Adaptive Traffic Signal Control System using Gradiant Boosting Regressor Model

Rajdip Kundu[1], Sayandeep Mondal[2], Saikat Roy[3], Ushnish Pal[4] and Md Ashifuddin Mondal[5][0000-0001-6642-703X]

[1,2,3,4,5] Narula Institute of Technology, Agarpara, Kolkata, West Bengal 700109

Abstract. For efficient traffic flow and to reduce congestion, traffic signal timing optimization is essential in traffic management. While the static traffic signal control systems can maintain traffic flow to some extent under stable and predictable conditions, they often fail to predict traffic in dynamic and changing environments. To overcome these limitations, this paper focuses on an adaptive as well as an advanced adaptive traffic signal control system that dynamically modifies signal timings in response to current traffic conditions. The proposed adaptive and advanced adaptive traffic signal control systems have trained Gradient Boosting Regression models that predict green time of each lane by application of Linear Regression and Gradient Boosting machine learning algorithms. The advanced adaptive traffic signal control system also considers the upcoming vehicles and predicts an overall green time for the present and upcoming vehicles on each lane. A multivariate dataset has been used to train both the adaptive and advanced adaptive system using Gradient Boosting Regression models. The simulation result shows that the static traffic signal control system is outperformed by the adaptive and advanced adaptive systems as these systems reduce excess green time and increase vehicle throughput contributing to better traffic flow.

Keywords: Adaptive Traffic Signal, Adaptive Traffic Signal Control, Linear regression, Gradient boosting, Machine Learning.

1 Introduction

The alarming rise in traffic accidents and congestion has become a pressing concern in urban centers worldwide. Statistics indicate that over 1.3 million people lose their lives in road accidents globally each year, with many more sustaining serious injuries [1]. Additionally, traffic congestion costs economies billions of dollars annually through lost productivity, wasted fuel, and environmental degradation [2].

Traditional fixed-time traffic signal control systems, while widely implemented, often fail to adequately address the dynamic and unpredictable nature of traffic flow. These rigid systems operate on predetermined signal timings, unable to adapt to fluctuations in vehicle volumes, road conditions, or unexpected events. As a result, traffic jams, delays, and sub optimal intersection performance persist, despite the presence of traffic signals [3].

To overcome the limitations of static signal control, researchers have turned to the development of adaptive traffic management systems. These innovative approaches leverage advanced technologies and machine learning algorithms [4] to dynamically adjust signal timings based on real-time traffic data. By continuously monitoring and predicting traffic patterns, adaptive systems can optimize intersection performance, minimize congestion, and enhance overall traffic flow.

This research paper proposes the implementation of a gradient boosting Regression based adaptive traffic signal control system. By incorporating real-time data and a dynamic learning framework, the system can adapt to evolving traffic conditions, offering a more responsive and efficient alternative to traditional fixed-time control methods. The study aims to demonstrate the superiority of the adaptive approach in handling diverse traffic scenarios, including unexpected disruptions, and provide insights for the practical deployment of such systems in urban transportation networks.

The rest of the paper presents as follows. “Literature Survey” discusses the works related to the Adaptive Traffic Signal Control system (ATSC). “Proposed Methodology” shows the working of the ATSC and advanced ATSC. “Simulation and Result Analysis” presents the simulation and result analysis of the ATSC and advanced ATSC. Finally, “Conclusion” gives a closure to this paper.

2 Literature Survey

Designing adaptive traffic signal systems has gathered significant interest among researchers due to its importance in managing traffic congestion at intersections. Traffic light control systems play a crucial role in maintaining traffic flow at junctions, that is the reason it is a key element of traffic management systems [5]. The traditional fixed-time traffic signal control system operates by cycling through green, red, and amber lights in a fixed sequence, with predefined durations for each signal. While suitable for steady traffic, this approach is less effective for handling unpredictable and irregular traffic patterns [6].

Researchers have utilized data, such as that found in [7-8], which contains comprehensive datasets of traffic sensor measurements and signal timing information for several intersections within the city. ATSC methods have been categorized based on various factors including topographic structure, decision-making time resolution, type of decision, objective function, cyclic/acyclic nature, and subcategories [9].

