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RESEARCH ARTICLE

Proactive Traffic Light Signal Control using Attention Transformer

Ali Hameed Mohsin^{1,*}, Sayed Mahmood Sabt¹, Jasim Al Safran¹, and Jafla Al Ammari¹

¹College of Information Technology, University of Bahrain, Sukhair, Bahrain

Emails: amohsin@uob.edu.bh; s.mahmoodsabt@gmail.com; ps2009@hotmail.com; jalamdari@uob.edu.bh

* Corresponding author: Ali Hameed Mohsin (amohsin@uob.edu.bh)

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Abstract

Urban traffic congestion challenges existing fixed-time and reactive controllers. This paper proposes ProACT, a proactive traffic signal control framework that utilizes an attention-transformer architecture. By integrating real-time IoT traffic data with historical patterns, ProACT constructs spatio-temporal representations to enable early congestion detection. Furthermore, the framework captures long-range dependencies across adjacent intersections to proactively optimize signal phases. Evaluated using a traffic prediction dataset and the SUMO simulator across multiple intersections, ProACT reduced delays by over 50% under normal conditions and by more than 65% during rush hours compared to traditional controllers. These results demonstrate the potential of ProACT to improve intersection throughput, alleviate congestion, and support sustainable smart city development.

1. Introduction

The rapid growth of vehicles worldwide compared to the limited capabilities of the current roads has introduced a challenge for the transportation network. This challenge has caused many problems such as congestion, unpredictable travel time, and many violations of traffic laws. For instance, according to the data in (Transportation, 2024) there are around 42 thousand new vehicles has been registered in the kingdom of Bahrain in 2024 and in (organization c. i., 2022) there are 743 thousand active vehicles in Bahrain in 2022. This is not aligned with the development and road widening projects. While local data shows 743 thousand active vehicles in Bahrain, global traffic data from the World Health Organization (WHO) (organization W. H., 2023) and the World Bank (Bank, 2021) indicates that urban congestion is an escalating international crisis contributing to severe economic losses, elevated greenhouse gas emissions, and deteriorating public health. These factors lead to high traffic in many regions which impacts economic productivity, quality of life (Arti et al, 2022), elevated fuel consumption, and a rise in harmful gas emissions that affect the environment and public health (Sun et al, 2022). The traditional traffic management strategies which are based on fixed timing traffic light signals or sensors-based adjustments are no longer sufficient to address the highly dynamic nature of traffic flows.

The current technologies that are available, especially in intelligent transport systems (ITS), can contribute to

addressing a solution to the traffic problem. For instance, the internet of things (IoT) which is a group of small sensors and actuators that are connected to many devices and send information via internet, can provide highly monitoring and control capabilities to devices related to ITS such as surveillance cameras, traffic light controllers, and sensors that detect the flows of vehicles on the roads. Another available and rapidly growing technology in Artificial Intelligence (AI), which can process the data produced by IoT and make complex decisions to manage the traffic lights wisely and based on current and historical data. The combination of these two technologies could open the door to finding adaptive and dynamic intelligent traffic control solutions.

Attention transformer (Vaswani, 2017) is considered one of the most influential architectures in AI that provides long-range dependencies in sequential and structured data. The idea behind self-attention is to compute the contextual importance of each element within a sequence and enable the model to capture the relationships between elements much more effectively than traditional AI models. The structure of RNN and LSTM could provide faster training and enhancement in scalability. By using this model, the attention transformer can help in finding the most relevant temporal and spatial features in traffic data such as vehicle density, queue length, and waiting time. This ability allows us to better recognize congestion and optimize the traffic light signals in real time. In general, attention transformer offers a powerful framework to provide more efficient traffic flow management in order to

reduce travel times and improve urban mobility.

Intelligent and proactive traffic control analysis can contribute significantly to environmental sustainability. First, it will minimize vehicle idling which in turn will reduce the emissions of gas and the consumption of fuels. This will improve energy consumption. Second, it will reduce congestion which means the violation of traffic laws will be reduced and the travel time will be decreased significantly. This will help the community to have a better quality of life and avoid the anxiety and tensions that happen on the roads. Finally, the proposed model can be used as a practical tool for policymakers to have safer and sustainable urban environments.

The current studies are focusing on improving prediction accuracy, or having reactive traffic light controllers, some of them also focus on forecasting but without the use of the attention transformer mechanism which may change the results significantly. To fill this gap, this study introduces a model design to proactively control the traffic lights signal based on both IoT devices and an attention transformer mechanism. The design of the model will have the ability to capture long-term dependencies while focusing on contextually relevant temporal features to improve both accuracy and computation performance. The outcome of this research can offer an effective solution for urban traffic light control in ITS and support the pursuit of having a sustainable smart city.

The rest of this section will be the research problem and research objectives, and the remainder of this paper is divided as follows, section 2 is the literature review, section 3 is the research methodology and the proposed model, section 4 is the experimental results and discussion, and section 5 is the conclusion.

1.1 The research problem

Despite recent progress in Adaptive Traffic Signal Control (ATSC), current systems remain largely reactive, lack proactive spatial reasoning, and are brittle under partial observability caused by outages, unexpected congestion, and heterogeneous intersection designs. This limits their ability to pre-empt upstream induced congestion and maintain stable performance in real-world urban networks. The proposed solution is to design an attention-based transformer architecture that enables proactive traffic signal coordination while remaining robust to unexpected congestion and reducing travel time across dense city-scale networks.

1.2 The research objectives

The aim of this study is to design and evaluate a proactive traffic light signal controller framework using the attention-transformer for traffic forecasting. The objectives of the research are as follows:

1. To develop an attention-transformer model that can capture and forecast the traffic flow in intersections.

2. To design a proactive traffic light controller mechanism that uses predicted traffic from the attention-transformer model to automatically adjust the time and phase of the traffic light signal.
3. To evaluate the performance of the proposed framework using the dataset and simulation in terms of delay, queue length, and waiting time.

