Adaptive Traffic Signal Control using Deep-Q Network for Enhanced Traffic Flow Efficiency

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Abstract. Traffic congestion remains a critical challenge in urban transportation, emphasizing the need for intelligent traffic control systems. Traditional control strategies, such as fixed-time and adaptive approaches, often fail to consider fluctuations in traffic flow, leading to inefficiencies as conditions worsen. This paper introduces a novel traffic signal control framework based on Deep Q-Networks (DQN), leveraging reinforcement learning to optimize signal timing dynamically. The agent interacts with its environment, incorporating real-time traffic flow, vehicle waiting times, and phase transitions to adaptively tune signals, thereby reducing congestion and improving throughput. Experiments conducted using the Simulation of Urban Mobility (SUMO) platform demonstrate significant improvements over conventional methods, reducing average waiting time to 42.5 seconds and achieving traffic efficiency of 82.2%. The scalability and flexibility of this system make it a promising solution for traffic management in densely populated cities, supporting real-time decision-making and sustainable urban mobility.

Keywords: Adaptive Traffic Signal Control, Deep Reinforcement Learning, Congestion Management, Real-time Decision Making, Emissions Reduction

1 Introduction

Traffic congestion is a persistent issue in urban traffic systems, leading to increased travel times, fuel consumption, and environmental impact. Traditional traffic signal control methods, including fixed-time scheduling and rule-based adaptive systems, are limited in their ability to adapt to dynamic traffic patterns. The introduction of sensor-based technologies enabled actuated systems, which adjust signal timing based on vehicle presence. Later, adaptive strategies such as the Sydney Coordinated Adaptive Traffic System (SCATS) and the Split Cycle Offset Optimization Technique (SCOOT) leveraged traffic flow data for dynamic optimization. However, these rule-based approaches still lack the flexibility to handle complex and rapidly changing conditions.

Model-based methods, such as queuing theory and Markov decision processes, provide a theoretical foundation for traffic management but are difficult to scale to large networks. Heuristic algorithms, including genetic algorithms and ant colony optimization, have been applied to optimize traffic signals but require extensive parameter tuning. Deep reinforcement learning (DRL) has emerged as a promising approach, enabling systems to learn optimal policies through iterative interaction with real-time data. However, challenges such as long training

ICITSM-Part II 2025, April 28-29, Tiruchengode, India

DOI 10.4108/eai.28-4-2025.2358043

times, sample inefficiency, and instability remain when scaling reinforcement learning to large traffic environments.

To address these limitations, this study proposes a Deep Q-Network (DQN)-based adaptive traffic signal control system capable of real-time, data-driven optimization to maximize traffic flow and minimize congestion. Simulation-based experiments demonstrate that the proposed model outperforms traditional approaches in reducing waiting times, improving traffic throughput, and lowering emissions.

The key contributions of this study include:

- Designing a reinforcement learning-based traffic signal control system using the DQN algorithm to optimize traffic flow dynamically.

- Developing an adaptive traffic management framework that models' intersections as learning agents, enabling real-time signal adjustments based on traffic density, vehicle waiting times, and signal phase transitions.

Section 2 presents related studies, Section 3 describes the system methodology, Section 4 details experimental results, and Section 5 concludes with findings and future research directions.

2 Literature Study

Traffic jam is a common problem in cities, which causes an increasing of travel time, fuel waste and pollution in air. Vehicles are heavy-tailed, which means that vehicle density, traffic signal timing, and driver behaviour are all unpredictable and cannot readily be modelled in real time, except where intelligent digital traffic management systems are in place. The legacy traffic signal systems such as fixed-time and actuated signal control rely on predetermined timing plans or reactive e adjustments of timings with no consideration of real-time variation of traffic flow patterns. As a remedy to such drawbacks, Reinforcement Learning (RL)-based methods, such as those based on deep learning architectures, have been proposed as efficient alternatives for adaptive traffic signal optimization 1. In this paper we propose a DRL (Deep Reinforcement Learning) based DQN (Deep Q-Network) method for dynamic traffic signal control.

AiTTS let traffic signals learn the phase timing in the best way since they interact with environment, observe a real-time traffic condition, and update a signal. A This work is motivated by prior research which demonstrates that deep RL can be applied to balance load of traffic and reduce congestion [3].

