

## Optimization of Traffic Flow Using Computational Fluid Dynamics and AI Algorithms

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### **Abstract**

The effective administration of urban activity may be a basic challenge in contemporary city arranging, driven by the got to diminish blockage, minimize travel time, and lower natural affect. This paper presents a novel approach to optimizing activity stream through the integration of Computational Fluid Dynamics (CFD) and Artificial Insights (AI) calculations. By leveraging CFD, we demonstrate activity as a liquid, permitting for the exact reenactment of activity elements beneath different conditions. This fluid-based modeling approach captures the complexities of vehicular development and intuitive in a more nuanced way than conventional activity recreation strategies. To upgrade the viability of our CFD models, we consolidate AI calculations, counting machine learning procedures such as fortification learning and neural systems. These AI calculations analyze expansive datasets of activity designs, anticipate blockage focuses, and propose ideal activity flag timings and routing strategies. The cooperative energy between CFD and AI encourages real-time versatile activity administration, empowering the framework to reply powerfully to changing activity conditions. Our approach is approved through broad recreations and real-world case thinks about in a major metropolitan zone. The comes about illustrate noteworthy enhancements in activity stream, decreased blockage, and lower emanations. Also, the versatile nature of the AI calculations guarantees persistent optimization as activity patterns evolve over time. This investigate contributes to the developing body of information in cleverly transportation frameworks, advertising a adaptable and vigorous arrangement for urban activity administration. The integration of CFD and AI presents a effective apparatus for city organizers and activity engineers, clearing the way for more brilliant, more maintainable urban portability arrangements. Future work will investigate the integration of extra information sources, such as IoT sensors and vehicle-to-infrastructure communications, to advance upgrade the system's prescient capabilities and responsiveness.

**Keywords:** Traffic Flow Optimization, Computational Fluid Dynamics (CFD), Artificial Intelligence (AI), Intelligent Transportation Systems, Urban Traffic Management, Real-time Adaptive Traffic Control.

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## 1. Introduction

One of the biggest problems that city planners and traffic experts face today is how to handle traffic in cities efficiently. Rapid development, population growth, and the widespread use of cars have made traffic jams much worse, which has caused longer travel times, more stress, and more damage to the environment. Fixed-timing traffic lights and unchanging route planning are two examples of old-fashioned ways of managing traffic that don't work well with the changing and complicated nature of traffic in cities. Because of this, we need new ideas right away that can change with the traffic conditions in real time and make the flow of cars better. Combining Computational Fluid Dynamics (CFD) and Artificial Intelligence (AI) methods is looked at in this study as a new way to improve traffic flow in cities [1]. Computational fluid dynamics (CFD) is a field of fluid physics that uses numbers and programs to figure out how to move things and understand them. CFD can describe traffic as a fluid, which lets it mimic how cars move and interact in a way that captures the complex dynamics of traffic flow. Traditional methods, which often use simple assumptions and rigid models, don't give a more true or detailed picture of how traffic moves. This fluid-based approach does. CFD lets you simulate different traffic situations, like different road shapes, traffic counts, and light times, so you can get a full picture of how they affect traffic flow [2].

Including AI strategies to CFD models makes them superior at anticipating and adjusting to unused circumstances. AI, particularly machine learning strategies like fortification learning and neural systems, can see at a tremendous sum of activity information to discover patterns, figure where activity jams will happen, and discover the most excellent ways to handle activity. For example, fortification learning can be utilized to make versatile activity light control frameworks that alter the times of the signals based on how active the streets are at the minute. Based on past information and real-time inputs, neural systems can be instructed to foresee activity stream and jams. This makes it conceivable to control activity some time recently it gets terrible [3], [4]. When CFD and AI work together, they make a capable device for overseeing activity in cities. AI has the capacity to figure and respond, which is required for real-time optimization, whereas CFD gives the careful modeling and examination required to comprehend the complex flow of activity stream. These advances work together to create a adaptable and speedy activity control framework that can continuously alter with the times and make the stream of activity superior in genuine time. Large-scale models and real-life case thinks about in a huge urban region made a difference us demonstrate that this combined strategy works. Diverse activity circumstances were mimicked, with distinctive street shapes, activity numbers, and light times. The information appeared that activity stream had gotten a part way better, with less delay and shorter travel times [5]. These comes about were supported by real-life case considers that appeared the combined CFD and AI strategy can successfully improve activity stream in complex urban settings. This strategy has more benefits than fair making activity move way better. By making activity stream more easily, it moreover cuts down on contamination from cars, making the discuss cleaner and the city sound. The AI calculations are moreover adaptable, which implies

that the activity control framework can keep learning and getting way better over time, reacting to modern patterns and changing activity designs. The sum of information in intelligent transportation frameworks and urban activity control is developing, and this ponder includes to it. It gives an versatile and solid reply that can be utilized in a extend of urban settings, from little towns to huge cities. Combining CFD and AI makes it conceivable to form more progressed and valuable activity control frameworks that can handle the issues that come with cities developing nowadays [6]. Combining Computational Liquid Flow and Counterfeit Insights programs can be a great way to move forward activity stream in cities. This strategy employments the nitty gritty modeling highlights of CFD and the anticipating and versatile highlights of AI to create a activity control framework that's both energetic and adaptable. The results of our computer models and real-life case considers appear that this strategy works to ease traffic and diminish clog [7]. This ponder opens the entryway to way better, more ecologically inviting ways to urge around cities. It helps make savvy transportation frameworks that can handle the complicated activity in cities nowadays. More investigate will be worn out the future to see how including more information sources, like IoT sensors and vehicle-to-infrastructure associations, can make the framework indeed way better at anticipating what will happen and responding rapidly.