Addressing the complexity of urban traffic systems, researchers in [10] presented a linear programming approach to adjust green signal times based on average waiting time and vehicle density. Additionally, to facilitate real-time traffic flow analysis, several IoT-based Congestion Control Frameworks for Intelligent Traffic Management Systems have been proposed [11].

In [12], a mixed-integer linear programming (MILP) formulation was provided to represent the Network-level multiband signal coordination scheme based on vehicle trajectory data (NMBSC). Another widely adopted approach involves the use of machine learning models to predict traffic patterns and optimize signal timing [4]. Models such as Neural Networks, Q-Learning, Deep Reinforcement Learning, and Neuro-fuzzy Inference systems have been utilized to maximize traffic flow rate while minimizing average delay and total travel time.

For example, [13] implemented a Q-learning-based reinforcement learning model to dynamically adjust signal timings based on real-time traffic data, resulting in reduced delays and increased throughput. Similarly, another paper proposed a reinforcement and multi-agent reinforcement learning framework for coordinated ATSC [14-15], where each intersection's signal controller learns to optimize its timings based on the collective behavior of the network.

While the papers [16-18] highlights different use cases of gradient boosting algorithm, the current research aims to contribute to the existing body of knowledge by utilizing a gradient boosting regression model to demonstrate techniques for achieving adaptive traffic signal control.

3 Proposed Methodology

This section presents the detailed methodology of our ATSC and advanced ATSC. This paper proposes a Gradient Boosting Regression approach which dynamically optimizes green signal duration of each lane based on factors such as vehicle capacity, cycle time, waiting time, flow ratio and time of day in order to reduce excess green time and increase vehicle throughput.

3.1 Overview of the system

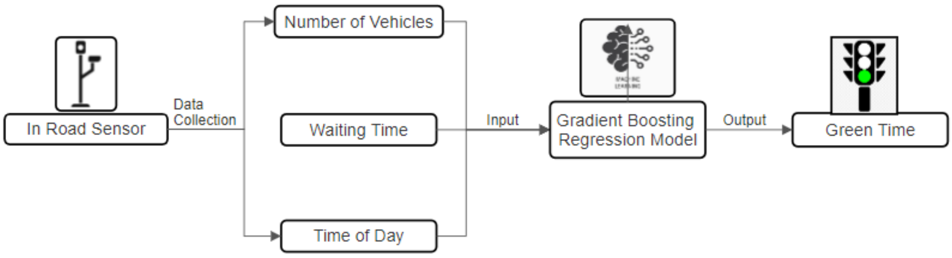

Fig. 1 Block Diagram of the Proposed System

The proposed system for adaptive and advanced adaptive traffic signal control has been presented in Fig. 1. The system makes use of real-time information gathered from advanced sensor technologies and passes the information to the processing unit which controls signal timings. This data includes number of vehicles of each lane, waiting time and the time of day. Using the observed traffic conditions, a machine learning algorithm called the Gradient Boosting Regression model uses this data as input to predict green time for each lane. In the advanced adaptive traffic signal control system, the observed data also includes the upcoming number of vehicles of each lane. The advanced adaptive traffic signal system thus uses Gradient Boosting Regression models in order to predict an overall green time of each lane from their present and upcoming green times. The system uses this predictive model to dynamically modify the timing of signals including cycle time to reduce traffic jams and enhance traffic flow across the entire road network. The system can efficiently allocate resources to prioritize high traffic directions, minimize excess green time at intersections, increase vehicle passing capacity and improve overall transportation efficiency by optimizing green times based on current traffic.

3.2 Overview of Gradient Boosting

In this section, the detailed methodology of the proposed work is described. The basic building block of the proposed technique is Gradient Boosting Regression Model of Machine Learning. Gradient Boosting Regression is a machine learning technique that builds models for classification and regression problems step-by-step. In order to improve the accuracy of the model, this ensemble learning technique combines predictions from several baseline estimators; most commonly decision trees [16]. The algorithm starts with an initial model and, to correct the errors generated by earlier models, introduces a new base learner (usually a decision tree) at each iteration. Using the residuals from previous predictions, the new model is trained, and the loss function is minimized using gradient descent optimization with the new base learner's parameters [15]. In [17], it is said the base learner of gradient boosting algorithm is CART (Classification and Regression Trees).