Contribution:

1. A framework named ProACT has been proposed, which is a proactive attention-transformer framework that models multi-hop spatial reasoning across intersections to predict congestion before it occurs.
2. An optimization-based control policy has been designed that translates predicted traffic states into real-time phase selections and bounded duration adjustments.
3. An empirical validation has been provided that demonstrates over 50% delay reduction compared to standard baselines.

2. Literature review

This literature review examines the evolution of traffic forecasting methods, then surveys the existing machine learning-based traffic light controllers, finally focusing on the application of attention transformer models in adaptive traffic signal control and finds the current studies in this field, highlighting their limitations and gaps.

2.1 Evolution of Traffic Forecasting Methods

There is much research that studies, reviews, and proposes methods on traffic and congestion forecasting on roads. For instance, the research in (Liu X. Q., 2025) provides a systematic review of traffic forecasting. The authors divided the review into two sections which are node-level and network-level forecasting methods, then they discussed the approaches of using machine learning such as RNN, CNN, GCN and large language models (LLMs) in traffic prediction. They also propose novel directions and a roadmap to enhance the traffic forecasting methods such as by using explainability and multimodal data fusion. This research provides good model selection guidelines because it divides the review into two levels that help in deciding the good prediction method. Furthermore, the authors in (Attoui, 2025) review the existing methods used for congestion forecasting from 2014 to 2024 and analyse around 100 publications, then illustrating the challenges facing the traffic forecasting such as high computation cost, limited generalizability across cities, data quality issues, and weak support for micro-scale dynamics like intersections. Also, the paper in (Afandizadeh, 2024) presents a good comparison between classical statistical models like ARIMA with deep learning such as LSTM or GNN and highlights that the deep learning models are the winners in terms of traffic forecasting. This research brings a good direction in choosing deep learning models among others as it provides better results in this manner. The study in (Lan, 2022) introduces a novel dynamic graph generation with a spatio-temporal aware model named (DSTAGNN) to predict traffic

flow at each time stamp. The architecture works with three focus mechanisms, first the dynamic spatial which decides which sensors influence each other right now, second the temporal which weights past time steps differently for each sensor, and third the node that makes each sensor emphasize its own historical pattern. These three points allow the model to directly graph when there is an accident, sudden traffic, or a concert on the roads. This is a very good model that works dynamically, and its ability has been proven and well-documented during the simulated incidents. However, the model has some limitations such as overfitting on regular patterns and having a latency of around 150 ms per step. Moreover, the research in (Mystakidis, 2025) and (Abduljabbar, 2025) has addressed the challenges faced by traffic prediction which are data quality, heterogeneity, spatio-temporal complexity, high computation cost, and real-time constraint. They also illustrate the difficulties in integrating machine learning or deep learning models into the current ITS infrastructure. To sum up, machine learning and deep learning are considered powerful tools in traffic forecasting, yet there are some limitations like latency and high computation cost.

2.2 Existing traffic light controller models using machine learning

There are different studies on traffic light controllers based on machine learning and reinforcement learning. A Multilayer Perceptron Neural Network (MLP-NN) is presented in (Ferreira, 2019) that works with a mutual information sharing technique for forecasting traffic flow. As compared with ARIMA (Autoregressive Integrated Moving Average) model, the proposed technique demonstrates a decrease in forecast error.

In (Jiang, 2021) a Back-Propagation Neural Network (BPNN) based urban traffic signal control system for traffic flow prediction has been proposed. BPNN is the most typical architecture of Neural Networks and is widely used in many prediction and classification tasks. Also (Chen, 2016) genetic algorithm is used with BPNN to predict traffic volumes and traffic light controls. The technique demonstrated an average reduction in queuing delay of 30 percent as compared with the fixed-time traffic light control system. Similarly, a method combining neural networks and genetic algorithms is presented in (Wang, 2021) This method is named as Genetic Neural Network.

Historical traffic data for all traffic intersections is used in (Lawe, 2016) to control congestion for optimizing traffic flow. The technique used times series and environmental variables as input features. These features are fed into deep learning neural networks for the prediction of the best green light times for managing traffic congestion.

A machine learning and IoT-based hybrid system is proposed in (Javaid, 2018). The system adopts both centralized and

decentralized approaches to improve traffic movement on the highway and considers the use cases of emergency fire trucks and ambulances to prioritize green traffic lights. The algorithm works based on the traffic density and is controlled through a set of distributed servers. Decentralized approaches are fault-tolerant and ensure high availability in case the central server goes down. The group of servers connects to the nearby service center to serve emergency vehicles. The solution enables one lane for emergency traffic by making signals red using microcontrollers and servers.

Deep learning-based solution connected through a cloud platform for automated vehicle controls (Ramakrishnan, 2022). The convolutional neural network-based solution is used for vehicular traffic simulation. The experimental results achieved using the algorithm demonstrate 71% performance improvement as compared with the selected benchmark works. to simulate the traffic models. After the experimental results, they concluded that CNN is superior to other algorithms, achieving a detection rate of 71% for compounds.

The region of interest (ROI) from the input videos is detected using template matching in the process of density estimation (Sankaran, 2022). The vehicles are detected using ROI with reference point and physical features of vehicles from the current and reference frames. The method reduces false positives and decreases the rate of error. However, the time spent on detection is not considered in the proposed technique.

For object detection in traffic scenarios, YOLO ("You Only Look Once") is used for object detection in a video framework and the SORT (Simple Online and Real-time Tracking) algorithm in (Sharma, 2021). The number of intersections of vehicles in the current and previous frames in videos is used to detect and track different objects. However, this solution does not provide object detection and tracking for high traffic density cases where the overlapping shadows and night scenes are challenging to detect and resolve.