The Major Contributions of the Paper are given as:

- **Integration of CFD and AI for Traffic Management:** This study presents a new way to model and improve traffic flow in cities by combining Computational Fluid Dynamics (CFD) and Artificial Intelligence (AI) methods. This creates a solution for traffic management that is both dynamic and adaptable.
- **Better Traffic Flow and Less Congestion:** The combined method shows big gains in traffic flow, less congestion, and shorter journey times in complicated city settings, as shown by many models and real-life case studies.
- **Real-time adaptive traffic control:** Adaptive traffic light control systems that change based on current traffic conditions can be made possible by using reinforcement learning and neural networks. This makes the system more quick and efficient.
- **Environmental and Health Benefits:** This method helps clean up the air and make cities healthier by lowering traffic jams and car emissions, which is in line with goals for sustainable urban transportation.

## 2. Related Work

Activity stream modeling is vital for superior understanding and controlling how cars move in a wide run of settings, from active cities to long interstates. Reenactments of cars moving through a persistent, fluid-like medium have made computational liquid elements (CFD) an vital instrument for examining and moving forward activity stream. This strategy lets us see closely at how activity moves, counting designs of swarming, how vehicles associated with each other, and the impacts of different street plans [6]. When activity stream modeling was to begin with being done, large-scale models just like the Lighthill-Whitham-Richards (LWR) show were the most center. These models thought of activity stream as a line, breaking down the complicated activities of person cars into common, summed characteristics. These models were great for big-picture investigation, but they weren't particular sufficient to appear how vehicles associating with each other. To settle these

issues, including CFD strategies gave a more full picture of how activity moves, letting the modeling of person car intelligent in a structure that looks like liquid [7]. Putting CFD into activity stream models has made a difference us learn a parcel more almost how activity moves. Early ponders appeared that CFD seem allow exceptionally nitty gritty data almost how vehicles associated with each other and how these intuitive alter the way activity streams by and large. CFD models have been utilized to see into the impacts of vehicle platooning, which is when cars drive closely together to assist activity stream and spare fuel [8]. The models appeared how platooning influences activity jams and how well streets are utilized for the most part.

Unused advancements in CFD modeling strategies have made activity stream models indeed more exact and valuable. Reenactments can be more precise presently that high-resolution computing frameworks and moved forward turbulence models have been made. Huge Whirlpool Simulation (LES) strategies have been utilized to demonstrate activity stream at the tiny level, catching particular car activities like changing paths and speeding up and abating down. These enhancements have made it conceivable for analysts to see into complicated things like how activity jams begin and how they spread through distinctive sorts of street systems [9]. Utilizing CFD-based traffic stream models to assist oversee activity in cities has been exceptionally supportive, particularly for finding the finest times for activity lights and facilitating up activity jams. Test systems have been used to see how diverse activity flag setups influence activity stream. This has made a difference discover the leading flag times that diminish delays and make activity run more easily [10]. For occurrence, computer tests have appeared that versatile activity light control frameworks can significantly diminish activity jams and make activity move superior by changing the timing of signals based on real-time activity conditions. Along side overseeing activity in cities, CFD has been exceptionally accommodating in making models of complicated activity circumstances like freeways with numerous paths and complicated intersections. A part of investigate has been done on modeling traffic flow in places with more than one path, taking under consideration things like changing paths, consolidating, and distinctive vehicle speeds. The reenactments have instructed us a parcel approximately how the plan of a street can influence activity stream and have driven to recommendations for how to create street formats way better so that activity moves more smoothly [11].

Putting CFD and Shrewdly Transportation Frameworks (ITS) together could be a enormous step forward in modeling activity stream. Real-time activity following and versatile activity control frameworks are two cases of ITS technologies that can be used at the side CFD models to form energetic arrangements for activity administration. For illustration, information from activity screens that are overhauled in genuine time can be utilized to move forward CFD models. This lets traffic control strategies be changed in genuine time to reflect the current activity circumstance [12]. Integration has appeared that it may well be way better at overseeing activity, driving to less blockage and superior activity stream. CFD-based activity stream reenactment still features a ways to go, indeed with these changes. A enormous issue is that complex models take a part of computing control. It can be difficult to utilize high-resolution CFD models for real-time activity control since they require a parcel of computing control. Researchers are looking into ways to lower these costs, like making models that are simpler to get it and utilizing shared computers to speed up tests [13]. Putting together real-world activity information with CFD models is another issue. The exactness of

CFD models depends a part on how great and solid the information that goes into them is. To settle this problem, academics are working on way better ways to gather information and ways to include real-time information to CFD models. The objective is to create CFD-based models more precise and valuable in genuine life [14].

