# Real-Time Traffic Signal Optimisation Using Deep Q-Network Algorithm and Camera Data

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## ABSTRACT

Traffic congestion has become a problem in developing countries' urban areas. This is largely caused by traffic signals that have fixed-timing which causes them to fail to adapt to changing traffic conditions in real-time. This research introduces a Reinforcement Learning-based solution using a Deep Q-Network algorithm to optimise traffic signal lights control, aiming at reducing congestion and enhancing traffic flow efficiency. The system is developed in a virtual environment using PTV VISSIM simulation software and the real-time traffic data is collected using simulated cameras. The collected traffic data is then processed using Deep Q-Network algorithm which is implemented using Python and TensorFlow. By optimising traffic signal light timings to be adaptive, the system introduces significant improvements in reducing traffic waiting times at intersections and improving traffic flow on the road in comparison to the traditional fixed-timing systems. The system ensures scalability and effectiveness in offering a promising framework for adaptive traffic management in urban roads.

**Keywords --**Traffic Signal Optimisation, Deep Q-Network, Reinforcement Learning, Urban Mobility, Real-Time Simulation, PTV VISSIM.

## INTRODUCTION

Traffic congestion presents a growing challenge across many cities in developing countries, slowing economic growth, reducing quality of life and contributing to environmental degradation by emitting harmful gases (Lu et al., 2021). Traditional traffic signal systems with fixed-timing fail to account for changing traffic patterns, resulting in prolonged traffic delays and inefficient intersection throughput. This research makes use of reinforcement learning, specifically the Deep Q-Network (DQN) algorithm to optimise traffic lights in real-time using data that is collected by cameras. The approach is utilised within a simulated environment using PTV VISSIM and is trained using real-time data that is collected from simulated cameras.

### A. Background of Study

Developing countries' road infrastructure especially in urban areas, is facing significant challenges due to growing vehicle ownership, underdeveloped public transport systems and poor traffic signal management. The current traffic signal lights with fixed-timing do not adapt to changing traffic volumes which results in frequent congestion, especially during peak hours (Munuhwa, 2020). With rising economic activities and urban expansion, there is a growing need for efficient traffic management solutions. Since advanced technologies like machine learning and smart city innovations are gaining momentum globally, developing countries have an opportunity to advance into the field of intelligent traffic systems (Papageorgiou, et al., 2019).

Methods like agile and other flexible solutions like the Deep Q-Network (DQN) based traffic signal control system offer great promises in advancing the efficiency of traffic signal management systems. Deep Q-Network algorithm is a form of reinforcement learning (RL). It is utilised for adapting traffic signal timings based on real-time data inputs to improve traffic flow efficiency by reacting to real-time traffic scenarios (Qi, et al., 2022). Real-time traffic data is collected using virtual cameras in the simulation environment, which captures key metrics like vehicle counts and traffic density (Cornell University, 2019).

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With the increasing availability of comprehensive traffic datasets and increasing usage and improvements of Deep reinforcement learning techniques, developing countries can utilise reinforcement learning (RL) for traffic signal control. A key question for applying RL to traffic signal control is how to define the reward and state. The ultimate objective in traffic signal control is to reduce the travel time, which is difficult to reach directly (Jiang, et al., 2021). Existing studies often define reward as an ad-hoc weighted linear combination of numerous traffic measures. However, there is no guarantee that the travel time will be optimised with the reward. Recent RL approaches use more complicated state (e.g., image) in order to describe the full traffic state. None of the existing studies has discussed whether such a complex state representation is necessary (Jiang, et al., 2022).

This research explores and addresses these challenges, aiming to provide a scalable solution to improve urban traffic management and reduce congestion.

**Related Work**

The traffic signal control sector has gone through significant transformations over the past two decades primarily driven by technological advancements that cater for growing vehicle ownership for convenience, real-time updates, and integrated services. Some studies include traditional methods that use pre-timed and actuated signals (Haimerl, FHWA, and Haddad). They are restricted in adaptability as well as allowing for integration. Multi-agent reinforcement learning shows potentials to solve the heavy traffic problems. It adopts centralised or distributed strategies but suffers from scalability issues (Kim & Jeong, 2020: Kolat, 2023: Ge et al., 2022). DRQN models combine Long Short Term Memory (LSTM) with Deep Q-Network for temporal awareness (Ma et al., 2025) but require more data and training complexity. However, in some developing countries these innovations are not yet fully leveraged.

