complex traffic scenarios in ITS. Hence, the implementation of the proposed scheme is performed using analytical research methods that will offer more flexibility to implement and extensively test the proposed model of traffic management. Fig. 1 highlights the architecture of the proposed scheme.

A closer look at Fig. 1 shows that it is classified into two core operational blocks. The first operational block is meant to harness the potential of the machine learning approach to facilitate effective traffic management in ITS, while the second operational block is meant to harness the potential of CI for further optimizing the performance. According to this architecture, the first step of implementation is constructing a traffic model that considers essential elements of the road network and the characteristics of vehicles. This is followed by constructing a novel conditional logic toward traffic environment formulation. The further reinforcement learning model is used in framing up triple attributes (reward, action, and state) that are further subjected to an LST network

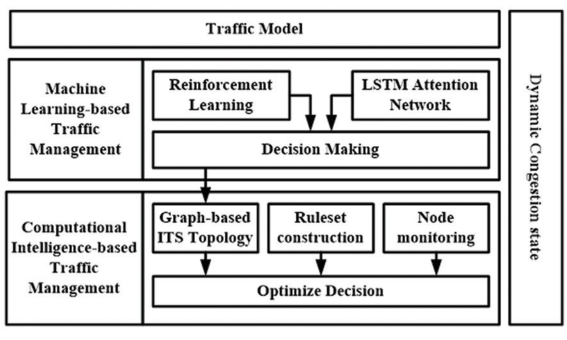

Fig. 1. Proposed architecture of traffic management

with an attention graph to facilitate effective decision-making. On top of the first operation block, the proposed scheme constructs a novel topology of ITS considering triple parameters (location data, vehicle direction, and vehicle speed) that are finally deployed to construct a graph.

This part of the implementation further constructs a novel objective function in incorporating CI with a sole agenda to frame an integrated ITS network system. The scheme also introduces a requestor and non-requestor node in the integrated network that is further subjected to the module of optimizing the service relaying in an ITS environment. Hence, the second operational block acts as a complementary model to the first operational block, where the overall network structure assists in traffic management. A unique use case is adopted for the practical scenario of vehicular movement affected by various road conditions on varying lane densities. Hence, the adopted research methodology targets generating an effective decision-making process that positively and intelligently structures traffic management in the ITS environment.

From the prior discussion, it is noted that the overall implementation of the proposed scheme was performed using two discrete operational blocks in the presented architecture. This section elaborates on the core system implementation associated with the operational blocks of the architecture.

4.1. Machine Learning-Based Traffic Management

This is the primary implementation module, which is responsible for undertaking an intelligent decision-making system in traffic management using a machine learning approach (Fig. 2). The first step in implementation is defining three variants of congestion in traffic, such as high, low, and medium, while specific dimensions, speed, gap between the vehicles, and time of journey characterize each vehicle. These parameters are practically chosen to suit the model deployment, considering actual vehicular characteristics in ITS. The scheme makes use of the CityFlow simulator [40] in a traffic environment where a different number of vehicles are deployed on multiple junctions of the road with a definitive speed and computed congestion. Furthermore, the scheme applies a reinforcement learning approach

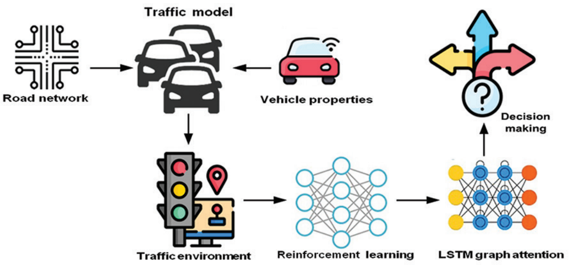

Fig. 2. Machine learning-based traffic management

where the formulation of state, action, and reward is carried out. The primary logic behind applying the reinforcement algorithm is to optimize the signal quality and control the power consumption in the presence of various degrees of congestion. The scheme designs its objective function to ensure lower congestion and higher signal quality to choose the path for the movement of vehicles. Different from any existing scheme, the scheme utilizes average queue length to represent the congestion attribute. The proposed scheme uses a Memory Graph Attention Network, where LSTM is used in its three hidden layers to predict the upcoming possibilities of traffic scenarios for appropriate decision-making. The prime novelty of this approach is that the majority of existing studies have used only LSTM, in which case the system can only undertake decisions on a local level with respect to its agent. However, by applying attention-based LSTM, the system is now capable of realizing the global perspective of the ITS environment to make more accurate decisions. Another significant contribution is that all the agents of the reinforcement learning model can now share their biases and weights using graph attention. This method eventually offers a better understanding of global traffic parameters, considering interdependencies among congestion levels on each lane. Therefore, the system contributes toward yielding a discrete mode of decision with respect to the current congestion level on each route, which is not seen in any existing research work on ITS-based traffic management. The outcome of the study is in the form of optimal paths that offer a better movement option with the least distance and the least fuel consumption, along with reduced power utilization among the infrastructural units.