Assuming N number of trees. Tree1 is trained using labels y and feature matrix X. Training set residual errors, s1, are calculated using predicted labels y1(hat). Then Tree2 is trained using labels from Tree1's residual errors, s1, along with feature matrix X. Residual s2 is determined using predicted outcomes s1(hat). This process repeats until all M trees are trained.

$$y(pred) = y1 + (eta * s1) + (eta * s2) + \ldots\ldots. + (eta * rN) \qquad \ldots\ldots(i)$$

The equation is used to estimate the final prediction.

Algorithm

Step 1: Assuming p and q are the input and target having X samples. The goal is to learn the function f(p) that maps the input features p to the target variables q. The boosted trees (i.e. the sum of trees). The loss function is the difference between the actual and the predicted variables.

$$L(f) = \sum_{i=1}^{X} L(q_i, f(p_i)) \qquad \dots\dots(ii)$$

Step 2: minimizing the loss function L(f) with respect to f.

$$\widehat{f_0}(p) = \min L(f) = \min \sum_{i=1}^{X} L(q_i, f(p_i)) \quad \dots\dots(iii)$$

If our gradient boosting algorithm is in K stages then To improve the f_k the algorithm can add some new estimator as h_k having $1 \le k \le K$

$$\widehat{q_i} = F_{k+1}(p_i) = F_k(p_i) + h_k(p_i) \qquad \dots\dots(iv)$$

Step 3: For M stage gradient boosting, the steepest Descent finds $h_k = -\rho_k g_k$. Where ρ_k is constant and known as step length and g_k. is the gradient of loss function L(f)

$$g_{ik} = -\left[\frac{\delta L(q_i,\ f(p_i))}{\delta f(p_i)}\right]_{f(p_i)=f_{k-1}(p_i)} \qquad \dots\dots(v)$$

Step 4: Solution

The gradient Similarly for K trees:

$$f_k(p) = f_{k-1}(p) + \left(\min\left[\sum_{i=1}^{X} L(q_i,\ F_{k-1}(p_i) + h_k(p_i))\right]\right)(p) \qquad \dots\dots(vi)$$

The current solution will be

$$f_k(p) = f_{k-1}(p) - \rho_k g_k \qquad \dots\dots(vii)$$

3.3 Working Procedure

This section presents the working procedure of the ATSC and advanced ATSC. It shows how the system relies on the Gradient Boosting Regression technique for the prediction of green signal duration after the processing unit receives data from in road sensor technologies.

Working of the adaptive traffic signal control system.

The working procedure of the ATSC is shown in Fig 2. A Gradient Boosting Regressor model is used by this adaptive system to forecast the green times for each lane (EW and NS lanes) based on current vehicle counts, cycle times, flow ratios, and the time of day. In order to forecast green times of each lane, it counts the maximum number of vehicles that can pass through the EW and NS lanes. The predicted green time of one lane becomes the current waiting time for the other lane. The prediction of green times of both lanes marks the completion of one cycle. For example, if we consider that the predicted green time of NS lane marked the completion of the cycle, then it becomes the current waiting time for the EW lane in the next cycle. This process is repeated, effectively adjusting traffic patterns and optimizing signal timings. This concludes the working of the adaptive traffic signal control system.

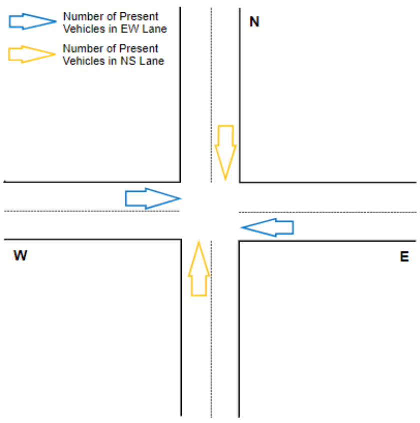

Fig. 2 Adaptive Traffic Signal Control System

Working of the advanced adaptive traffic signal control system

The working procedure of the advanced ATSC is shown in Fig 3. In this system, two Gradient Boosting Regressor models are used to forecast the green time based on both present and upcoming number of vehicles in each lane. Following a single cycle, it forecasts green times of each lane based on present and upcoming vehicle counts, cycle times, flow ratios and time of day. One of the Gradient Boosting Regressor models predicts the green time for current vehicles while the other one predicts the green time for the upcoming vehicles on each lane. Through this method, signal timings are efficiently optimized in both directions.