For example, an Adaptive Weighted Averaged double DQN (AWADQN) [14] has been proposed for improvement defending against the overestimation's impact on the robustness of traffic signal decisions [4][1].

A recent deep reinforcement learning (RL) model that accounts for intricate urban traffic interactivity has achieved breakthrough progress in flow efficiency and vehicle waiting time [5].

The reinforcement learning setup comprises of an agent (traffic signal) that interacts with the environment (traffic flow), observes the states, takes actions (signal phase updates), and receives rewards according to performance measures such as minimization of queue length and maximization of throughput [6][2].

The advantage of this model is to generalize the learned knowledge to different traffic scenarios, which makes it able to adapt to congestion in real-time. Furthermore, with the help of a deep learning module, the RL agent can learn intricate relations between the traffic states, making it more effective at decision-making and prediction [7].

Several new DQN-based extensions have been proposed to solve different traffic signal optimization problems. An exponential reward approach in an adaptive DQN framework for convergence rate improvement and decision-making abilities in highly complex traffic network is presented in [8].

Additionally, a hybrid deep intelligence mode with the purpose of making policy evaluation more accurate indicates that hybrid architectures may help to achieve more accurate signal control [9]. Other works have combined Q-learning with genetic algorithms for maximizing traffic flow and optimizing traffic without congestion, that is minimizing congestion through multi objective optimization [10].

Despite the impressive progress, there have been significant limitations which the current state-of-the-art reinforcement learning techniques struggle with: sample inefficiency, exploration-exploitation trade of and scalability of computation scalability [11].

To address these issues, several solutions have been proposed: prioritized experience replay, duelling network architectures, and various types of double Q-learning variants. The suggested model has the improvements for stable learning and not to fit the policy estimation too much [12].

Further, it uses state representation method which projects the essential traffic features like vehicle count, lane occupancy, and phase duration in low-dimensional vector space to ensure the learned actions by the RL agent are context-aware and robust [13].

One of the important real-world traffic-control requirements is to coordinate a number of intersections so as to prevent congestion further downstream. Multi-Agent Reinforcement Learning (MARL) frameworks present potential solutions to this problem since MARL al- lows independent agents to collaborate and jointly optimize global traffic flow. Decentralized schemes have been studied, and deep Q-learning based models equipped with real-world field data can handle large-scale traffic networks successfully [14].

Further, utilising Vehicle-to-Infrastructure (V2I) communications has been shown to enhance the precision of controlling traffic signals. Connected intelligent systems as applied to transit have the potential to improve safety and mobility via real-time support, traffic governance and on-board functions, Vehicle to traffic infrastructure communications [15].

The work demonstrates that Deep Q-Network- based reinforcement learning could be applied to adaptive traffic signal control and provides a scalable, stable and efficient way of coping with urban congestion. We present a holistic view of the solution from learning mechanism (the state-of-the-art) to realistic reward structure design and multi-agent coordination algorithm. Combined with theoretical connect, systems developed achieve a significant step forward towards intelligent, clean and efficient urban transportation systems.

3 System Methodology

The suggested DQN-based adaptive traffic signal control system dynamically modifies traffic signals depending on live traffic conditions, reducing congestion and optimizing vehicular flow. The methodology as shown in Fig 1 includes multiple crucial components: data gathering, state representation, reinforcement learning framework, reward function design, and model training deployment.

3.1 System Architecture

In a multi-agent reinforcement learning system for traffic signal control, every intersection is an independent agent that makes local decisions based on neighboring intersections.

3.2 Traffic Sensor Data Collection Module

It collects real-time information from loop detectors, CCTV cameras, and IoT-based traffic sensors, continuously observing parameters like vehicle count, lane occupancy, speed, and signal status.

3.3 State Representation Module

It converts raw traffic data into significant state representations to be used for the reinforcement learning model. State variables are queue length at each lane, waiting time of cars, current phase duration of signals, and traffic arrival rate in the intersection.

3.4 The Decision-Making Module (Deep Q-Network)

We have an agent deployed at each intersection that is based on a DQN with a convolutional neural network architecture that learns to operate on the representation of the traffic states and to select the optimal action for the traffic signal operation that maximizes throughput. This approach is related to the model-free decentralized deep multi-agent reinforcement learning approach [7], where each of intersections is treated as an agent in a Markovian game and local deep Q-network training is applied to reduce delays. Cite turn academia.