(Spatharis & Blekas, 2024) Introduced a concept whereby traffic lights at individual intersections are treated as autonomous agents. They collaborate in managing signal control, taking into account real time traffic conditions and optimising their actions to alleviate congestion. This approach mimics a decentralised decision making system, where each traffic light adapts its timing based on local traffic dynamics (Spatharis & Blekas, 2024).

A multi-element traffic light system featuring blue, yellow and red displays was proposed and it aimed at improving the communication between traffic lights and drivers, making signal intentions more intuitive. Genetic algorithms (GA) were used to adaptively adjust and efficiently control these multi-element traffic lights. This approach highlighted the importance of human computer interaction and user centric design in traffic control (Haimel et al., 2022).

(Zheng et al., 2019) Proposed a deep recurrent Q-network (DRQRN) technique that combines a recurrent neural network (RNN) with a deep Q-network (DQN) to learn various traffic environments. The DQRN minimises the total number of waiting vehicles before the stop line (Liu et al., 2023: Zheng et al., 2019). The proposed model defined the queue length parameter in the same sense as the travel time of the vehicles.

Studies on reinforcement learning, in particular deep Q—Networks have shown that artificial intelligence (AI) driven systems can outperform traditional methods by dynamically adjusting to traffic conditions (Qi, et al., 2022).

**Research Gap**

Existing frameworks and traffic control systems are relevant, but, they are mainly applicable to developed infrastructures (Cui et al., 2020). There is lack of camera data to enhance the environment for training the traffic systems to adjust dynamically to changing scenarios (Wang et al., 2021). These traffic lights should be used for collecting data on vehicle counts, waiting times and traffic flow at intersections.

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# METHODOLOGY

The simulation research methodology guided the iterative design, analysis, and validation of the system model, enabling a controlled and repeatable evaluation of urban traffic scenarios using a virtual environment. This methodology facilitated the systematic modelling, simulation, and refinement of the Deep Q-Network-based traffic signal control system, ensuring that it effectively addresses the challenges of congestion at intersections while contributing to the broader domain of intelligent transportation systems, see Figure 1.

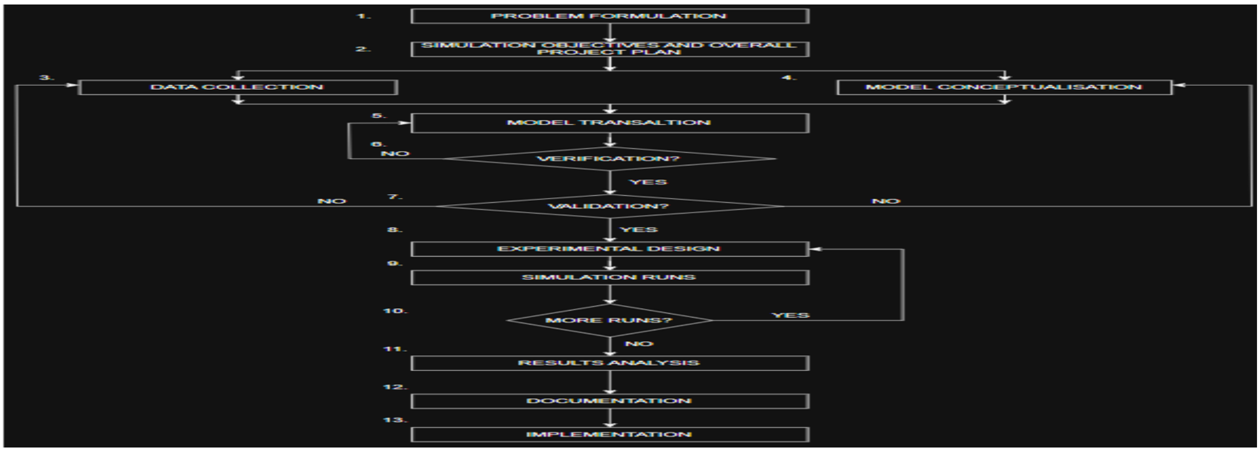


Figure 1: Simulation Research Methodology Steps for the Research.

For the technical implementation, the agile Kanban methodology, a lightweight, visual project management approach, was adapted to support flexible, efficient, and iterative software development. Kanban enables a clear visualisation of the progress of tasks, continuous delivery of requirements and adaptation to changing requirements throughout the development of the system.

By aligning simulation-based research objectives with modular software development goals, the combined use of simulation research methodology and agile Kanban ensured that the system was not only experimentally validated but also practically implementable. This dual approach ensured that the resulting platform is robust, adaptable and capable of supporting real-time traffic signal optimisations in rapid changing environments like urban cities.