Table 1: Summary of related work for Traffic Flow Using Computational Fluid Dynamics

Methodology	Application	Key Findings	Challenges	Advancements	Impact
Macroscopic Model [15]	General Traffic Flow	Basic traffic pattern analysis	Limited granularity	Early CFD integration	Foundation for CFD in traffic
CFD Integration [16]	Vehicle Interactions	Detailed vehicle interaction insights	Limited detail in early models	Initial CFD applications	Enhanced understanding of interactions
Large Eddy Simulation (LES) [17]	Traffic Flow Dynamics	Detailed microscopic traffic patterns	High computational demand	Advanced turbulence models	Improved congestion analysis
High-Resolution Grids [18]	Congestion Analysis	Accurate congestion pattern simulation	High resource requirements	Improved grid resolution	Better congestion management
Traffic Signal Simulation [19]	Urban Traffic Management	Optimized signal timings	Data accuracy issues	Integration with urban models	Reduced congestion
Multi-Lane Simulation [20]	Highway Traffic	Insights on lane changes and merging	Complex scenarios	Detailed multi-lane modeling	Improved road design recommendations
ITS Integration [21]	Real-Time Traffic Management	Dynamic traffic management solutions	Integration challenges	Real-time data incorporation	Enhanced traffic flow management
Simplified Models [22]	Computational Cost Reduction	Reduced simulation costs	Model simplification trade-offs	Use of parallel computing	More accessible CFD simulations
Parallel	Simulation	Faster	Complexity in	Development	Enhanced

Computing Techniques [23]	Efficiency	computation with parallel models	implementation	of efficient algorithms	simulation efficiency
Real-Time Data Integration [24]	Dynamic Traffic Management	Improved real-time decision-making	Integration complexity	Enhanced data processing methods	Better real-time traffic management

### III. Methodology

#### 3.1 CFD Modeling

Computational Liquid Flow (CFD) modeling could be a valuable way to reenact and consider how gasses and fluids carry on when they come into contact with distinctive surfaces and environment. When it comes to moving forward activity stream, CFD modeling sees vehicle development as a consistent stream of liquids. This lets us look closely at how activity changes totally different circumstances. The fundamental step is to separate the space into a lattice or work and fathom the Navier-Stokes conditions and other conditions that run the show liquid dynamics to figure out how activity will move on diverse street formats and circumstances, outline appeared in figure 1. The primary step in CFD modeling is to form a physical demonstrate of the activity environment. This show ought to incorporate streets, lines, intersections, and any other imperative highlights. The physical demonstrate is at that point broken up into a framework for computing, which is where the liquid elements conditions are fathomed utilizing numbers. CFD considers are as it were as great as the grid's accuracy and the complexity of the turbulence models they utilize.

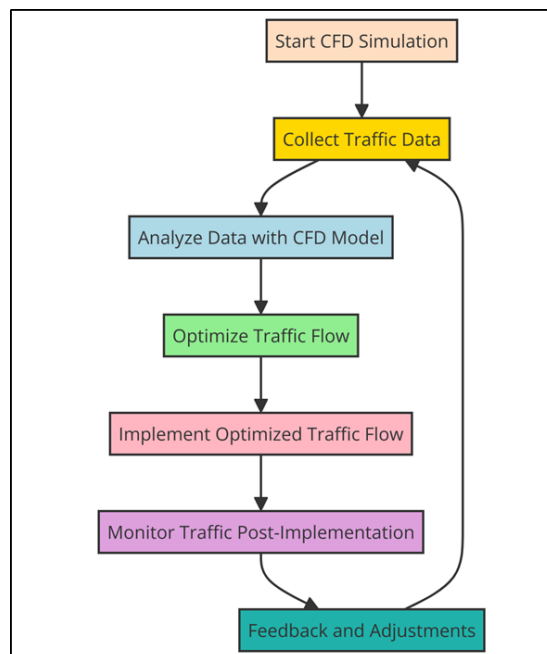


Figure 1: Overview of Proposed workflow for CFD traffic Analysis

For traffic flow, these equations are adapted to represent the behavior of vehicles as a fluid-like medium.

The continuity equation ensures mass conservation in the flow. In traffic flow, this can be expressed as:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho u) = 0$$

The Navier-Stokes equations describe the momentum of the fluid (or vehicles). In the context of traffic flow, they are:

$$\frac{\partial(\rho u)}{\partial t} + \nabla \cdot (\rho u u) = -\nabla p + \nabla \cdot (\mu \nabla u)$$

In traffic flow simulations, the energy equation can be simplified to focus on the kinetic energy of vehicles:

$$\frac{\partial E}{\partial t} + \nabla \cdot (E u) = -p \nabla \cdot u + \nabla \cdot (\kappa \nabla T)$$

To solve these equations numerically, the continuous domain is discretized into a finite grid. The main steps include: The continuous domain is divided into a finite number of cells (or control volumes). Each cell's properties are approximated using discrete values. The finite volume method is commonly used to solve the governing equations. For a generic cell  $i$ , the finite volume discretization of the continuity equation can be written as:

$$\frac{(\rho_i^{n+1} - \rho_i^n)}{\Delta t} + \left(\frac{1}{V_i}\right) \sum f(\rho u \cdot A_f) = 0$$