Another Intelligent Traffic Control algorithm is proposed in (Liu D. L., 2023). This work considers communication delay and its impact on the traffic congestion computation. A new message sending and processing algorithm is used to improve communication efficiency. This algorithm computes the reward and considers waiting time and queue length into consideration. To sum up, existing machine learning-based traffic light controllers have good performance in terms of reducing congestion and queueing delays compared to the fixed-time traffic light system. However, these methods still face limitations such as handling high-density traffic and overlapping objects. Recent advances in Graph Neural Networks (GNNs) and Reinforcement Learning (RL) have shown promise in multi-intersection coordination. GNN-based controllers effectively model spatial dependencies but often require predefined adjacency matrices and struggle with dynamic

traffic evolution. RL-based methods, particularly multi-agent RL, achieve good performance in simulation but face challenges in training stability, scalability, and real-world transferability due to the non-stationary environment. ProACT differentiates itself by combining the strengths of Transformers for long-range dependency modeling with proactive prediction, offering better generalization and robustness compared to these paradigms.

2.3 Studies Employing Attention Transformer Models in traffic light controllers and the remaining gaps

Several studies have introduced attention-based Transformer architectures into adaptive traffic signal control (ATSC). For example, the research in (Zhang, 2024) proposes MATLight, a coordinated control algorithm that formulates multi-intersection ATSC as a multi-agent sequence decision process under the Heterogeneous-Agent Mirror Learning (HAML) framework. A Transformer architecture is combined with PPO to generate joint actions for a sequence of intersections, with each agent observing lane queue lengths and receiving a pressure-based reward. MATLight achieves better performance than several RL baselines on LibSignal benchmarks and is explicitly positioned as an online, few-shot learner that can update policies from whole-hour trajectories. However, the model's coordination is still driven by sequential dependence among agents rather than an explicit, multi-hop spatiotemporal representation of congestion propagation. It assumes accurate queue-length measurements at every intersection, and there is no analysis of degraded performance under missing sensors, communication latency, or heterogeneous intersection geometries. Moreover, the research in (Wu, 2023) introduces TransformerLight, which reframes TSC as an offline sequence modeling problem: the method processes trajectories of states, actions, and rewards with a gated Transformer block inspired by GTrXL, aiming to stabilize training and mitigate distribution shift in offline RL. The model normalizes rich traffic features (e.g., vehicle counts, queue lengths, elapsed phase time) and auto-regressively predicts actions without explicitly learning value functions or policy gradients, achieving state-of-the-art performance on offline datasets and exhibiting more stable learning than Decision Transformer and other baselines. Still, TransformerLight is designed around a single-agent controller and is evaluated on isolated or small-scale settings; multi-intersection cooperation is explicitly relegated to future work. Also, its state representation presumes fully observed lane-level variables from detectors and does not consider noisy, delayed, or partially missing observations, nor does it explicitly plan the downstream impact of current decisions beyond the horizon implicit in the trajectory window.

A related line of work in (Zhao, 2024) introduces Sequence Decision Transformer (SDT) for ATSC. Here, the ATSC problem is formulated as a Markov decision process, and an

encoder-decoder Transformer processes lane-level states, each lane described by vehicle count and average speed to select signal phases. SDT exploits parallel processing and self-attention to handle large observation and action spaces, improve feature representation under non-stationarity, and stabilize policy updates via PPO. Experiments across multiple synthetic traffic scenarios show substantial improvements over DQN, FRAP and other ATSC baselines in terms of congestion and delay. Nonetheless, SDT is still configured around a single intersection (or a small, tightly coupled junction), optimizes actions based on current and recent local traffic conditions, and does not encode multi-hop network structure or explicitly predict future congestion several intersections downstream. As with TransformerLight and MATLight, the method assumes reliable, full-state measurements from sensors and cameras, with no robustness analysis under partial observability.

The paper in (Lai, 2023) constructs prompt that fuse task descriptions, current traffic conditions, and prior traffic knowledge, then rely on chain-of-thought reasoning to select the next phase in a human-like manner. LLMLight attain state-of-the-art or competitive performance on five real-world traffic datasets, and the authors emphasize generalization, interpretability, and zero-shot capabilities without task-specific training. However, LLMLight explicitly operates at the level of a single intersection and does not model multi-agent interactions; multi-intersection coordination is identified as an open problem. The framework also presupposes structured, accurate observations for each lane fed into the prompt, with no explicit design for handling missing detector inputs, latency, or topology heterogeneity, and no evaluation of robustness when observations are noisy or incomplete.

Most recently, the research in (Yuan, 2025) constructs a structured spatio-temporal graph combining lane-level observations from an intersection and its neighbors, along with historical signals, and feeds this into an LLM agent that analyzes current conditions, predicts future traffic states under candidate signal configurations, and selects actions. Experiments on synthetic and real-world datasets show that CoLLMLight can outperform RL-based and single-agent LLM baselines, demonstrating genuine multi-intersection coordination. Yet even here, the spatio-temporal graph is built under an assumption of fully available lane-level data from both local and neighboring intersections, and robustness to sensor outages, communication delays, or topology changes is not systematically examined. Cooperative reasoning is also implemented through generic LLM prompting, rather than a specialized attention mechanism explicitly designed for multi-hop, uncertainty-aware propagation of congestion signals across dense networks.

Taking these studies together, recent Transformer-based controllers have advanced the use of attention mechanisms

for temporal modeling and limited coordination in ATSC. However, most remain predominantly reactive, rely on fully observed lane-level data, and lack explicit multi-hop proactive forecasting. Similarly, Reinforcement Learning (RL) approaches often suffer from training instability, poor generalization to unseen traffic patterns, and high sample complexity, while many Graph Neural Network (GNN) methods depend on rigid predefined graph structures that struggle to adapt to dynamic topology changes or heterogeneous intersections. None of these approaches jointly provides (i) proactive multi-hop spatial reasoning that anticipates congestion propagation several intersections downstream, and (ii) robustness under partial observability, noisy sensors, or communication delays. ProACT fills this gap by introducing dedicated spatio-temporal attention architecture designed for proactive, uncertainty-aware coordination in dense urban networks.