In this system, a lane's final green time is determined by two factors: average is calculated if present exceeds upcoming, and present time is maintained to avoid longer waiting times if present exceeds upcoming. This demonstrates how versatile Gradient Boosting is in managing intricate datasets and effectively maximizing traffic flow. All things considered, the system dynamically adjusts, improving traffic efficiency and easing congestion. This concludes the working of the advanced adaptive traffic signal control system.

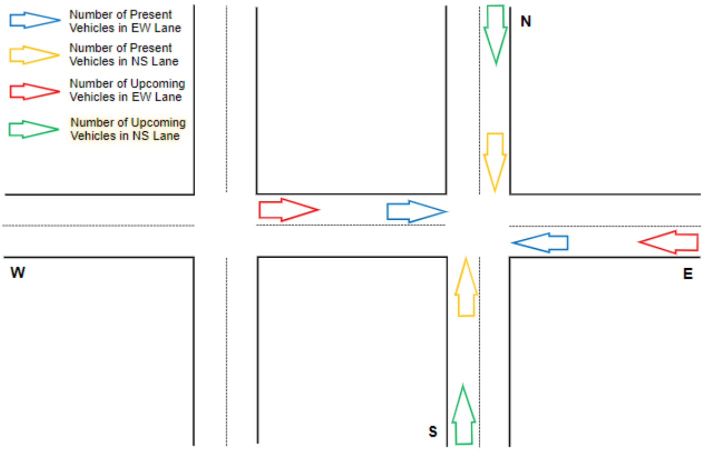

Fig. 3 Advance Adaptive Traffic Signal Control System

4 Simulation and Result Analysis

This section presents the simulation and result analysis of the proposed adaptive and advanced adaptive traffic signal control system. The simulation has been done based on Python. The result of the proposed system has been compared with the static traffic signal control system.

4.1 Simulation of the proposed system

In this section, the simulation of the adaptive and advanced adaptive traffic signal has been performed using Python. The simulation scenario has been presented in Table 1.

Table 1 Simulation scenario

Number of present vehicles				Number of upcoming vehicles			
Lane 1	Lane 2	Lane 3	Lane 4	Lane 1	Lane 2	Lane 3	Lane4
12	76	48	12	76	12	76	76

The simulation contrasts an advanced adaptive traffic signal control system with an adaptive one. Based solely on the number of vehicles that are currently on the road, the adaptive traffic signal control system predicts green times using Gradient Boosting Regression technique. The system first determines the maximum number of vehicles from each lane and then based on the factors of cycle time, waiting time, flow ratio and time of day, it calculates the green times for lanes 1-3 and 2-4 in turn, which adds up to an overall excess green time of 13 seconds. This system does not account for upcoming vehicles and permits 148 vehicles to pass. On the other hand, the advanced adaptive traffic signal control system employs two Gradient Boosting Regression models to forecast the green times for present and upcoming vehicles. Similar to the adaptive system, it determines the average green times for lanes 1-3 and 2-4 from their present and upcoming green times, adding up to 24 seconds of excess green time overall. In comparison to the adaptive system, this one allows 196 vehicles to pass, including those that are approaching, demonstrating superior efficiency and throughput. Therefore, the advanced ATSC can anticipate and adjust to approaching traffic, even with a small delay, which improves intersection performance.

4.2 Performance Metrics

To analyze the performance of the adaptive and advanced adaptive traffic signal control system, the paper considers the following metrics and compares the performance with the static traffic signal control system:

Excess green time
Reduction in excess green time can minimize delays and result in better traffic flow.

Vehicle throughput
Higher vehicle throughput results in shorter travel times, less traffic and increased system efficiency.

$$vehicle\ throughput\ = \frac{number\ of\ vehicles\ passed}{time} \quad \dots\dots(viii)$$

4.3 Performance Analysis

To analyze the performance of the different traffic signal systems, the concepts of even and uneven traffic scenarios have been considered and now lets us see how these static, adaptive and advanced adaptive traffic signal control systems handle these situations.