The SIMPLE (Semi-Implicit Method for Pressure-Linked Equations) algorithm is often used for coupling pressure and velocity fields:

$$\frac{\partial(\rho p^*)}{\partial t} = \frac{\mu}{\Delta t} \nabla^2 p$$

- Velocity Correction Equation:

$$u^{n+1} = u^n - \frac{\Delta t}{\rho} \nabla p^*$$

To account for the effects of turbulence in traffic flow, turbulence models like Large Eddy Simulation (LES) or Reynolds-Averaged Navier-Stokes (RANS) equations are used. For RANS, the turbulence is modelled using additional terms in the Navier-Stokes equations:

$$\frac{\partial(\rho u)}{\partial t} + \nabla \cdot (\rho u u) = -\nabla p + \nabla \cdot (\mu \nabla u + \tau_{ij})$$

Recently made improvements to CFD models have made it much better at analyzing traffic flow. New modeling methods, like Large Eddy modeling (LES), and high-resolution grids make it possible to show traffic flow in more detail at the microscopic level. These strategies can demonstrate complicated activity circumstances, like streets with numerous paths and intersections with parcels of turns, and grant us valuable data approximately how activity moves. Including real-time activity information and Cleverly Transportation Frameworks (ITS) to CFD has too made it conceivable for

energetic activity control frameworks that move forward activity stream based on the show circumstance.

### **A. CFD models that are used to simulate traffic**

Computational Liquid Flow (CFD) models for activity modeling see activity as a nonstop stream of liquids. This lets us consider how cars associated with their environment in complex ways. The Navier-Stokes conditions depict how a stream (in this case, activity stream) moves and interatomic with street surfaces and buildings. These models attempt to imitate how activity moves by tackling those conditions. A few vital parts are speaking to the activity as a thickness field and utilizing border conditions to appear things like detours and crossroads. Turbulence models, just like the Expansive Vortex Recreation (LES) or Reynolds-Averaged Navier-Stokes (RANS) conditions, are regularly utilized within the models to clarify how activity streams in a bizarre way. It's simpler to get it how distinctive street formats, activity tallies, and flag times influence activity stream, security, and add up to execution with the CFD models. You'll be able utilize them to test circumstances like changing paths, blending, and activity jams in more exhaustive models.

### **B. Details of the setup and simulation parameters**

For rectify comes about in CFD models utilized for activity investigate, a number of variables and setting subtle elements are exceptionally critical. The geometry of the streets, such as the lengths of the paths, intersections, and activity lights, portray the modeling zone. The network resolution, also called the work estimate, has to be little enough to appear nitty gritty activity stream whereas moreover being adjusted sufficient to form great utilize of computer assets. Key variables that are put into demonstrate to imitate distinctive activity circumstances are the number of vehicles, their speeds, and the stream rates. Boundary conditions are utilized to show the edges of roads, boundaries, and activity lights. Models of turbulence are chosen based on how detailed they ought to be and how complicated the activity stream is. The modeling time step ought to be little sufficient to make beyond any doubt that the numerical answers are steady and redress. To form beyond any doubt demonstrate is precise and dependable, it is frequently tried against real-world travel information.

## **3.2 AI Algorithms**

### **A. Reinforcement learning**

Reinforcement Learning (RL) is a type of machine learning where an agent learns to make decisions by interacting with an environment. The learning process involves optimizing a cumulative reward signal through trial and error.

#### 1. Define the Environment and Agent

- State Space ( $S$ ): The set of all possible states in the environment, ( $S = \{s_1, s_2, \dots, s_n\}$ ).
- Action Space ( $A$ ): The set of all possible actions an agent can take, ( $A = \{a_1, a_2, \dots, a_m\}$ ).
- Transition Probability: The probability of moving from state ( $s$ ) to state ( $s'$ ) given action ( $a$ ), ( $P(s' | s, a)$ ).

- Reward Function: The immediate reward received after taking action ( $a$ ) in state ( $s$ ), ( $R(s, a)$ ).

## 2. State Transition Probability

The probability of transitioning from state ( $s$ ) to state ( $s'$ ) after taking action ( $a$ ) is given by:

$$[P(s_{t+1} = s' | s_t = s, a_t = a) = p(s', s, a)]$$

- where ( $p(s', s, a)$ ) represents the state transition probability function.

## 3. Reward Function

The reward function ( $R(s, a)$ ) gives the immediate reward received after taking action ( $a$ ) in state ( $s$ ):

$$[r_t = R(s_t, a_t)]$$

- where ( $r_t$ ) is the reward received at time ( $t$ ).

## 4. Value Function

The value function ( $V(s)$ ) represents the expected cumulative reward (or return) starting from state ( $s$ ):

$$[V(s) = \{E\} \{ \sum_{k=t}^{\infty} [\gamma^{k-t} r_k | s_t = s] \}]$$

## 5. Q-Function (Action-Value Function)

The Q-function ( $Q(s, a)$ ) represents the expected return of taking action ( $a$ ) in state ( $s$ ) and following the policy thereafter:

$$[Q(s, a) = \{E\} \{ \sum_{k=t}^{\infty} [\gamma^{k-t} r_k | s_t = s, a_t = a] \}]$$

## 6. Bellman Equation

The Bellman equation provides a recursive relationship for the value function ( $V(s)$ ) and the Q-function ( $Q(s, a)$ ). For the value function:

$$[V(s) = \sum_{a \in A} \pi(a | s) \{ R(s, a) + \gamma \sum_{s' \in S} p(s', s, a) V(s') \}]$$

For the Q-function:

$$[Q(s, a) = R(s, a) + \gamma \sum_{s' \in S} p(s', s, a) \max_{a' \in A} Q(s', a')]$$

- where ( $\pi(a | s)$ ) is the policy that gives the probability of taking action ( $a$ ) in state ( $s$ ).