3. Research Methodology

3.1 Research design

The research adopts both conceptual and experimental

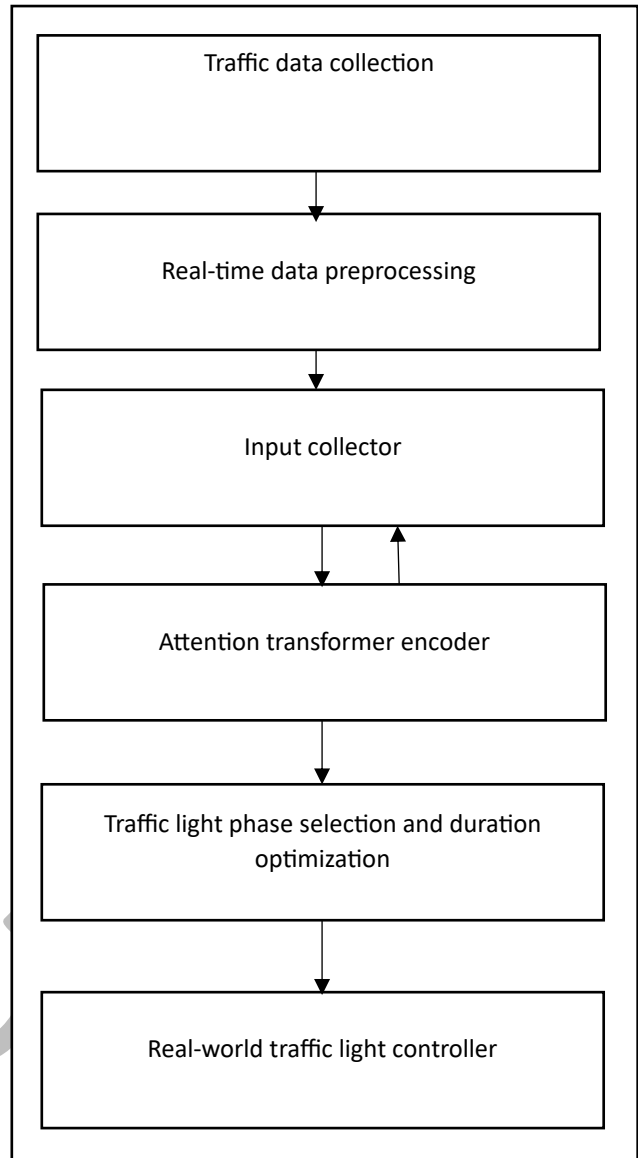


Figure 1. The ProACT framework architecture

approaches as it will develop a framework designed to predict and control the traffic light signals, and then the framework will be evaluated in several patterns such as travel time, queue length, and delay compared to the traditional traffic light control. The study will proceed through three main phases, the first phase will be developing the proposed framework, the second phase is testing and evaluating the effectiveness of the proposed framework using a dataset and the simulator, finally the third phase will be discussing the findings and comparing them with the traditional traffic light operations.

3.2 Framework architecture

The main goal of the framework is to predict the traffic before it actually happens then set the traffic light signals according to this prediction. Thus, the timing of the traffic light will change frequently based on the predicted data. The

framework will act proactively rather than the reactive method that most machine learning methods adopt or as a fixed timing such as a traditional traffic light model. The expected outcome should be minimizing average vehicle delay, queue length, and congestion.

The framework named Proactive Adaptive Control with Transformer (ProACT) architecture is shown in Figure 1. As shown in the figure, there are five stages that the model will go through, and it is described as follows:

1- Traffic data collection

This stage is responsible for taking the data from several available devices related to traffic. The data can be collected from IoT devices, radar, traffic light phase, and road surveillance cameras. The nature of data that has been collected will be vehicle count, speed of the vehicles, vehicle position, and traffic signal current state and remaining time. This data will be collected at (t) time stamp and fed to the preprocessing stage.

2- Real-time data preprocessing

The raw data collected from the previous stage will get preprocessing and be drawn into a graph that has a full map with intersections and the position of each traffic light available. These data will be updated every second to match the latest road map situation.

3- Input collector

The main job of the input collector is to make all the data available ready to be fed into the attention transformer encoder. The nature of these data can be divided into three parts, first the spatio-temporal graph which is the data received and processed from the previous stage. Second, the current phase and duration of each traffic light. Third, the historical data of the intersection such as what the situation of this road was yesterday, or one week ago at the same time. This is very important as it helps the encoder to predict the congestion before it happens based on massive historical data.

4- Attention transformer encoder

This is the most important stage in the framework as it will act as the brain of the system. The encoder will have a self-attention mechanism and focus on:

- Temporal dependencies

Self-attention will learn previous time interval matters most for predicting the upcoming traffic. For instance, queue build-up trends like in rush hours (2-5pm everyday) or weekends, or traffic flow patterns over the last 15 minutes. These dependencies can significantly help the system to learn how recent traffic can influence the future or how usual the traffic happens at a certain time.