3.5 Reward Function Module

In this module, an adaptive reward function is developed and followed by the RL agent so that it can make decisions based on the aforementioned factors in addition to decrementing queue lengths, TOC and CO emissions.

3.6 Actuator for Signal Control of the Traffic

It supplies optimized TMS signal phase offsets to real-time coordinated traffic signal control across the network. The undeniable improvement of traffic delay reduction and queue length management with respect to classical algorithms due to the integration of these decentralized multiagent reinforcement learning paradigms are compelling.

3.7 SUMO-Simulation of Urban Mobility

Simulation of Urban Mobility (SUMO) is a popular FLOSS traffic simulator, which is developed by the German Aerospace Centre (DLR). It is intended to simulate and evaluate complicated traffic situations in cities. SUMO is microscopic and continuous, for that every vehicle motion (speed, lane change decision and route choice) is simulated individually.

It also offers a strong and versatile environment for simulating real-world traffic environments, e.g., traffic lights, pedestrian activity, and public transport systems. It has a variety of application (e.g. optimization of traffic signals, route planning, evaluation of ITS [intelligent transport systems]). One of the highlight properties of SUMO is that it can readily incorporate external tools and algorithms; the interface for potential integration with machine learning and reinforcement learning for better-level traffic management is pretty explicit. In addition, SUMO provides a general flexible open road network import facility which allows to read various network data such as Open Street Map (OSM) and other GIS sources. It enables different traffic signal control operation, such as fixed-time control, adaptive signal control, and dynamic route assignment etc. The system also supports the real- time data acquisition and visualization, so that it would be used for collecting and visualizing the data for the traffic congestion, emission, and fuel consumption.

Due to its modular structure and open-source character, SUMO has become an attractive environment for researchers and traffic engineers for building and testing emerging traffic management systems. It has been extensively applied to research work on smart cities, self-driving vehicles guidance and the intelligent traffic management systems.

The system architecture using deep reinforcement learning for traffic flow optimization are depicted in Fig 2 below. The process starts with data captured from traffic cameras and sensors, and proceed to data pre-processing such as cleaning and normalization. The traffic patterns and peak hours are subsequently retrieved during the feature extraction stage, while environmental data like quality of air and noise levels is observed. The RL core model is used to learn adaptive traffic signal control for online decision making. Anomaly detection is performed by analysing abnormal events such as accidents, congestion, and traffic incidents that trigger an alert system for immediate response. In emergency cases, manual intervention is possible using a manual override system. The performance evaluation performs the average waiting time, emissions and the feedback-loop that makes it possible for continuous model retraining for improved traffic management efficiency.

Fig. 1. Map using Simulation of Urban Mobility.