4.2. CI-Based Traffic Management

This is an extension of the prior implementation module, which is mainly meant to optimize decision-making in ITS. Different from existing methodologies, the system constructs a graph-based ITS topology considering vehicular speed, vehicular direction, and location data (Fig. 3). The system assesses the effective

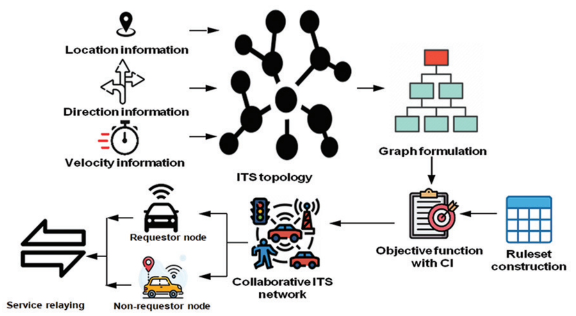

Fig. 3. Computational intelligence-based traffic management

path and position considering spatial distances among the vehicles, while the optimal probability of a better road is determined considering fuzzy logic. The core idea of this approach is to reduce the waiting time for vehicles on specific routes. The study model considers the requestor node as a vehicle seeking assistance with navigation by forwarding a request message to neighboring vehicles. Such a neighboring vehicle can be both a requestor node by itself and a non-requestor node (such a vehicle node does not forward any request for navigational assistance).

The proposed scheme uses CI to construct its objective function. It is to be noted that fuzzy-based rulesets are constructed as a part of CI to guide the type of traffic state. This is further followed by assigning a specific neighboring channel to formulate the outcome toward optimal routes. The next part of the implementation is associated with dispersing the ultimate traffic command over the intersection. The novelty of this study's contribution is that the proposed system generates a unique route for each vehicle on the basis of their best route to a destination, and thereby, it generates distinct and unique traffic commands for each vehicle. The majority of existing schemes generate the same traffic commands for all the waiting vehicles in a lane, while the proposed scheme allows the propagation of unique traffic commands for each vehicle waiting at an intersection point. This clearance signal and its distinctiveness in relaying are significant novelties of the proposed system that is not witnessed in existing methodologies for traffic management in ITS. Apart from this, the scheme also constructs a temporary memory system where each decision to be relayed is stored and subjected to its match with the existing traffic condition. This process also offers a benefit in lowering the computational processing effort by optimizing the analytical operation undertaken for each traffic unit ready to forward optimized navigational information. Hence, a better form of optimized traffic management is presented in the proposed scheme.

5. Results

The complete implementation mentioned in the prior section has been scripted in a Python environment, while the analysis of the optimized outcome is performed in a MATLAB environment. The study considers 800 vehicular nodes bearing the IEEE 802.11 wireless standard that is spread over a monitoring area of 1,000 × 1,000 m^2. Considering synthetically generated data, the analysis was carried out on the mean travel time for both emergency and normal vehicles, as well as power consumption. The study outcome is compared with the relevant work of Wei et al. (2019), where the CoLight model has been presented using a learning-based approach to mitigating similar traffic-related problems in ITS.

Fig. 4 showcases the simulation outcome with a four-channel system for one junction point in the ITS environment. The sample instantaneous visuals of the simulations show various vehicle deployments in a two-lane system with vehicles traversing in two opposite directions on the lanes. The numbers within the simulation show the total number of vehicles that received the traffic command from the controller, either to clear the junction, to wait, or to stop. The numerical outcome of the study is shown in Tables 1-5.