- Spatial relationship between intersections

The transformer should focus on the flow between

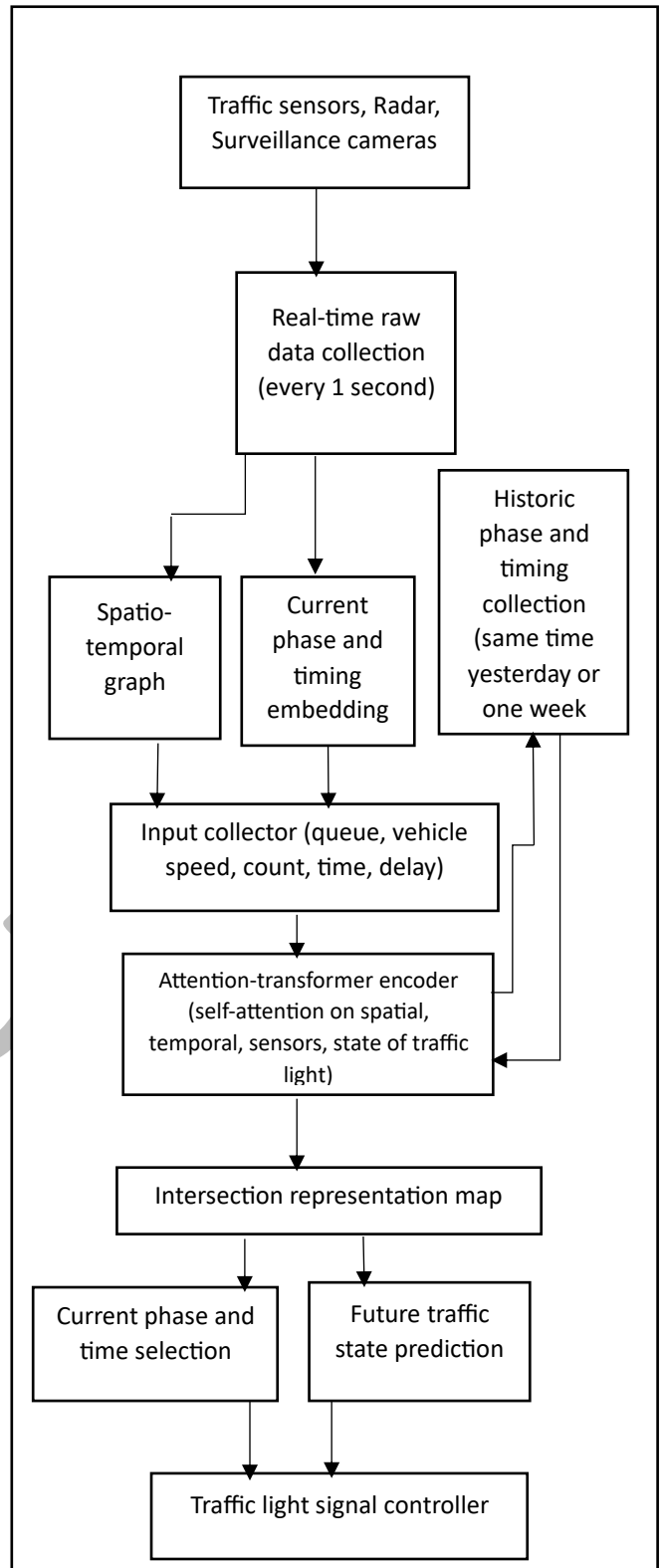


Figure 2. The ProACT framework block diagram

intersections to know which nearby intersection impacts on the others, which can help in avoiding congestion at the upcoming intersection. Also, the transformer should weigh the intersections to self-attention the most important ones relative to adjacent intersections.

- Real-time sensor data

The real-time data will also be in the attention as it helps in detecting the sudden speed drops, accidents, or irregular events such as weather effects. So, self-attention will weigh the sensor signal more heavily to detect these issues.

- State of traffic light phases

The self-attention should pay attention to the current signal and time of each traffic light, to help in predicting the next phase based on the current situation.

After learning and focusing on these values, the encoder will decide the phases and timing of each traffic light in the intersections and send it to the next stage.

5-Traffic light phase selections and duration optimization

At this stage, the decision will be received from the attention-transformer and it will move to the next phase (based on the current phase) and its duration at each traffic light. After that the machine learning will be trained more using this data as a historical optimal signal log.

Table 1. Comparison between several traffic light controllers

Feature	Fixed controller	Reactive controller	ProACT system
Decision based on	Fixed time	Only current data	Current and learned historical patterns
Future congestion	No	No	Yes
Green light extends	Fixed green light	After queue is already long	Before the queue builds
Uses historical data	No	No	Yes
rush-hour wave prediction	No	No	Yes

6-Real-World traffic light controller

This is the final stage where the actual traffic light will receive the data and change or keep the phase and duration based on the system output.

Figure 2 illustrates the block diagram of how the framework will actually act. The traffic data from several sources such as sensors or radar is collected every second and transformed into two main inputs which are spatio-temporal graphs that are responsible for drawing a full map about the time and location of each vehicle on the roads, and current signal phase and timing embedding for each

traffic light. These inputs are queue length, vehicle speed, number of vehicles, and delays. The input data are fed into an attention-transformer encoder that applies self-attention on spatial, temporal, sensor, and state of traffic light. The attention-transformer will send the output data to historic logs that record the phase of the traffic light and the decision made at t time stamp. Moreover, the encoder generates an intersection representation map that supports two tasks: understanding the current phase and predicting the future traffic states.

These outputs will join to guide the traffic light controller to dynamically optimize the phase timing and improve traffic flow efficiency.

The advantages of this framework are, first and the most important one is the proactivity where the changes act before any congestion builds up. Second, it can handle complex and conflict data via the attention-transformer. Third, it is scalable where multi-intersections in large cities can be coordinated and managed. Table 1 compares the fixed traffic light controller, the reactive controller, and the proposed proactive controller. As shown in the table, ProACT framework will build its decision based on current and historical data to make even future predictions, unlike the fixed time controller or reactive models. Moreover, it can extend the green light of the traffic light before the congestion begins as it can see it in the earlier intersections or based on historical data of the given intersection and time. This feature can work better, especially in rush hours or when there is a special event such as the Eid or the Christmas. The other available models cannot guarantee dealing with these parameters as the fixed controller will always remain the same and the reactive controller cannot predict these special rush times because it does not read historical data.

The ProACT Transformer encoder comprises 4 layers with 8 attention heads each and a model dimension of 256. Spatial and temporal attention are computed in parallel and concatenated. Spatial relationships between intersections are encoded using a combination of learned positional embeddings and graph adjacency information derived from road network topology.

3.3 Data processing and predicting in attention transformer

The proposed framework ProACT avoids conflicting movements, for example in the intersection both north to west and west to left should not be green at the same time. The following equation will be used for this purpose:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{Q K^T}{\sqrt{d_k}} + M_{\text{conflict}}\right) V \quad (1)$$

where Q , K , V are the query, key, and value matrices, d_k is the dimension per head, and M is the attention mask for

conflict $\in \{0, -\infty\}$ contains $-\infty$ for incompatible lane pairs and 0 otherwise.