Table 2 Scenario 1 (Even traffic distribution)

Number of present vehicles				Number of upcoming vehicles			
Lane 1	Lane 2	Lane 3	Lane 4	Lane 1	Lane 2	Lane 3	Lane 4
12	12	12	12	12	12	12	12
48	48	48	48	12	12	76	76
48	12	76	76	76	76	12	48
30	25	35	28	35	25	28	30
40	38	42	44	28	35	40	38
:	:	:	:	:	:	:	:

Table 3 Scenario 2 (Uneven traffic distribution)

Number of present vehicles				Number of upcoming vehicles			
Lane 1	Lane 2	Lane 3	Lane 4	Lane 1	Lane 2	Lane 3	Lane 4
12	48	76	12	12	12	12	12
12	76	48	12	76	12	76	76
76	48	48	48	76	76	12	48
12	76	12	76	12	76	12	76
12	48	12	76	76	12	76	12
:	:	:	:	:	:	:	:

The even and uneven traffic distribution scenarios have been presented in Table 2 and Table 3 respectively. Static traffic signal control systems perform best with fixed timing plans in even traffic scenarios, when vehicles are evenly distributed. This reduces excess green time and maximizes vehicle throughput. These systems ensure smooth traffic flow and lessen the chance of congestion by providing consistent and predictable timing plans. Even though there might be small differences, static systems handle them well. In a similar vein, adaptive and advanced adaptive traffic signal control systems are also capable of effectively controlling even traffic distribution. However, they might not require frequent modifications even though they are more dynamic and can modify timing plans in response to shifting traffic conditions. Even in situations where traffic is distributed evenly, these systems can still maintain an efficient flow. Tables 4, 5 and 6 show the variations in excess green time and vehicle throughput based on even traffic distribution scenarios in static, adaptive and advanced adaptive systems respectively.

Table 4 Determination of excess green time and vehicle throughput based on Scenario 1 (static system)

Lane 1-3 Green Time	Lane 2-4 Green Time	Total Excess Green Time	Total Cycle Time	Total Present Vehicle Throughput	Total Vehicle Throughput
60	60	96	120	48	48
60	60	24	120	192	192
60	60	0	120	180	180
60	60	57	120	118	118
60	60	34	120	164	164
:	:	:	:	:	:

Table 5 Determination of excess green time and vehicle throughput based on Scenario 1 (adaptive system)

Lane 1-3 Green Time	Lane 2-4 Green Time	Total Excess Green Time	Total Cycle Time	Total Present Vehicle Throughput	Total Vehicle Throughput
28	27	31	55	48	48
55	56	15	111	192	192
81	81	10	162	212	212
40	35	12	75	118	118
45	48	7	93	164	164
:	:	:	:	:	:

Table 6 Determination of excess green time and vehicle throughput based on Scenario 1 (advanced adaptive system)

Lane 1-3 Green Time	Lane 2-4 Green Time	Total Excess Green Time	Total Cycle Time	Total Present Vehicle Throughput	Total Vehicle Throughput
28	28	32	56	48	96
67	69	40	136	192	256
80	85	13	165	212	238
38	33	8	71	118	134
44	46	4	90	164	172
:	:	:	:	:	:

Assessing the data in Table 3, we can see that the number of present and upcoming vehicles in lane 1-3 and lane 2-4 have a significantly large difference. Fixed phase durations in a static traffic signal control system can result in excess green time even in directions with little traffic, which can cause delays and inefficiencies. Insufficient real-time adjustments lead to traffic jams in busy areas and inefficient use of green time during periods of low traffic. On the other hand, real-time data and predictive Gradient Boosting Regressor models are used by adaptive and advanced adaptive traffic signal control systems to dynamically modify signal timings, improving traffic flow and reducing congestion. By adjusting cycle lengths and allocating green time in accordance with actual traffic demand, these systems can decrease excess green time in underutilized directions and increase it where necessary. The adaptive and advanced adaptive systems maximize vehicle throughput and ensure smooth intersection movement by continuously adapting to changing traffic conditions. Because of its flexibility, drawbacks of static systems are addressed and traffic flow is improved. It also improves overall traffic management and resource utilization. Tables 7, 8 and 9 show the variations in excess green time and vehicle throughput based on uneven traffic distribution scenarios in static, adaptive and advanced adaptive systems respectively.