Fig. 5 showcases the clearance controller value for the distinct number of vehicles at each junction point with respect to all four test channels. The computation of this parameter is carried out as

$$C_{cv} = avg\sum_{i=1}^{m} t_c^{\,m} \tag{1}$$

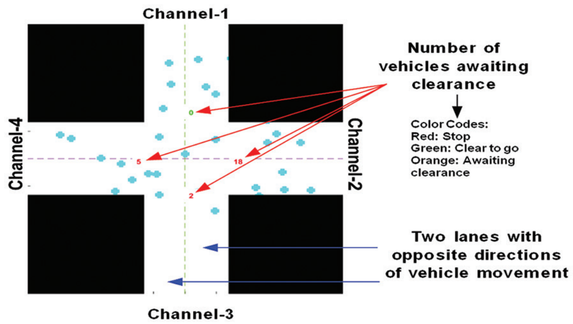

Fig. 4. Simulation outcome of the proposed model

Table 1. Mean duration of journey

Model	6×6 uniflow	6×6 biflow	New York	Hangzhou
	MD-1	MD-2	MD-3	MD-4
Normal	198	197	1210	210
Dynamic	150	149	600	185

Table 2. Cumulative power utilization

Model	6×6 uniflow	6×6 biflow	New York	Hangzhou
	MD-1	MD-2	MD-3	MD-4
CoLight	220	225	1210	165
Proposed	209	210	1,009	151

Table 3. Algorithm processing time

Model	6×6 uniflow	6×6 biflow	New York	Hangzhou
	MD-1	MD-2	MD-3	MD-4
CoLight	0.59	0.52	0.83	0.62
Proposed	0.34	0.37	0.54	0.39

In the above Eq. (1), the computation of the clearance controller value is carried out considering *m* as the maximum number of junction points where distinct traffic commands, t_c, are relayed by the controller. It is to be noted that the value of traffic command t_c is unique for each requestor vehicle. The accomplished outcome in Fig. 5 showcases that there is no significant difference in clearing the vehicle from overall junction points. It implies that the outcome of relaying the clearance signal offers higher consistency for the overall traffic system. This trend of consistency can also be seen in the outcome shown in Fig. 6.

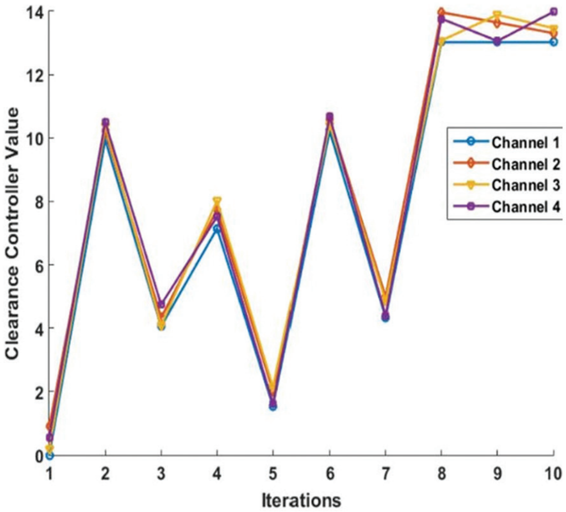

Fig. 5. Simulation outcome of clearance controller value

Table 4. Clearance counter and number of vehicles cleared

Channels	Clearance counter	No. of vehicles cleared
Ch_1	34	451
Ch_2	44	700
Ch_3	34	500
Ch_4	39	750

The outcome exhibited in Fig. 6 is an extensive version of the prior result of controller values. It is mathematically exhibited as,

$$cons\ (C_{cv}) = [array\ C_{cv}{}^{m}] \quad (2)$$

The above Eq. (2) showcases the computation of the consistency of generating a clearance signal. Cons (C_{cv}) is fundamentally a secondary assessment parameter considering the array of obtained traffic commands. However, this computation is carried out with respect to the time of generating the traffic command, and hence, its unit is seconds. The prime notion is to exhibit consistency of duration spent in junction points for relaying the clearance signal.

The graphical results shown in Figs. 7 and 8 show individual outcomes for four different forms of map datasets considered for analysis with respect to the mean duration of journey and cumulative power utilization, respectively. The computation is carried out as follows:

$$M_{dj} = mean\ (d_{ch})^{m} \quad (3)$$

$$P_u = \sum_{i=1}^{m} \Delta p_{v_m} \quad (4)$$

Eqs. (3) and (4) are meant to exhibit the computation of the mean duration of journey, M_{dj}, and power utilization, P_u. The system computes the duration for each channel *dch* with respect to all the junction points *m* and finds its average. It is to be noted that this duration computation starts from the instance the traffic command is relayed. From the perspective of power computation, the system allocates an initialized power (*pinit*) and considers that amount of power (*pd*) is required to forward *d* size of data in one second. Hence, the individual power utilized by a vehicle is computed as Eq. (5)

$$\Delta p_v = pinit\text{-}pd \quad (5)$$

This computation is carried out for all *m* junctions to finally obtain the cumulative utilized power P_u.