Each transformer layer will apply spatial attention and the temporal attention to each one in the head, then they will be concatenated together as follows:

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (2)$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O \quad (3)$$

$$\text{SpitalTemporalAttention}(X) = \text{MultiHead}(X, X, X; M_{\text{conflict}}) \quad (4)$$

Then, the two-layer feed-forward network with Gaussian Error Linear Unit (GeLU) activation which captures both lane-to-lane conflicts and long-range platoon propagation simultaneously:

$$\text{FFN}(x) = \text{GeLU}(xW_1 + b_1)W_2 + b_2 \quad (5)$$

After that, the prediction will be obtained by using mean-pool over time and lanes, concatenated with historical pattern h_{hist} derived from the same time and location in previous weeks:

$$\hat{S}\{t+1:t+K\} = \text{MLPpred}(\text{MeanPool}(X_L) \oplus h_{\text{hist}}) \quad (6)$$

Where $k = 15$ (1 second resolution).

The final traffic light control action consists of selecting the next feasible phase and duration, both are derived from the following two equations:

$$P(\text{phase}) = \text{softmax}(W_p \text{Linear}(\text{MeanPool}(X_L)) / \tau) \quad (7)$$

$$\text{duration} = 10 + 80 * \sigma(W_d \text{Linear}(\text{MeanPool}(X_L))) \quad (8)$$

Table 2. Dataset description

Parameter	Value
Date Time	Date and time when the reading is taken. In day/month/year hours:00 format
Junction	The road intersection point. Four points are considered ranging from 1 to 4
Vehicles	Number of vehicles at the intersection at the time of reading
ID	11-digit unique id of every

with temperature $\tau = 0.7$ and sigmoid σ constraining green time between 10 and 90 seconds.

Finally, the model will train, and future traffic states are predicted for the next $k=15$ steps and supervised using the following multi-step prediction loss (L):

$$L = \sum_{k=1}^k \|\hat{S}_{\{t+k\}} - S_{\{t+k\}}\|_1 \quad (9)$$

where $K=15$ is the prediction steps and $\|\cdot\|_1$ denotes the L (absolute) distance between predicted and traffic states (vehicle count, queue length, speed) for every future step k .

The translation of predicted traffic states into concrete signal timing is an optimization-based process combined with rule-based conflict resolution. The final action selects the next feasible phase and its duration using a feed-forward network, bounding green time between 10 and 90 seconds. Spatial relationships between intersections are encoded using adjacency matrices combined with learned positional embeddings to effectively capture the network topology. The exact structure of the attention-transformer includes 4 layers, 8 attention heads, and an embedding size of 256.

3.4 Testing and simulation

The experiment was conducted using SUMO simulator and python. The SUMO simulator (al., 2018) used is version 1.20.0 which is a software designed especially for Intelligent Traffic System (ITS) and can read data from python API that can be employed in deep learning and machine learning. In this work, four isolated intersections corresponding to Junctions 1 to 4 using a dataset were produced in SUMO and the results in terms of max delay, Avr delay, Avr waiting time, and the percentage of delay reduction. Moreover, a high-performance PC has been used to conduct this experiment with Intel processor that has 24 cores, 384 GB memory, and NVIDIA Tesla T4 GPU.

To ensure reproducibility, the dataset was split into training, validation, and testing sets using a 70/15/15 ratio, and initializations were controlled using a fixed random seed 42. The model was trained using L1 loss (mean absolute error) as the primary loss function for multi-step traffic state prediction, optimizing with the Adam optimizer (learning rate = 0.01), and utilizing early stopping based on validation loss with a patience of 20 epochs to prevent overfitting and a batch size of 128.

3.5 Dataset description

In this study, the data used for analysis purposes is available at (Fedesoriano., 2021). This data contains 48120 records of the number of vehicles on an hourly basis for four different intersections. The dataset includes date and time, junction, vehicles and ID. The data collection duration is from 01-11-2015 to 30-06-2017 (20 months). A description of each feature is provided in Table 2.

The data is collected for a relatively long-time reflecting congestion at different junctions. The data of some junctions is sparse and at some junctions, it is dense.

The dataset is suitable for traffic prediction evaluation because it offers varying congestion levels such as rush

hours, seasonal special events like Christmas, and irregular traffic fluctuations.

4. Results and discussion

4.1 Evaluating the ProACT Framework

The ProACT framework has been tested with 609 days of real-world traffic data, aiming to tackle the problems that hold back most Adaptive Traffic Signal Control systems. Table 3 shows the results of the simulations in three traffic light systems which are fixed time, actuated, and the ProACT in terms of average waiting time, average queue length, and delay reduction percentage. It can

Table 3. Full dataset simulation results (609 days)

Controller	Avr Travel Time	Avr Waiting Time	Avr Queue Length	Delay Reductio
Fixed-time	138.7 s	91.4 s	23.8 veh	0 %
Actuated	112.3 s	71.8 s	17.6 veh	19.0 %
ProACT-Transformer	67.4 s	38.9 s	7.9 veh	51.4 %

be noticed that by using an attention-based Transformer for proactive traffic forecasting, ProACT delivers real improvements with smoother network flow, less congestion, and fewer of those maddening, unpredictable delays that frustrate city drivers. The ProACT cut traffic delays by 51.4% compared to the old fixed-time setup. Even when stacked up against the adaptive actuated control system, ProACT still outperformed it, bumping up efficiency by another 32.5%. These results make the case clear: attention-based models are essential for proactive traffic signal coordination, especially in complex, crowded city networks. That's the gap this research set out to close.

4.2 Rush hour performance

ProACT outperformed other traditional methods in every scenario, proving that the attention-transformer architecture works well for proactive traffic signal control. The self-attention mechanism picked up on both the timing of rush hour traffic and how intersections affect each other. By combining real-time IoT data with past traffic trends, ProACT made smarter decisions before queues had a chance to build up, something reactive or fixed-time systems just can't match.