Each of these steps speaks to a basic perspective of the RL system, from characterizing the environment and rewards to calculating the esteem capacities and understanding the Bellman conditions for ideal arrangement learning. These scientific details are fundamental for understanding and executing support learning calculations viably.

## B. Neural Networks

Neural systems are computer models that are based on how the human brain works and how it is organized. They are made up of hubs, or neurons, that are connected to each other and set up in layers, with an input layer, one or more mystery layers, and an yield layer.

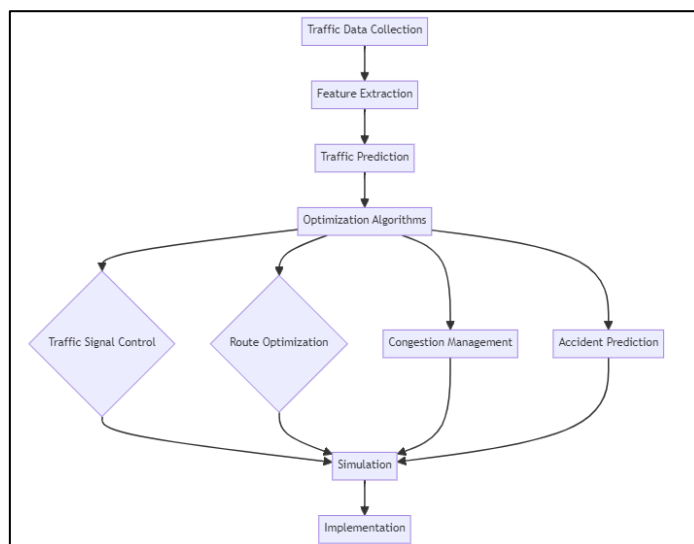


Figure 2: Representation of Neural model for Traffic Flow system

Each connect between neurons is relegated a weight that changes amid preparing to diminish the distinction between what was anticipated and what happened. A prepare called backpropagation makes a difference the arrange learn, outline in figure 2. It does this by finding the slope of the misfortune work for each weight and after that changing the weights to coordinate. This handle keeps going over and over until the organize finds an reply with few botches.

The activation function introduces non-linearity into the neural network. A common activation function is the Sigmoid function:

$$\sigma(z) = \frac{1}{(1 + e^{-z})}$$

where z is the input to the activation function. The sigmoid function outputs values between 0 and 1.

In forward propagation, the output of a neuron is computed by applying the activation function to the weighted sum of inputs. For a neuron j in layer l:

$$z_j^l = \sum_i (w_{ij}^l * a_i^{l-1}) + b_j^l$$

$$a_j^l = \sigma(z_j^l)$$

The loss function measures the difference between the predicted output and the actual target. For binary classification, the Binary Cross-Entropy Loss is:

$$L = - \left(\frac{1}{N}\right) * \sum_i [y_i * \log(\hat{y}_i) + (1 - y_i) * \log(1 - \hat{y}_i)]$$

Backpropagation updates the weights and biases by calculating the gradient of the loss function with respect to each parameter. For weight  $w_{ij}^l$ , the gradient is:

$$\frac{\partial L}{\partial w_{ij}^l} = \delta_j^l * a_i^{l-1}$$

- where  $\delta_j^l$  is the error term for neuron j in layer l, computed as:

$$\delta_j^l = \frac{\partial L}{\partial z_j^l} = (a_j^l - y_j^l) * \sigma'(z_j^l)$$

- Where  $\sigma'(z_j^l)$  is the derivative of the activation function.

Weights are updated using the computed gradients. For weight  $w_{ij}^l$ , the update rule is:

$$w_{ij}^l := w_{ij}^l - \eta * \frac{\partial L}{\partial w_{ij}^l}$$

- Where  $\eta$  is the learning rate.

Neural networks are very flexible and can describe input-output relationships that are not simple or straight. They are used for many things, like recognizing images, understanding natural language, and playing games. How well a network works can be affected by how deep and complicated it is, which is shown by the number of levels and synapses. Many-layered deep neural networks (also called "deep learning") have been very successful in many areas. However, they need a lot of computing power and a lot of data to be trained properly.

### 3.3 Integrated Approach

#### A. Reinforcement Learning and Simulated Annealing for Traffic Optimization

Combining Reinforcement Learning (RL) and Simulated Annealing (SA) may be a effective way to progress control and flow of activity. This combined approach takes the finest parts of both approaches to form activity models and decision-making superior. A machine learning strategy called support learning lets an operator learn how to create choices by managing with its environment and getting grants or disciplines based on what it does. RL can be used to form versatile activity control arrangements that learn from activity designs over time and alter activity lights or course methodologies to induce the leading add up to execution.