## Ethical Considerations

To maintain the integrity of the research and ensure compliance with ethical standards this study was conducted with a strong emphasis on confidentiality and data protection. All information gathered from and datasets, free sources and from stakeholders such as city officials, transport authorities and road users were securely stored to protect the privacy of individuals involved. Participants who contributed feedback during prototype demonstrations and usability testing were fully informed of the research objectives, and their explicit statements were obtained prior to their involvement. This ensured they were aware of their rights and the voluntary nature of their participation. Additionally, in line with data protection regulations special care was taken to avoid the collection and misuse of any sensitive or personal information. Although the system uses simulated data in a virtual environment, future implementations involving real-time camera data will adhere to ethical standards regarding surveillance, public safety and individual privacy.

## System Architecture

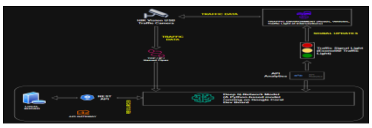

Figure 2: System Architecture for Real-Time Traffic Signal Optimisation System.

The system architecture shown in Figure 2 consists of three layers, the local server layer being the workstation, the Deep Q-Network model layer and the traffic environment layer which were illustrated as a simulated environment. The HIK Vision traffic cameras sends traffic data in image form to the model. The Deep Q-Network model is python based and runs on a Google Coral Dev Board mini-computer which is responsible for all traffic data processing and sends traffic signal light timings to the traffic lights at controlled intersections. The server provides resources such as power, more storage and cooling mechanism to the Google Coral Dev Board. The local server grants permissions to the PTV VISSIM simulation application, in which the traffic cameras and traffic environment are simulated, and provides it with the resources to run this environment. The simulation layer provides collected traffic data to the server and model through the COM API (Component Object Model) and API analytics respectively. The model receives traffic data collected in the simulation environment, analyses the data and makes decisions based on the Deep Q-Network algorithm. It also sends signals to the local server if ever there are special resources needed to run the desired traffic optimisation. This type of architectural design promotes easier debugging and consistent data flow.

## Implementation

The development of the system followed an object-oriented design approach, facilitating the modular and iterative implementation of system components. This enabled flexible development and integration of simulation, data processing, and optimisation modules.

### A. System Components and Integration

Three key intersections within Bulawayo’s Central Business District (in Zimbabwe), a developing country, were modelled using the map functionality in PTV VISSIM. These included the intersections of Ninth Avenue and Fort Street, Ninth Avenue and Hebert Chitepo Street, and the uncontrolled intersection at Ninth Avenue and Joshua Mqabuko Nkomo Street. These locations were chosen due to their high congestion levels and varying traffic light control schemes.

Simulated traffic environment: The traffic simulation environment was constructed to mirror the real-world geometry and behaviour of vehicles, intersections, and traffic signals. The simulation was configured to observe naturalistic vehicle interactions at intersections, highlighting traffic build-up and delays as would occur in physical urban settings.

Traffic signal and camera setup: At each intersection, simulated Econolite Cobalt Series traffic lights were deployed. Additionally, four simulated HIK vision traffic cameras were placed per junction, each covering one approach to capture vehicle counts and movements. These cameras facilitated real-time vehicle detection via the COM API, enabling data-driven optimisation.

Vehicle modelling: The simulation included diverse vehicle models to replicate realistic traffic scenarios. Vehicles were assigned stochastic behaviours across lanes and directions, reflecting real-world traffic dynamics.

### B. Functional Implementation

The core Python script, main.py, controlled system behaviour. It imported modules for traffic analysis and signal control, calling functions in a continuous loop every 10 seconds. The system collected traffic data, determined the optimal green light configuration using the DQN model, and applied the decision to the traffic environment.

Using PTV VISSIM’s Component Object Model (COM) API, traffic cameras collected data on vehicle speeds, volumes, and lane occupancy within a fifty metres capture radius. This data was logged into CSV files and represented the system's primary input for DQN training and inference.

DQN model training: The Deep Q-Network was implemented using TensorFlow v2.18.0 in Python. It was trained on a dataset of 64 episodes covering many traffic flow conditions. Each episode corresponded to

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different lane combinations and signal scenarios. Training aimed to reduce queue lengths and waiting times by learning the optimal signal policies based on observed states.

Data processing and decision making: Once trained, the model processed incoming traffic data in real time. It compared vehicle volumes across opposing lanes and selected the highest congestion paths to receive a green signal. Decision rules were based on learned policies that maximise throughput and minimise delay.