The outcome in Figs. 7 and 8 shows that the mean travel time for the proposed scheme is approximately 25% reduced compared to the CoLight model. An extensive test environment has

Table 5. Comparison with modern methods

Approaches	Computational effort
Proposed	Low–Medium
Neural network (Bıyık & Yigitcanlar, 2020; Damaj et al., 2022; Zhou et al., 2021)	High
Fuzzy (Haghighat et al., 2020; Ojala et al., 2020; Servizi et al., 2021; Shi et al., 2022; Simić et al., 2021; Tang et al., 2021)	High
Computational intelligence evolutionary (Chen et al., 2022; Husnain et al., 2023; Jain et al., 2022)	High
Analytical learning method (Chavhan et al., 2021; Eom & Kim, 2020; Iliopoulou & Kepaptsoglou, 2019; Lee et al., 2021; Qadri et al., 2020)	Medium–High
Artificial intelligence (Akhtar & Moridpour, 2021; Benterki et al., 2020; Lytras et al., 2020; Malek et al., 2021; Tak et al., 2021)	High

DOI: 10.6977/IJoSI.202506_9(3).0003
I. Appaji, P. Raviraj/Int. J. Systematic Innovation, 9(3), 20-30 (2025)

been considered, adopting 6×6 uniflow, 6×6 biflow, New York, and Hangzhou as the frequently adopted urban transportation maps, where both the proposed and existing CoLight models were assessed. The prime reason for the accomplished outcome is that CoLight uses reinforcement learning in combination with a graph attentional network (which is also used in the proposed scheme), and it offers a benefit to perform prediction for hundreds of traffic signals without much dependency on indexing neighboring intersections.

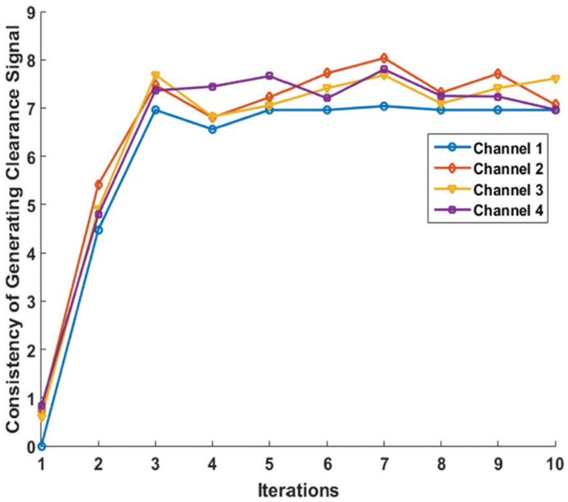

Fig. 6. Simulation outcome of consistency

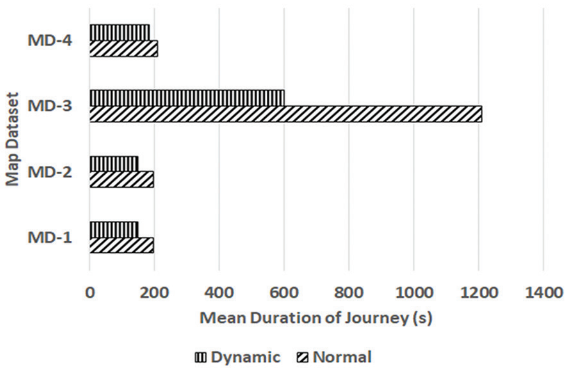

Fig. 7. Analysis of the mean duration of journey

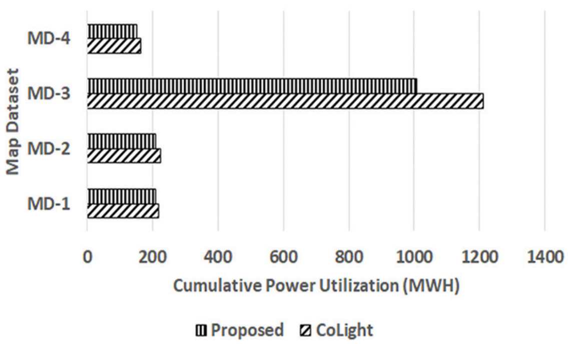

Fig. 8. Analysis of cumulative power utilization

However, the proposed scheme adds upon LSTM that can further handle complex forms of variable-length sequences by allocating different weights to distinct parts of sequences. This significantly improves the predictive performance of the proposed system in shorter time ranges. Apart from this, the proposed model is also proven highly adaptable to different traffic scenarios (e.g., 6 × 6 uniflow, 6 × 6 biflow, New York, and Hangzhou), which causes less power consumption even in the presence of fluctuating traffic conditions. From a computational burden viewpoint, the proposed scheme can be used on different locations and is highly adaptive to different traffic, with only one-time training.