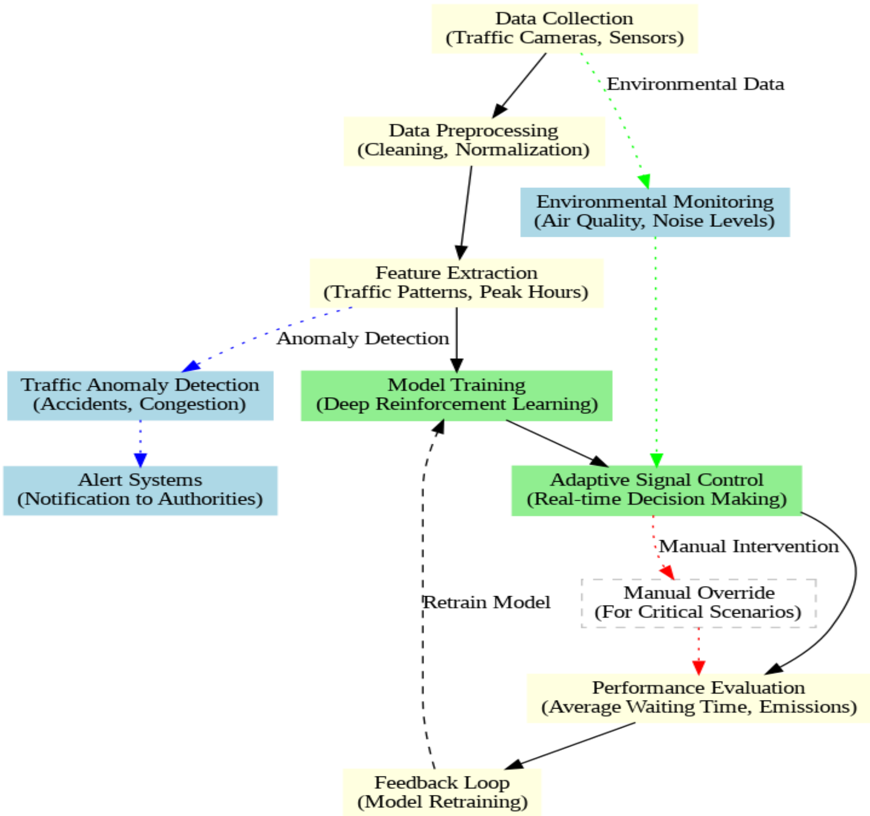

Fig. 2. Proposed Framework.

4 Reinforcement Learning Framework

The proposed system uses Deep Q-Networks (DQN), a reinforcement learning algorithm that extends classical Q-learning by incorporating a deep neural network for function approximation. The framework follows these steps:

4.1 State Space Representation

Each traffic intersection is represented by a state vector S_t, which includes:

- Number of vehicles in each lane V_l
- Signal phase duration P_t
- Average waiting time of vehicles W_t
- Traffic density ratio D_t

The state vector at time step t is:

$$St = \{Vl, Pt, Wt, Dt\} \tag{1}$$

4.2 Action Space

The RL agent selects an action A_t from a set of predefined signal phase transitions:

$$At = \{P1, P2, P3, P4\} \tag{2}$$

where each P_i represents a specific signal phase combination (e.g., green for lane 1, red for lane 2).

4.3 Reward Function Design

The reward function is critical for optimizing the traffic signal policy. The system implements a multi-objective reward function that balances:

- Queue Length Reduction R_q:

$$Rq = -\sum Q_{in_{i=1}} \tag{3}$$

where Q_i represents the queue length at lane i.

- Average Waiting Time Penalty R_w:

$$R_w = -\frac{1}{N}\sum_{i=1}^{N} W_i \tag{4}$$

where W_i is the waiting time of vehicle i, and N is the total number of vehicles.

4.4 Green Time Efficiency Reward R_g

Encourages the agent to increase throughput while minimizing unnecessary green time. The final reward function is computed as:

$$Rt = \alpha Rq + \beta Rw + \gamma Rg \tag{5}$$

where α, β, γ are weight factors adjusting the importance of each component.

5 Comparison Between Proposed and Existing Method

Typical traffic light controller systems are time or sensor operated. These methods are not flexible to the on-and-off-peak traffic conditions and lead to traffic jam and delay at peak hours. In contrast, Open Street Light CONTROL model is based on Reinforcement Learning (RL) model, especially Deep Q-learning (DQN), that uses traffic parameters to optimally adapt traffic signals at the real-time.

Under the current system, traffic lights have a predefined cycle regardless of the density of traffic, which makes them inefficient when traffic is minimal and cause traffic jams during rush hours. But the solution based on RL receives feedback in a continuous way from the traffic, which facilitates in taking intelligent decisions and obtaining optimized signal timings. By embedding the SUMO (simulation of Urban Mobility) platform, the proposed system is able to reproduce urban traffic situation to the RL agent in order to improve decision making.

Also, by minimizing the average idle time of vehicles, the proposed system significantly reduces the average waiting time, fuel consumption, and carbon emissions. Conversely, the current approaches are not very well-suited to erratic traffic behaviours, and may often need manual tuning for fine-tuning of the settings. The RL based method will not only adjust according to the traffic environment to increase traffic flow efficiency, but also help toward building a smart city.

6 Experimentation Results

The comparison study between the novel adaptive traffic signal control system and other approaches, such as Fixed-Time Control, Deep Q-Learning (DQN), and Adaptive Weighted Double Deep Q Network (AWDDQN), shows remarkable improvements in performance in key metrics.