Table 7 Determination of excess green time and vehicle throughput based on Scenario 2 (static system)

Lane 1-3 Green Time	Lane 2-4 Green Time	Total Excess Green Time	Total Cycle Time	Total Present Vehicle Throughput	Total Vehicle Throughput
60	60	12	120	132	132
60	60	12	120	132	132
60	60	12	120	204	204
60	60	48	120	144	144
60	60	48	120	132	132
:	:	:	:	:	:

Table 8 Determination of excess green time and vehicle throughput based on Scenario 2 (adaptive system)

Lane 1-3 Green Time	Lane 2-4 Green Time	Total Excess Green Time	Total Cycle Time	Total Present Vehicle Throughput	Total Vehicle Throughput
81	56	13	137	148	148
56	81	13	137	148	148
81	55	12	136	220	220
20	80	12	100	176	176
18	80	10	98	148	148
:	:	:	:	:	:

Table 9 Determination of excess green time and vehicle throughput based on Scenario 2 (advanced adaptive system)

Lane 1-3 Green Time	Lane 2-4 Green Time	Total Excess Green Time	Total Cycle Time	Total Present Vehicle Throughput	Total Vehicle Throughput
80	57	13	137	148	174
68	80	24	148	148	196
80	67	23	147	220	266
22	81	15	103	176	206
50	81	43	131	148	234
:	:	:	:	:	:

Fig. 4, 5 and 6 clearly shows that the adaptive and advanced adaptive traffic signal control systems outperform the static traffic signal control system. The proposed ATSC and advanced ATSC have a lot to offer over static traffic signal control system in terms of excess green time as shown in Fig. 4 and vehicle throughput as shown in Fig. 5 and 6. The adaptive and advanced adaptive systems, as opposed to static ones, dynamically modify signal timings in response to current traffic conditions, minimizing excess green time by effectively allocating green time to meet actual traffic demand. Delays are decreased and traffic flow is improved because of this optimization. Furthermore, the adaptive and advanced adaptive systems give priority to directions with higher demand or volume of traffic, maximizing the number of vehicles. that can pass through intersections in each amount of time. In summary, the adaptive and advanced adaptive approach guarantees improved traffic control, reduces traffic, and boosts transportation effectiveness, all of which contributes to a better driving experience for drivers.

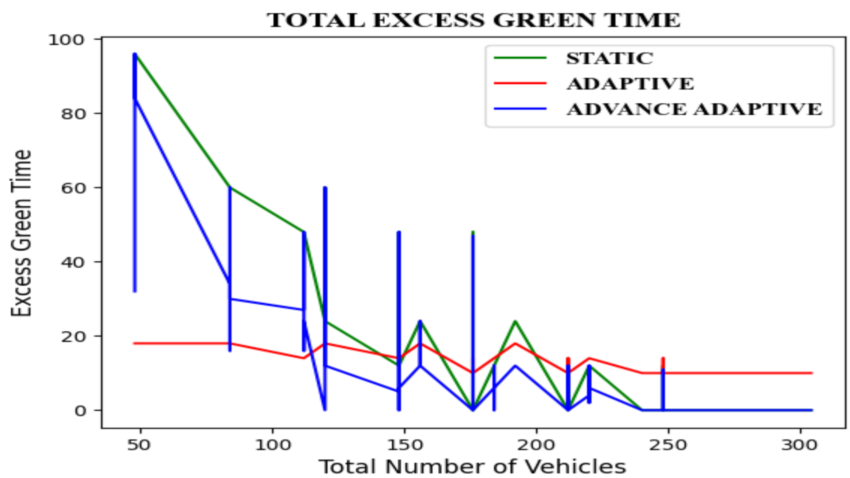

Fig. 4 Graphical analysis of total excess green time with respect to variable scenarios