The next part of the implementation performs an analysis for a counter for clearance and quantity of vehicles being cleared in a defined traffic location, as exhibited in Fig. 9. The outcome in Fig. 9 showcases four test channels, which represent adjoining lanes at an intersection point of traffic. Fig. 9a shows that the proposed scheme is capable of maintaining nearly similar consistency of vehicle occupation and clearance on all four tests connected lane systems in an intersection, while Fig. 9b exhibits a maximum number of vehicles being observed to be cleared from each channel. The outcome evidently showcases that the proposed scheme can maintain better consistency on multiple lanes irrespective of any dynamic congestion occurrences in the ITS environment.

Furthermore, Fig. 10 showcases the analysis of time complexity by evaluating the algorithm processing time consumed by the existing CoLight and

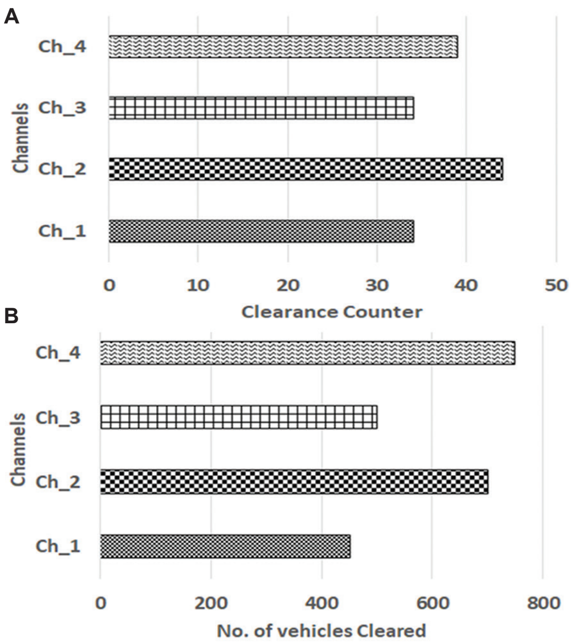

Fig. 9. Analysis of vehicle clearance system. (A) Counter for clearance. (B) Quantity of cleared vehicles

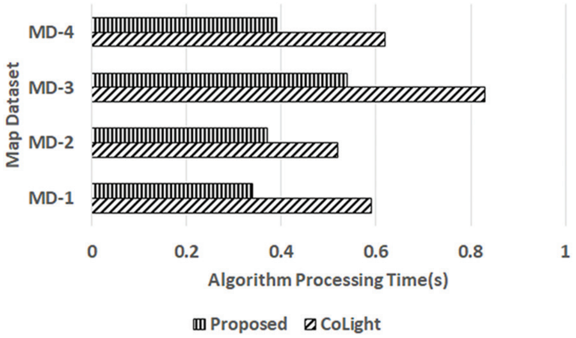

Fig. 10. Analysis of time complexity

the proposed system. It shows that the proposed system consumes approximately 23% of reduced processing time as compared to the existing CoLight. The prime reason behind this is that the existing CoLight does not offer a comprehensive attribute of traffic to undertake global decisions, whereas the proposed system uses both local and global attributes using CI to make the decision easier and faster. Further, the computational effort of the proposed scheme has been compared with the relevant approaches to find that the proposed scheme excels in reduced computational effort in Table 5. The prime reason behind this is that the proposed scheme extracts various intrinsic features, e.g., direction, dimension, and speed of vehicles, along with consideration of lane capacity, to carry out modeling. Acquisition of such information takes less time as it can be derived straight from the ITS infrastructure, while less training is required owing to highly adaptive operations carried out by the LSTM-based attention graph model. This phenomenon turns the proposed scheme into less iterative and more progressive, causing less involvement of computational resources while performing dynamic traffic management in the ITS environment.

6. Conclusion

This paper presented a novel computational model for performing autonomous traffic management with an explicit deployment of a vehicular network in the ITS environment. The proposed study model was designed using analytical research methodology by harnessing the potential of AI- and CI-based approaches. The essential and novel contribution of the study model implementation is as follows:

- Deployment of LSTM with attention network and reinforcement learning assists in realizing an appropriate state of dynamicity in the traffic environment that can offer precise decision-making in the ITS environment.
- The proposed model has been tested over multiple traffic environment data (Hangzhou, New York, 6 × 6 biflow, 6 × 6 uniflow). The outcome exhibited approximately 96% minimized power consumption and 85% minimal travel time.
- The scheme presents a generalized evaluation platform where traffic management problems can be assessed and solved effectively.
- The proposed system model also presents a novel ITS distributed graph-based topology constructed using the velocity, direction, and location information of vehicles.
- A novel CI-based scheme has been implemented using a fuzzy ruleset toward facilitating effective decision-making for clearing the congestion and thereby contributing toward optimized service relaying in ITS.