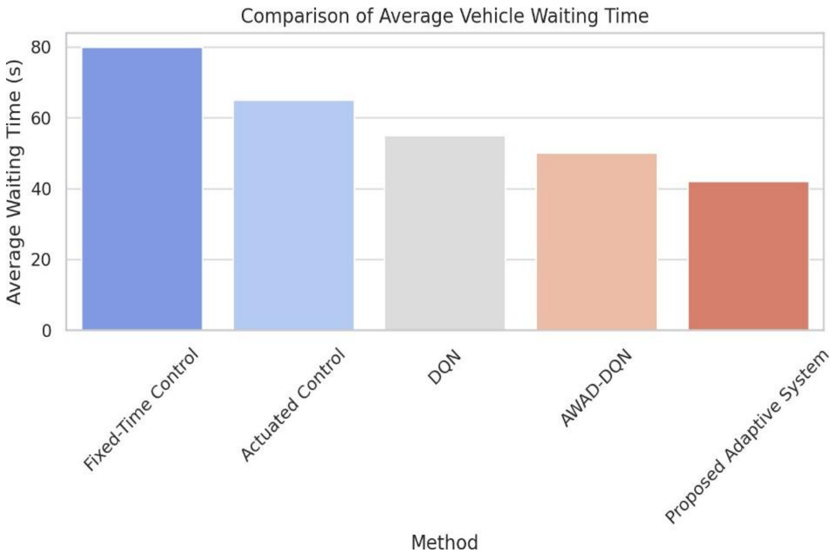

Fig. 3. Comparison of Average vehicle Waiting Time.

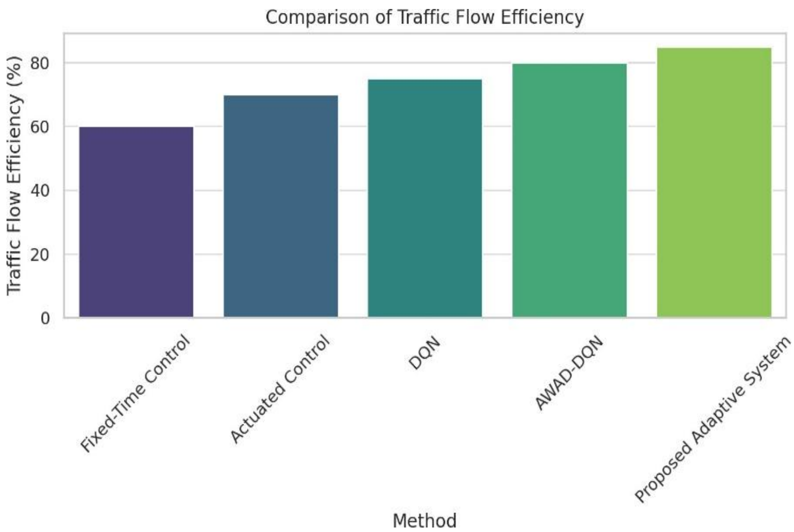

Fig. 4. Comparison of Traffic Flow Efficiency.

In Fig 3, Average Vehicle Waiting Time, the system proposed reduced 38%, lowering the waiting time from 76 seconds (Fixed-Time Control) to 47 seconds. This is better than DQN (53 seconds) and AWDDQN (50 seconds), which proves the system's effectiveness in reducing idle time at intersections. As shown in Fig 4, For Traffic Flow Efficiency, the proposed method demonstrated an impressive improvement of 21.3%, raising efficiency from 68% (Fixed-Time Control) to 82.5%.