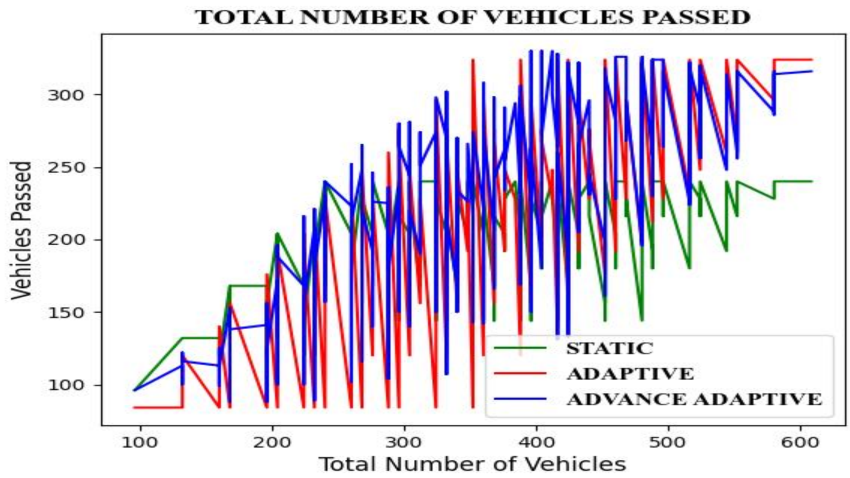

Fig. 5 Graphical analysis of total vehicle throughput with respect to variable scenarios

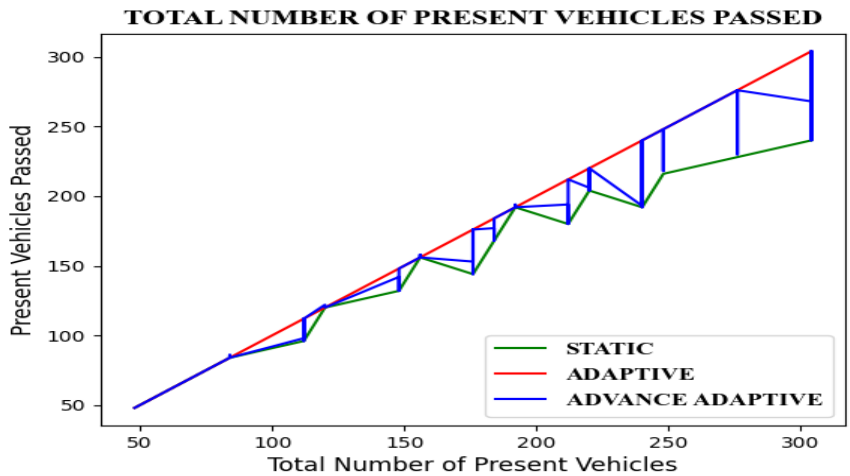

Fig. 6 Graphical analysis of present vehicle throughput with respect to variable scenarios

5 Conclusion

The enormous potential of adaptive traffic signal control system using cutting edge machine learning techniques specifically Gradient Boosting Regression has been brought to light by this research. This paper proposes an adaptive and an advanced adaptive traffic signal control system using Gradient Boosting Regression models which will predict green time for each lane taking into consideration a variety of factors such as number of vehicles on each lane, cycle length, waiting time, flow ratio and time of day. The advance adaptive traffic signal system also considers the green time for the upcoming vehicles and predicts an overall green time for each lane. These adaptive systems have a better performance than the static traffic signal control system as they dynamically modify signal timings and cycle length in response to current traffic conditions. From the simulation results, it is clearly seen that the proposed adaptive and advanced adaptive traffic signal control systems outperform the static traffic signal control system by increasing vehicle throughput and decreasing overall excess green time, thus ensuring more effective traffic management and minimizing congestion, ultimately improving drivers' overall driving experience. Hence, application of these proposed adaptive systems will gradually improve traffic flow in urban areas

6 References

[1] Sharma, B. R. (2008). Road traffic injuries: A major global public health crisis. Public Health, 122(12), 1399–1406. https://doi.org/10.1016/j.puhe.2008.06.009

[2] Ponweiser, W. (2018). ECTRI Position Paper "Zero crashes, zero congestion, and zero emissions - Future Research in Traffic Management". In ECTRI Position Paper "Zero crashes, zero congestion, and zero emissions - Future Research in Traffic Management"

[3] Tomar, Ishu & Sreedevi, Indu & Pandey, Neeta. (2022). Traffic Signal Control Methods: Current Status, Challenges, and Emerging Trends. https://doi.org/10.1007/978-981-16-6289-8_14

[4] R M, Savithramma & Ranganathaiah, Sumathi & H S, Sudhira. (2022). A Comparative Analysis of Machine Learning Algorithms in Design Process of Adaptive Traffic Signal Control System. Journal of Physics: Conference Series. https://doi.org/10.1088/1742-6596/2161/1/012054