References

Akhtar, M., & Moridpour, S. (2021). A review of traffic congestion prediction using artificial intelligence. *Journal of Advanced Transportation*, 2021, 1-18. https://doi.org/10.1155/2021/8878011

Barodi, A., Zemmouri, A., Bajit, A., Benbrahim, M., & Tamtaoui, A. (2023). Intelligent transportation system based on smart soft-sensors to analyze road traffic and assist driver behavior applicable to smart cities. *Microprocessors and Microsystems*, 100, 104830. https://doi.org/10.1016/j.micpro.2023.104830

Benterki, A., Boukhnifer, M., Judalet, V., & Maaoui, C. (2020). Artificial intelligence for vehicle behavior anticipation: Hybrid approach based on maneuver classification and trajectory prediction. *IEEE Access*, 8, 56992–57002. https://doi.org/10.1109/access.2020.2982170

Bıyık, C., & Yigitcanlar, T. (2020). Intelligent transport systems in Turkish urban environments: a comprehensive review. *International Journal of Knowledge-Based Development*, 11(4), 382. https://doi.org/10.1504/ijkbd.2020.115037

Chavhan, S., Gupta, D., Chidambaram, R.K., Khanna, A., & Rodrigues, J.J.P.C. (2021). A novel emergent intelligence technique for public transport vehicle allocation problem in a dynamic transportation system. *IEEE IEEE Transactions on Intelligent Transportation Systems*, 22(8), 5389–5402. https://doi.org/10.1109/tits.2020.3011198

Chen, Z.G., Zhan, Z.H., Kwong, S., & Zhang, J. (2022). Evolutionary computation for intelligent transportation in smart cities: *A survey [review article]. IEEE Computational Intelligence Magazine*, 17(2), 83–102. https://doi.org/10.1109/mci.2022.3155330

Chowdhury, A., Kaisar, S., Khoda, M.E., Naha, R., Khoshkholghi, M.A., & Aiash, M. (2023). IoT-based emergency vehicle services in

Intelligent transportation system. *Sensors (Basel, Switzerland)*, 23(11), 5324. https://doi.org/10.3390/s23115324

Damaj, I., Al Khatib, S.K., Naous, T., Lawand, W., Abdelrazzak, Z.Z., & Mouftah, H.T. (2022). Intelligent transportation systems: A survey on modern hardware devices for the era of machine learning. *Journal of King Saud University-Computer and Information Sciences*, 34(8), 5921–5942. https://doi.org/10.1016/j.jksuci.2021.07.020

Eom, M., & Kim, B.I. (2020). The traffic signal control problem for intersections: A review. *European Transport Research Review*, 12(1), 50. https://doi.org/10.1186/s12544-020-00440-8

Haghighat, A.K., Ravichandra-Mouli, V., Chakraborty, P., Esfandiari, Y., Arabi, S., & Sharma, A. (2020). Applications of deep learning in intelligent trans- portation systems. *Journal of Big Data Analytics in Transportation*, 2(2), 115–145. https://doi.org/10.1007/s42421-020-00020-1

Husnain, G., Anwar, S., Sikander, G., Ali, A., & Lim, S. (2023). A bio-inspired cluster optimization schema for efficient routing in vehicular ad hoc networks (VANETs). *Energies*, 16(3), 1456. https://doi.org/10.3390/en16031456

Iliopoulou, C., & Kepaptsoglou, K. (2019). Combining ITS and optimization in public transportation planning: state of the art and future research paths. *European Transport Research Review*, 11(1), 27. https://doi.org/10.1186/s12544-019-0365-5

Jain, R., Chakravarthi, M.K., Kumar, P.K., Hemake-Savulu, O., Ramirez-Asis, E., Pelaez-Diaz, G., *et al*. (2022). Internet of Things-based smart vehicles design of bio-inspired algorithms using artificial intelligence charging system. *Nonlinear Engineering*, 11(1), 582–589. https://doi.org/10.1515/nleng-2022-0242

Karthikeyan, H., & Usha, G. (2023). A secured IoT-based intelligent transport system (IoT-ITS) framework based on cognitive science. *Soft Computing*, 28, 13929–13939. https://doi.org/10.1007/s00500-023-08410-7

Kołodziej, J., Hopmann, C., Coppa, G., Grzonka, D., & Widłak, A. (2022). Intelligent transportation systems-models, challenges, security aspects. In: *Cybersecurity of Digital Service Chains*. Berlin: Springer International Publishing. pp56–82.