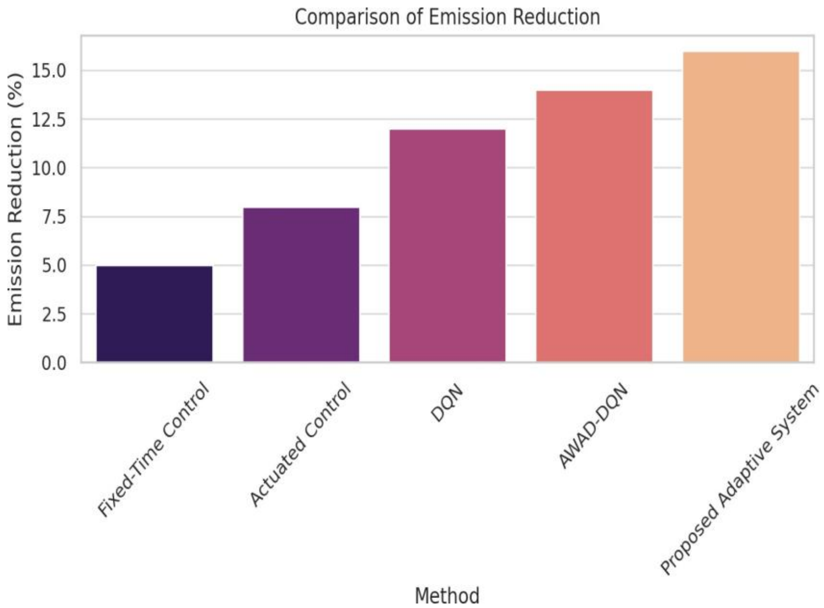

Fig. 5. Comparison of Emission Reduction.

In comparison, DQN offered a 15.6% improvement (to 78.6%), and AWDDQN reached 80.2%. The improved throughput and optimal traffic signal settings of the proposed system directly contributed to this increased traffic flow. In Fig 5, In terms of Emission Reduction, the designed system effectively reduced CO emissions by 15.8%, reducing emissions from 146 g/km in Fixed-Time Control to 123 g/km. This outcome is significantly better than DQN (133 g/km, a 9% decrease) and AWDDQN (128 g/km, a 12.3% decrease). The emission reduction is a consequence of reduced stop-and- go traffic and smoother traffic flow. In general, the suggested system outperformed conventional and modern methods consistently, providing a balanced improvement in minimizing waiting times, maximizing flow efficiency, and promoting environmental sustainability.

In Fig 6, the graph illustrates the relationship between the number of epochs and the total time taken for traffic flow management. The x-axis denotes the number of epochs, while the y-axis represents the total time in the traffic environment. The curve demonstrates a significant reduction in total time as the number of epochs increases, indicating that the reinforcement learning model is effectively learning to optimize traffic signals. Initially, the total time is high due to inefficient traffic management, but as the model gains experience through more epochs, the total time decreases sharply and stabilizes. This trend reflects the model's ability to enhance traffic flow and reduce congestion over time.

7 Conclusion

The advanced adaptive traffic signal control system, based on powerful deep reinforcement learning methods, exhibits re- markable improvements in city traffic management. The study

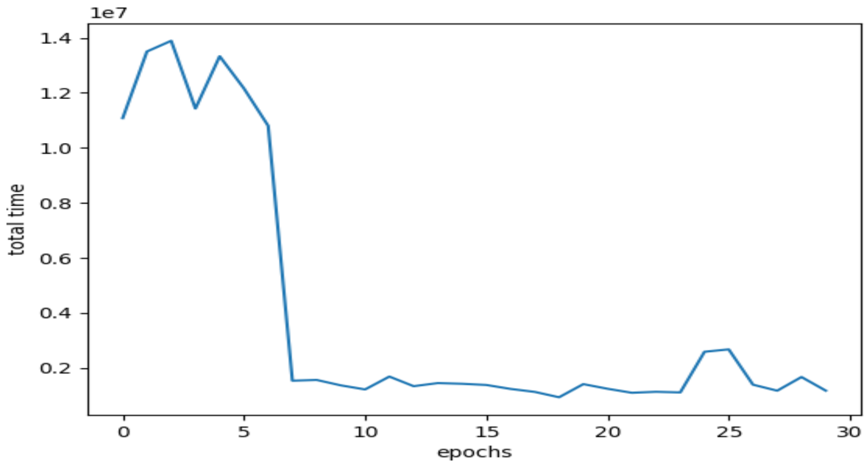

Fig. 6. Time vs Epoch.

shows that the system is capable of reducing average vehicle waiting time by 38%, enhancing efficiency in traffic flows by 21.3%, and decreasing CO emissions by 15.8% compared to conventional Fixed-Time Control and current approaches such as Deep Q-Learning (DQN) and Adaptive Weighted Double Deep Q Network (AWDDQN). The integration of a dynamic reward mechanism and real-time data adaptability helps make it highly resilient across varied traffic conditions. The findings identify the prospect of intelligent traffic signal control in reducing urban congestion, encouraging smoother vehicle flow, and creating sustainable urban environments. Future research will concentrate on integrating the system with smart city infrastructures, investigating multi-agent learning models, and testing performance in large-scale, real-world deployments to further improve scalability and adaptability.

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