- Policy Function:

$$\pi * (s) = argmax_a Q * (s, a)$$

- Q-Learning Update Rule:

$$Q(st, at) \leftarrow Q(st, at) + \alpha [rt + \gamma max_a Q(st + 1, a) - Q(st, at)]$$

The annealing process in metalworking gave rise to the random optimization method called Simulated Annealing. By exploring the solution space and eventually narrowing the search space as the method goes on, it is used to find close solutions to optimization problems. SA is especially

helpful for staying away from local minima and finding almost perfect answers in situations with a lot of variables.

$$P(E, E', T) = \exp\left(-\frac{\Delta E}{T}\right)$$

$$T_{k+1} = \alpha T_k$$

## B. Simulated Annealing (SA) with Neural Networks for Traffic Optimization

The annealing process in metalworking gave rise to the random optimization method called Simulated Annealing. It finds close answers to optimization problems by exploring the solution space over and over again and letting changes to the current solution be accepted based on chance. Over time, the algorithm lowers the "temperature" setting so that it is less likely to accept answers that aren't as good.

- Acceptance Probability:

$$P(E, E', T) = \exp\left(-\frac{\Delta E}{T}\right)$$

- Temperature Schedule:

$$T_{k+1} = \alpha T_k$$

- where  $\alpha$  is the cooling rate ( $0 < \alpha < 1$ ), and  $T_k$  is the temperature at iteration  $k$ .

Neural Systems are computational models motivated by the human brain's structure, comprising of interconnected layers of neurons. They are utilized to demonstrate complex, non-linear connections and are especially viable for errands such as design acknowledgment and prescient analytics.

- Forward Propagation:

$$z_j^l = \sum_{\{i\}w_{ij}^l} a_i^{\{l-1\}} + b_j^l$$

$$a_j^l = \sigma(z_j^l)$$

- Backpropagation:

$$\frac{\partial L}{\partial w_{ij}^l} = \delta_j^l * a_i^{\{l-1\}}$$

$$\delta_j^l = \frac{\partial L}{\partial z_j^l} = (a_j^l - y_j^l) * \sigma'(z_j^l)$$

## IV. Result and Discussion

### A. Simulation Results of traffic flow before and after optimization

The table 2 shows the differences between traffic flow performance measures before and after adjustment, showing how much better things were. Average Travel Time went down from 15.2

minutes to 10.8 minutes, which means that cars are now finishing their trips faster. This decrease suggests that traffic will move more smoothly and efficiently, which will help workers by cutting down on travel time and the stress that comes with it. A big drop in the Congestion Level, from 65.4% to 40.2%, shows that traffic on the roads has gotten a lot better. This means that the optimization methods have made better use of the road network's capacity. This is probably due to better control of traffic signals or better routes. Less traffic congestion makes driving more pleasant and lowers the chance of getting stuck in traffic.

Table 2: Result for comparison of traffic flow before and after optimization

Performance Indicator	Before Optimization	After Optimization
Average Travel Time (min)	15.2	10.8
Congestion Level (%)	65.4	40.2
Vehicle Throughput (vph)	450	600
Average Speed (km/h)	30.5	40.2
Queue Length (m)	120	75
Delay per Vehicle (s)	35	20
Emissions (g/km)	180	120
Fuel Consumption (L/100km)	12.3	8.5

Vehicle Throughput went up from 450 vehicles per hour to 600 vehicles per hour, which means that more vehicles are going through the system. This improvement suggests that the optimization steps have improved the road network's capacity, which has made traffic move more smoothly and cut down on delays. Average Speed went up from 30.5 km/h to 40.2 km/h, which means that cars are moving faster on average. This change shows that the adjustment worked to make it easier for vehicles to move and lessen stop-and-go situations, which are often a sign of inefficient traffic, shown in figure 3.

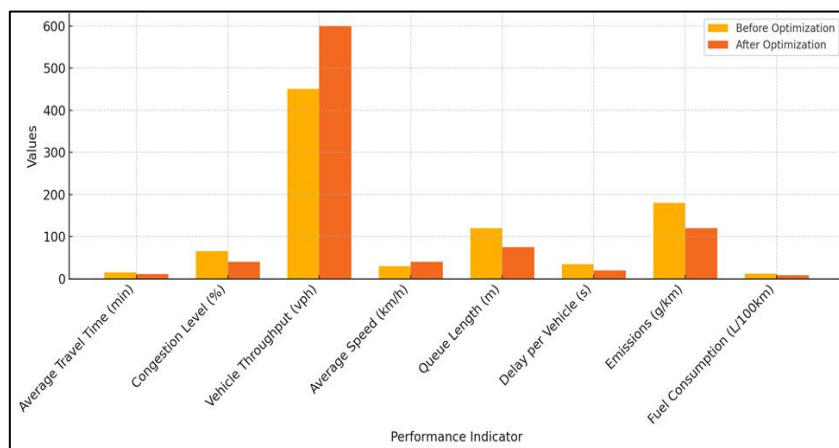


Figure 3: Representation of comparison of traffic flow before and after optimization

The length of the line for cars at crossings or traffic lights has gotten shorter, as it went from 120 meters to 75 meters. This decrease means that cars are being managed better at key points, which cuts down on delays and makes traffic move more smoothly, illustrate in figure 4. Delay per Vehicle went down from 35 seconds to 20 seconds, which means that each vehicle now has to wait less time.