Kumari, S., Kumari, S., Vikram, V., Kumari, S., & Gouda, S.K. (2020). Smart traffic management system using IoT and machine learning approach. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.3647656

Lee, S., Lim, D.E., Kang, Y., & Kim, H.J. (2021). Clustered multi-task sequence-to-sequence learning for autonomous vehicle repositioning. *IEEE Access*, 9, 14504–14515. https://doi.org/10.1109/access.2021.3051763

Li, C., Zhao, H., Huang, K., & Chen, Y.H. (2021). Optimal design for anti-skid control of electric vehicles by fuzzy approach. *Chinese Journal of Me-Chanical Engineering*, 34(1), 125. https://doi.org/10.1186/s10033-021-00642-8

Li, S., Shu, K., Chen, C., & Cao, D. (2021). Planning and decision-making for connected autonomous vehicles at road intersections: A review. *Chinese Journal of Mechanical Engineering*, 34(1), 133. https://doi.org/10.1186/s10033-021-00639-3

Liu, Y., Xu, Q., Guo, H., & Zhang, H. (2022). A type-2 fuzzy approach to driver-automation shared driving lane keeping control of semi-autonomous vehicles under imprecise premise variable. *Chinese Journal of Mechanical Engineering*, 35(1), 46. https://doi.org/10.1186/s10033-022-00706-3

Lu, Y., Lang, M., Sun, Y., & Li, S. (2020). A fuzzy intercontinental road-rail multimodal routing model with time and train capacity uncertainty and fuzzy programming approaches. *IEEE Access*, 8, 27532–27548. https://doi.org/10.1109/access.2020.2971027

Lytras, M.D., Chui, K.T., & Liu, R.W. (2020). Moving towards intelligent transportation via artificial intelligence and internet-of-things. *Sensors (Basel, Switzerland)*, 20(23), 6945. https://doi.org/10.3390/s20236945

Malek, Y. N., Najib, M., Bakhouya, M., & Essaaidi, M. (2021). Multivariate deep learning approach for electric vehicle speed forecasting. *Big Data Min. Anal*., 4(1), 56–64. https://doi.org/10.26599/bdma.2020.9020027

Mohammadi, S., & Farahani, G. (2020). Computational intelligence-based connectivity restoration in wireless sensor and actor networks. *EURASIP Journal on Wireless Communications and Networking*, 2020(1), 198. https://doi.org/10.1186/s13638-020-01831-0

Njoku, J.N., Nwakanma, C.I., Amaizu, G.C., & Kim, D.S. (2023). Prospects and challenges of Metaverse application in data-driven intelligent transportation systems. *IET Intelligent Transport Systems,* 17(1), 1–21. https://doi.org/10.1049/itr2.12252

Ojala, R., Vepsalainen, J., Hanhirova, J., Hirvisalo, V., & Tammi, K. (2020). Novel convolutional neural network-based roadside unit for accurate pedestrian localisation. *IEEE Transactions on Intelligent Transportation Systems,* 21(9), 3756–3765. https://doi.org/10.1109/tits.2019.2932802

Qadri, S.S.S.M., Gökçe, M.A., & Öner, E. (2020). State-of-art review of traffic signal control methods: Challenges and opportunities. *European Transport Research Review*, 12(1), 1-23. https://doi.org/10.1186/s12544-020-00439-1

Rajkumar, S.C., & Deborah, L.J. (2021). An improved public transportation system for effective usage of vehicles in intelligent transportation system. *International Journal of Communication Systems*, 34(13), e4910. https://doi.org/10.1002/dac.4910

Sayed, S. A., Abdel-Hamid, Y., & Hefny, H.A. (2023). Artificial intelligence-based traffic flow prediction: A comprehensive review. *Journal of Electrical Systems and Information Technology*, 10(1), 13. https://doi.org/10.1186/s43067-023-00081-6

Servizi, V., Pereira, F.C., Anderson, M.K., & Nielsen, O.A. (2021). Transport behavior-mining from smartphones: A review. *European Transport Research Review*, 13(1), 57. https://doi.org/10.1186/s12544-021-00516-z

Severino, A., Curto, S., Barberi, S., Arena, F., & Pau, G. (2021). Autonomous Vehicles: An analysis both on their distinctiveness and the potential impact on urban transport systems. *Applied Sciences (Basel, Switzerland)*, 11(8), 3604. https://doi.org/10.3390/app11083604

Shaaban, K., Elamin, M., & Alsoub, M. (2021). Intelligent transportation systems in a developing country: Benefits and challenges of implementation. *Transportation Research Procedia*, 55, 1373–1380. https://doi.org/10.1016/j.trpro.2021.07.122

Sharma, V., Kumar, L., & Sergeyev, S. (2021). Recent developments and challenges in intelligent transportation systems (ITS)-A survey. In: *Algorithms for Intelligent Systems*. Berlin: Springer Singapore. pp37–44.