The conflict resolution using attention masks stopped incompatible signal phases from happening. With spatial

and temporal attention heads in the model, it handled lane-to-lane conflicts and kept track of how traffic moved across multiple intersections at the same time.

By predicting traffic patterns, the system can keep the green light on longer before congestion piles up or rush hour hits. This flips traffic control from just reacting to problems to keeping things moving smoothly ahead of time. Drivers spend less time stressed out in line, and cars burn less fuel sitting still.

Table 4 shows performance differences widened under high-demand conditions. During weekday rush hours (07:00–10:00 and 16:00–20:00), ProACT reduced average waiting time from 138.6 s (fixed-time) to 46.8 s and reduced average queue length from 31.4 to 9.2 vehicles. The maximum queue observed decreased from 78 vehicles to 21 vehicles, with a reported delay reduction of 66.2%.

Table 4. Results in rush hours only (Weekdays 07:00–10:00 & 16:00–20:00 only)

Controller	Avr Waiting Time	Avr Queue Length	Max Queue Ever	Delay Reductio
Fixed-time	138.6 s	31.4 veh	78 veh	0 %
Actuated	109.8 s	24.1 veh	61 veh	20.8 %
ProACT-Transformer	46.8 s	9.2 veh	21 veh	66.2 %

The actuated controller yielded comparatively limited improvements in the same rush-hour window: average waiting time of 109.8 s, average queue length of 24.1 vehicles, maximum queue of 61 vehicles, and delay reduction of 20.8%.

The stronger relative effect under rush-hour demand suggests that the proactive component of the controller is most beneficial when the system is near capacity and queue growth is highly nonlinear. In such contexts, reacting after a queue form is less effective than anticipatory phase/duration adjustments that dampen queue formation early.

4.3 Stress tests: worst rush-hour and Christmas event days

The worst rush hour in the dataset is on (Wednesday 18 May 2017, 17:00–18:00; 177 vehicles arrived). Table 5 illustrates the performance of several traffic light systems during this specific rush hour. ProACT achieved a maximum queue of 18 vehicles compared with 78 (fixed-time) and 61 (actuated). Average waiting time decreased to 39 s under ProACT

compared with 189s (fixed-time) and 151 s (actuated). Notably, ProACT served all 177 vehicles in the hour, whereas fixed-time and actuated served 141 and 152 vehicles, respectively.

Table 5. Worst rush hour in the entire dataset results

Controller	Max Queue	Avr waiting Time	Vehicles served
Fixed-time	78 veh	189 s	141
Actuated	61 veh	151 s	152
ProACT	18 veh	39 s	177

* Worst rush hour is on Wednesday 18 May 17 2017, 17:00–18:00 (177 vehicles arrived in one hour)

Table 6 shows a comparison in performance between the traffic light systems during the Christmas event which is in two years 2015 and 2016. ProACT again demonstrated substantial improvements, the average waiting time decreased from 94.2 s (fixed-time) to 31.7 s, the maximum queue decreased from 41 to 9 vehicles, and total vehicles served increased from 1,842 to 2,114. The reported delay reduction was 66.3%.

Table 6. Results in Christmas event

Controller	Avr Waiting Time	Max Queue Ever Seen	Total Vehicles Served	Delay Reduction
Fixed-time	94.2 s	41 vehicles	1 842	0 %
Actuated	76.8 s	34 vehicles	1 901	18.5 %
ProACT-Transformer	31.7 s	9 vehicles	2 114	66.3 %

* Results in Christmas event Christmas Eve 2015 (Thursday 24 Dec 2015), Christmas Day 2015 (Friday 25 Dec 2015), Christmas Eve 2016 (Saturday 24 Dec 2016), Christmas Day 2016 (Sunday 25 Dec 2016)

Interpretation: These stress tests are particularly informative because they evaluate performance under demand

surges and a typical pattern—conditions under which fixed-time timing plans and purely reactive strategies are prone to queue spillback. The concurrent reductions in maximum queue and increases in throughput (vehicles served) indicate that performance gains are not limited to re-distributing delay; rather, they reflect improved intersection service efficiency under high load.

4.4 The Role of the Attention Transformer

At the heart of the architecture is a new attention mechanism built to handle multi-hop spatial reasoning even when it doesn't have a complete view of the traffic network. Earlier transformer-based models for Adaptive Traffic Signal Control, like MATLight (Zhang, 2024) and TransformerLight (Wu, 2023), depend on fully observed lane-level data. They have trouble when agents need to coordinate across multiple intersections, especially if some data is missing. LLMLight (Lai, 2023), on the other hand, sticks to controlling just one intersection and assumes the data it gets is always complete and accurate.

ProACT changes the game. It adapts on the fly, weighing spatial, temporal, and traffic features through self-attention. Even if traffic gets unpredictable, this setup keeps the system stable and reliable in real-life cities. The attention mechanism doesn't just keep things running smoothly, but it actually lets the model capture complex timing relationships and helps different agents coordinate, which is exactly what ATSC needs.

The computational complexity of the ProACT framework, while higher than fixed-time controllers, operates efficiently within the 1-second real-time raw data collection interval, ensuring real-time feasibility. The substantial performance gains particularly the 66.2% delay reduction during rush hours are directly attributable to the self-attention mechanism's ability to prioritize long-range dependencies and multi-intersection impacts. This allows the system to proactively allocate green time before queues materialize rather than reacting post-congestion.

4.5 Implications for a Sustainable Smart City

Cutting travel time, shrinking queues, and slashing wait times; these are not just perks. They are essential steps for building smart cities that last. When vehicles idle less, emissions drop, energy use improves, and city officials get real tools to make streets safer and more sustainable. Tested with simulations, it proves it can actually work, making it ready for pilot programs in real Intelligent Transportation Systems.