Signal optimisation and validation: Simulation outputs were validated by visual inspection of traffic flow progresses at the selected intersections. In scenarios with high traffic density, green light sequences were allocated to lanes with heavier volumes ensuring smoother flow and avoiding traffic accumulation.

**C. Tools and Technologies used for system development.**

Component Object Model (COM) is an API enabled Python-based interaction with PTV VISSIM, allowing for real-time data extraction and signal control. Visual Studio Code v1.97.2 was used as the integrated development environment (IDE) for Python and TensorFlow programming. It offered debugging, version control, and code management features. Deep Q-Network (DQN) algorithm combines Q-Learning with deep neural networks. It enables the system to process traffic data, learn optimal traffic light policies, and adjust signal timings dynamically. PTV VISSIM 2025 (SP05 – Student) is a leading microscopic simulation tool used to model urban traffic and interface with external control systems. Python v3.11.8 was used for algorithm implementation, simulation control, data processing, and model training due to its simplicity and robust libraries. TensorFlow v2.18.0 is a framework which provides a scalable and GPU-accelerated environment to build, train, and deploy the Deep Q-Network model effectively.

## RESULTS

The Traffic Signal Light Optimisation System was tested in a simulated environment and it successfully addressed the traffic congestion problem.

Figure 3: Traffic simulation on intersection of Ninth Avenue and Fort Street

Figure 4: Traffic simulation on Ninth Avenue and Hebert Chitepo Street

Figure 3 and Figure 4 show the optimisation of traffic signal lights at controlled intersections. The controlled intersections show signs of intelligence by minimising green light sequences for traffic lights facing lanes with fewer to no traffic at all whilst providing the advantage to the ones with congestion. Figure 4 shows heavier vehicles being given precedence at the intersection over less than four vehicles in lanes of comparison. The Deep Q-Network model uses multiple layers of neurons to extract patterns from traffic flow, vehicle density, and signal timing. It then learns an optimal traffic signal control policy by mapping observed states (traffic conditions) to the best possible actions (signal changes) to minimise congestion. This deep learning process is used in decision-making, helping the Deep Q-Network agent predict and select the best traffic light adjustments based on real-time data from the PTV VISSIM simulation. It then sends instructions of signal light timings to the traffic signal light which minimises congestion at intersections and the vehicles respond to the signal changes as expected.

The simulation shows that the developed system effectively prioritised congested lanes, demonstrating improved traffic optimisation in the simulation. A real-time traffic signal optimisation system using Deep Q-Network algorithm and camera data, to collect real-time traffic scenarios and process it using the Deep Q-Network trained model to optimise traffic flow at congested intersections to reduce traffic congestion was designed and implemented. Figure 5 shows a comparison of this developed system and other systems that are already in existence.

| System | SCOOT | InSync | Developed System |
|---|---|---|---|
| **Real-time Data Utilisation** | Uses inductive loop detectors | Powers video and radar sensors | Uses real-time camera data |
| **Algorithm Complexity** | Complex optimisation algorithms | Advanced machine learning | Deep reinforcement learning algorithm |
| **Scalability** | Scalable for large urban areas | Effective for both small and large networks | Suitable for large urban areas in developing countries |
| **Integration Capabilities** | Well-suited with various detection systems | Supports multiple sensor inputs | Integrates with existing surveillance infrastructure |
| **Congestion Decrease** | 10-20% decrease | 15-30% reduction | Significant reduction |
| **Safety Improvement** | Enhanced safety | Improved safety features | Reduced traffic jams during peak hours |
| **Challenges** | Complex calibration | High sensor costs | Lack of real-world deployment |

Figure 5: Comparison with similar systems

## CONCLUSION AND FUTURE WORK

To maintain relevance and scale impact, several enhancements are envisioned for future versions of the system. For future system improvements, OpenCV can be used for real-time traffic analysis, detecting vehicle density and movement from camera feeds. This data can improve the Deep Q-Network model's decision-making, leading to better traffic flow optimisation. Efforts will also be focused towards real-time deployment, which is essential for accurately reflecting the unpredictable complexities inherent in real-world scenarios, such as dynamic pedestrian movement and fluctuating traffic volumes. It is vital that the model undergoes rigorous testing with real-world traffic data obtained from actual surveillance systems. This approach will allow for the capture of the full spectrum of complexities, including variations in lighting, diverse weather conditions, and unpredictable driver behaviour. Furthermore, pilot testing conducted in a controlled real-world environment will be instrumental in collecting real-time operational data and gaining valuable perceptions into the model's performance stability and its readiness for wider, large-scale implementation.

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