Shi, Q., Wang, M., He, Z., Yao, C., Wei, Y., & He, L. (2022). A fuzzy-based sliding mode control approach for acceleration slip regulation of battery electric vehicle. *Chinese Journal of Mechanical Engineering*, 35(1), 72. https://doi.org/10.1186/s10033-022-00729-w

Simić, V., Lazarević, D., & Dobrodolac, M. (2021). Picture fuzzy WASPAS method for selecting last-mile delivery mode: A case study of Belgrade. *European Transport Research Review*, 13(1), 43. https://doi.org/10.1186/s12544-021-00501-6

Tak, S., Lee, J.D., Song, J., & Kim, S. (2021). Development of AI-based vehicle detection and tracking system for C-ITS application. *Journal of Advanced Transportation*, 2021, 1–15. https://doi.org/10.1155/2021/4438861

Tang, J., Zhang, X., Yin, W., Zou, Y., & Wang, Y. (2021). Missing data imputation for traffic flow based on combination of fuzzy neural network and rough set theory. *Journal of Intelligent Transportation Systems*, 25(5), 439–454. https://doi.org/10.1080/15472450.2020.1713772

Wei, H., Xu, N., Zhang, H., Zheng, G., Zang, X., Chen, C., *et al*. (2019). CoLight: Learning network-level cooperation for traffic signal control. In: *Proceedings of the 28th ACM International Conference on Information and Knowledge Management.*

Zhou, F., Yang, Q., Zhong, T., Chen, D., & Zhang, N. (2021). Variational graph neural networks for road traffic prediction in intelligent transportation systems. *IEEE Transactions on Industrial Informatics*, 17(4), 2802–2812. https://doi.org/10.1109/tii.2020.3009280

Zulkarnain, & Putri, T.D. (2021). Intelligent transportation systems (ITS): A systematic review using a Natural Language Processing (NLP) approach. *Heliyo*n, 7(12), e08615. https://doi.org/10.1016/j.heliyon.2021.e08615

DOI: 10.6977/IJoSI.202506_9(3).0003
I. Appaji, P. Raviraj/Int. J. Systematic Innovation, 9(3), 20-30 (2025)

AUTHORS BIOGRAPHIES

Impana Appaji holds an M.Tech in Software Engineering, Post-Graduation from SJCE Mysuru, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, INDIA in 2014. She also received a B.E. degree in Computer Science from GSSSIETW, Mysuru, and was affiliated with Visvesvaraya Technological University, Belagavi, Karnataka, India, in 2009. She has 13 years of Teaching Experience. She is currently working as a Senior Analyst at Infosys. She has published 12 research papers in international journals and conferences from 2009 to 2023. She can be contacted at email: impana.appaji@gmail.com.

Dr. Raviraj Pandian completed his doctorate degree in Computer Science and Engineering in the area of Image Processing. He holds the position of Professor and Head in the Department of Computer Science and Engineering, GSSS Institute of Engineering and Technology for Women, Mysore. In addition, he also serves as an IQAC Director at GSSS Institute of Engineering and Technology for Women, Mysore. He has 16 years of teaching and research experience and has published over 90 papers in International journals and conferences and 8 book chapters. He serves as an Editorial Board Member and Reviewer for over 15 International Journals. He is also a life member of professional bodies such as ISTE and CSI. He has been guiding Ph.D. research scholars in the areas of Image Processing, Pervasive and Cloud Computing, Bio-Inspired Algorithms, and Robotics. He received a project grant of Rs 5 Lakhs from the VGST, Government of Karnataka for the "Underwater Robotic Fish for Surveillance and Pollution monitoring." He served as the chairperson and keynote speaker for many National and International Conferences and as a Board of Studies member, Subject expert, and Ph.D thesis evaluator for various universities and autonomous institutions. He has reviewed many articles in International conference proceedings and journals. He has received various awards such as "Rhastriya Gaurav Award-2015," "Shri P.K.Das Memorial Best Faculty Award-2012," "Young Achiever Award-2016," and "Best Circuit Faculty Finalist Award-2017" for his outstanding academic achievements and contributions.