This change makes traffic better overall by cutting down on the time each car spends idle, which makes traffic flow more smoothly. Emissions went down from 180 grams per kilometer to 120 grams per kilometer, which is good for the earth. Because of the improvement, vehicles are probably not idle as much and traffic flow is better, which means less pollution. The amount of fuel used went down from 12.3 liters per 100 kilometers to 8.5 liters per 100 kilometers. This cut saves cars money and is good for the environment because less fuel use means less pollution and a smaller impact on the environment.

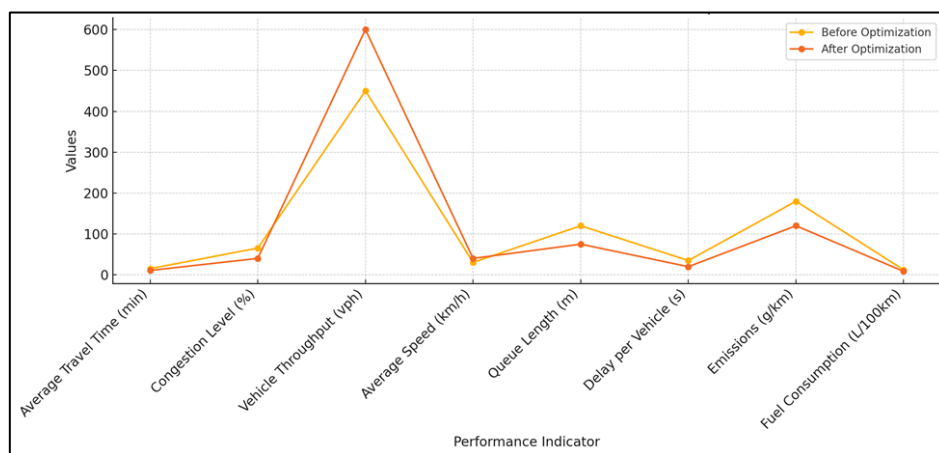


Figure 4: Trends in Performance Indicators

### B. AI Algorithm Performance

Table 3 shows how well three different AI algorithms Reinforcement Learning, Neural Networks, and a Hybrid Approach work at improving traffic flow. Different success measures show that each method has its own unique benefits, which shows how effective they are at making business better. An average trip time of 12.5 minutes shows that Reinforcement Learning (RL) is working well, which is better than traditional traffic control but not as well as Neural Networks and Hybrid methods. The amount of congestion is now 45.0%, which means that traffic on the roads is getting a little better. The number of cars that go through RL each hour is 550, and the average speed is 32.0 km/h. This shows that the traffic flow is pretty good. With a delay of 28 seconds per car, the line length under RL is 90 meters, which shows some progress in cutting down on wait times. RL, on the other hand, puts out 160 grams of pollution per kilometer and uses 10.5 liters of fuel per 100 kilometers. This means that even though it makes traffic move better, it might not be the most environmentally friendly choice.

Table 4: Evaluation of AI algorithm effectiveness in optimizing traffic flow

Performance Metric	Reinforcement Learning	Neural Networks	Hybrid Approach
Average Travel Time (min)	12.5	11.0	10.2
Congestion Level (%)	45.0	42.3	38.7
Vehicle Throughput (vph)	550	580	620
Average Speed (km/h)	32.0	34.5	36.7
Queue Length (m)	90	80	65
Delay per Vehicle (s)	28	22	18

Emissions (g/km)	160	150	130
Fuel Consumption (L/100km)	10.5	9.0	7.5

Neural Networks (NNs) do better in a number of important ways. The average travel time drops even more, to 11.0 minutes, which shows that things are running more smoothly. The amount of congestion goes down to 42.3%, which means that more of the available capacity is being used than in RL. NNs get a higher car flow of 580 vph and a higher average speed of 34.5 km/h, which shows that they are better at managing traffic. With NNs, the length of the line drops to 80 meters and the time it takes for a car to arrive drops to 22 seconds, illustrate in figure 5.

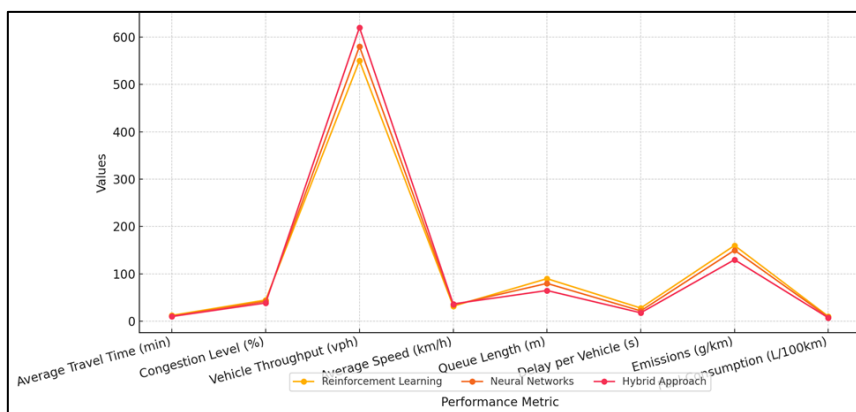


Figure 5: Representation of Trends In Performance Metrics Across Different AI Model

This means that traffic moves more quickly and people don't have to wait as long. When compared to RL, NNs are better for the earth because they use less fuel and emit less pollution (150 grams per kilometer vs. 9.0 liters per 100 kilometers). The best total success comes from the Hybrid Approach, which takes the best parts of both RL and NNs.