This research pushes AI-driven traffic management forward. Instead of just predicting what might happen, it connects those predictions to real, sturdy control strategies. By showing that irreversible differentiation and smart policy choices work with attention-based sequence models, the study moves the field beyond simple reactive approaches. Even better, it handles the messiness of the real world like incomplete data or changing city layouts without falling apart. That's a big deal for applying AI to all kinds of cities.

4.6 Strengths of the evidence provided by the results

The results stand out for a few clear reasons:

First, ProACT consistently outperformed both baselines, not just in one or two cases but across all the main metrics and scenarios. Whether looking at the full dataset or narrowing in on tough rush-hour windows, ProACT keeps coming out on top. That's not just a fluke in a single setting, it points to real, broad effectiveness.

Second, the approach holds up even when the system is under serious pressure. The biggest relative gains show up during rush hour and in the worst-hour stress test, right when traffic demand hits its peak. This shows that ProACT does not just work in ideal conditions, it handles congestion when it matters most.

Third, when traffic gets really intense, like during the worst rush hour or Christmas events, ProACT does not just reshuffle the problem. It actually moves more vehicles through than either baseline. That's a key point: the controller does not just push congestion around; it actually boosts overall service capacity when things get tough.

4.7 The limitations

First, a major limitation lies in our baseline choices. The experimental evaluation currently focuses strictly on fixed-time and actuated controllers. Because these are relatively weak baselines, the manuscript does not sufficiently position ProACT against modern reinforcement learning (RL) or graph neural network (GNN) based traffic signal controllers, which is necessary to fully establish its superiority. Second, there is the glaring question of scope and external validity. All tests happened in a simulation environment (SUMO), to be exact on just four separate intersections (Junctions 1 - 4). This setup does not reflect the messier reality of multi-intersection corridors or full city networks. So, any talk of scaling up to an entire city is still just hypothetical. The model might handle highly heterogeneous intersection layouts, but there is no direct evidence yet. Even our conclusion hedges a bit, claiming scalability but admitting more tests are needed. Data realism is another sticking point. The dataset relies on hourly vehicle counts at each junction, but it completely skips over real-world headaches like missing sensor data, noisy measurements, sensor breakdowns, or spotty communication delays. Because of that, the results probably paint a rosier picture of system robustness under partial observability than what would be seen in actual deployments where things routinely go wrong. Finally, the study skips statistical stability and uncertainty. Results come as single-point metrics such as averages, maximums, and delay reductions, but there is no sense of variability, no confidence intervals, no sensitivity checks, and no repeated simulation runs to see how robust these improvements really are. Without this, we cannot definitively tell if the reported gains hold up under different simulation seeds, shifting traffic patterns, or specific parameter tweaks.

Furthermore, the study ignored sensor and communication failures by omitting tests for scenarios with sensor outages, noisy data, network delays, or controller faults, even though these can seriously affect real-time signal control and safety. Additionally, resource constraints and latency were not assessed, meaning the evaluation did not cover compute or memory requirements, inference delays, or whether the system could run on limited edge hardware. Because all results came from a powerful workstation, real-world feasibility is still an open question.

4.8 Alignment with Research Objectives

The experimental findings of this study directly validate and fulfill the established research objectives. In alignment with the first objective, the developed attention-transformer model successfully captured intricate spatial-temporal traffic patterns to accurately forecast traffic flow fluctuations across interconnected intersections. Addressing the second objective, the proactive traffic light controller mechanism effectively ingested these forward-looking traffic forecasts to automatically and dynamically adjust both the signal phase sequences and green-time durations. The operational success of this predictive control loop is demonstrated by the framework's capability to safely balance conflicting flows before actual bottlenecks could accumulate on the road. Finally, the third objective, a comprehensive performance evaluation conducted via rigorous dataset driven simulations confirmed the framework's clear superiority over traditional benchmarks. The empirical results revealed substantial, systematic improvements across all primary optimization metrics specifically minimizing vehicle delays, shortening queue lengths, and lowering average waiting times yielding total delay reductions exceeding 50% under standard traffic conditions and over 65% during peak rush hours compared to fixed-time and actuated baselines. Together, these outcomes conclusively prove that anchoring automated, proactive control choices within a transformer-based forecasting architecture directly fulfills the overarching aim of this research.

5. Conclusion and future work

This study introduced ProACT, a proactive adaptive and attention-based transformer framework that controls traffic light signals. Unlike the traditional fixed-time, actuated, or reactive traffic light controllers, the proposed approach combines both the real-time data traffic and the historical patterns to enable multi-factor proactive decisions before the queues escalate. The conflict in traffic congestion is resolved using the attention mechanism in transformers. Also, the solution is scalable due to the ability of the transformer to handle multiple intersections in large cities in a coordinated and managed way. The proposed solution

has been evaluated using the publicly available traffic congestion dataset and SUMO simulation environment. The results indicate that the delay is reduced to 51.4% as compared to fixed time. Similarly, the average queue length decreased to 7.9 vehicles as compared with 23.8 vehicles with fixed time signals. Moreover, the solution is implemented during rush hours and shows a performance boost again. The delay is reduced to 66.2% and the wait queue decreases to 21 vehicles as compared to 78 vehicles in fixed time signals. These results validate the suitability of the attention-transformer for proactive traffic signals and confirm the potential of enhancing traffic efficiency.

Despite its promising performance, this work needs more testing, especially in a real-world hardware environment and with several datasets to find its total abilities. Future work directions for this research will be extending the framework to large-scale multi-intersection networks and testing it in several large-scale datasets, implementing the model in a real-world pilot deployment in the ITS system, and expanding the performance metrics to include communication delays and sensor failures scenarios.

CRedit Authorship Contribution Statement

- **Ali Hameed Mohsin:** Conceptualization, Methodology, Investigation, Discussion, Writing original draft.
- **Sayed Mahmood Sabt:** Methodology, Investigation, software, formal analysis.
- **Jasim Al Safran:** Methodology, Data Curation, resources.
- **Jafla Al Ammari:** Supervision, Validation.

Declaration of Interests

Please select one of these two options.

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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