[5] Mondal, M.A., Rehena, Z. Priority-Based Adaptive Traffic Signal Control System for Smart Cities. *SN COMPUT. SCI.* **3**, 417 (2022). https://doi.org/10.1007/s42979-022-01316-5

[6] Wided, Ali. (2023). Traffic Management system and Traffic Light Control in Smart City to Reduce Traffic Congestion. International Journal of Automation and Smart Technology. 13. https://gigvvy.com/journals/ausmt/articles/ausmt-2023. https://doi.org/10.5875/ausmt.v13i1.2464.

[7] Yan, Huimin & Yu, Jiaying & Li, Meng & Wang, Yinhai & He, Fang. (2019). Network-level multiband signal coordination scheme based on vehicle trajectory data. Transportation Research Part C Emerging Technologies. 107. 266-286. https://doi.org/10.1016/j.trc.2019.08.014

[8] Eddelbüttel, J., and M. Cremer. "A new algorithm for optimal signal control in congested networks." Journal of Advanced Transportation 28.3 (1994): 275-297. https://doi.org/10.1002/atr.5670280307

[9] van Katwijk, Ronald & De Schutter, Bart & Hellendoorn, J (2006). Traffic adaptive control of a single intersection: A taxonomy of approaches.

[10] Eddelbüttel, J. and Cremer, M., 1994. A new algorithm for optimal signal control in congested networks. *Journal of Advanced Transportation*, *28*(3), pp.275-297. https://doi.org/10.1002/atr.5670280307.

[11] Mondal, M.A., Rehena, Z. (2021). An IoT-Based Congestion Control Framework for Intelligent Traffic Management System. In: Chiplunkar, N.N., Fukao, T. (eds) Advances in Artificial Intelligence and Data Engineering. AIDE 2019. Advances in Intelligent Systems and Computing, vol 1133. Springer, Singapore. https://doi.org/10.1007/978-981-15-3514-7_96

[12] Yan, Huimin & Yu, Jiaying & Li, Meng & Wang, Yinhai & He, Fang. (2019). Network-level multiband signal coordination scheme based on vehicle trajectory data. Transportation Research Part C Emerging Technologies. https://doi.org/10.1016/j.trc.2019.08.014

[13] Lu Shoufeng, L. Ximin and D. Shiqiang, "Q-Learning for Adaptive Traffic Signal Control Based on Delay Minimization Strategy," 2008 IEEE International Conference on Networking, Sensing and Control, Sanya, China, 2008, pp. 687-691, https://doi.org/10.1109/icnsc.2008.4525304

[14] A. M. Annaswamy, A. Guha, Y. Cui, S. Tang, P. A. Fisher and J. E. Gaudio, "Integration of Adaptive Control and Reinforcement Learning for Real-Time Control and Learning," in IEEE Transactions on Automatic Control, vol. 68, no. 12, pp. 7740-7755, Dec. 2023, https://doi.org/10.1109/TAC.2023.3290037

[15] Kuyer, L., Whiteson, S., Bakker, B., Vlassis, N. (2008). Multiagent Reinforcement Learning for Urban Traffic Control Using Coordination Graphs. In: Daelemans, W., Goethals, B., Morik, K. (eds) Machine Learning and Knowledge Discovery in Databases. ECML PKDD 2008. Lecture Notes in Computer Science (), vol 5211. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-87479-9_61

[16] Natekin, Alexey & Knoll, Alois. (2013). Gradient Boosting Machines, A Tutorial. Frontiers in neurorobotics. 7. 21. https://doi.org/10.3389/fnbot.2013.00021

[17] Shi, Yu & Li, Jian & Li, Zhize. (2018). Gradient Boosting With Piece-Wise Linear Regression Trees. https://doi.org/10.48550/arXiv.1802.05640

[18] D. Sangani, K. Erickson and M. A. Hasan, "Predicting Zillow Estimation Error Using Linear Regression and Gradient Boosting," 2017 IEEE 14th International Conference on Mobile Ad Hoc and Sensor Systems (MASS), Orlando, FL, USA, 2017, pp. 530-534, https://doi.org/10.1109/mass.2017.88