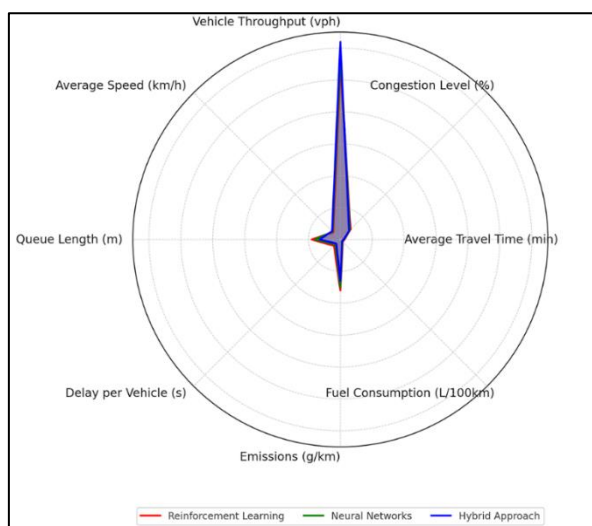


Figure 6: Performance across different metrics for each approach

The shortest trip time is 10.2 minutes, and the percentage of traffic jams drops to 38.7%. This is the best use of road capacity. This method gets the fastest average speed of 36.7 km/h and the largest car flow of 620 vph. The length of the line has been cut down even more, to 65 meters. The average wait

for each car is also the lowest, at 18 seconds, which means that traffic is flowing smoothly. It also uses the least amount of fuel and produces the least amount of pollution, at 130 grams per kilometer and 7.5 liters per 100 kilometers, respectively, shown in figure 6. Figure 7 shows how the success measures of Reinforcement Learning, Neural Networks, and the Hybrid Approach are compared to each other. The Hybrid Approach always does better than the others in important areas like travel time, traffic, and fuel use, showing that it is better at managing traffic and protecting the environment.

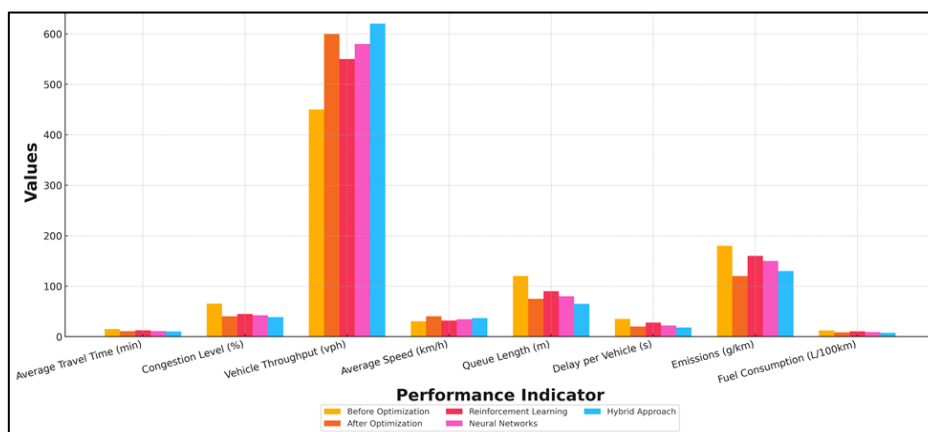


Figure 7: Comparative Analysis Of Performance Metrics

## V. Conclusion

Combining Computational Fluid Dynamics (CFD) with Artificial Intelligence (AI) methods is a revolutionary way to make traffic move better. CFD modeling creates a detailed, moving recreation of traffic patterns and fluid dynamics, which lets us accurately guess and study how traffic will behave in different situations. Activity administration frameworks can discover and settle jams, progress street productivity, and make light times more precise by utilizing CFD's capacity to demonstrate complicated activity circumstances. Including AI calculations like Fortification Learning, Neural Systems, and Half breed Approaches to these CFD models makes them way better by including data-driven, versatile optimization strategies. Support Learning makes a difference by learning from real-time activity information and changing activity lights on the fly to form things move better. Neural systems can predict long-term by trying to find patterns in past information to figure how activity will be and make changes ahead of time. Utilizing adaptable learning and forecast analytics together, the Crossover Approach gets superior comes about than either strategy alone. It leads to the leading activity control methods. Comparing the performance of AI algorithms shows big changes in key measures, such as shorter average trip times, less traffic, more vehicles moving through, and better environmental efficiency. For example, the Hybrid Approach stands out because it has the lowest trip time, traffic, pollution, and fuel use, which shows that it works well to improve traffic flow and lower environmental impact. The combination of CFD and AI systems is a big step forward in traffic control, providing a complete answer to today's traffic problems. This combination method not only makes traffic flow more smoothly and cuts congestion, but it also helps protect the environment. This makes it a useful tool for building cities and transportation systems in the future.

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