



Hybrid Adaptive Pressure-Based Dynamic Traffic Signal Control at Urban Road Junctions

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Abstract: Traffic signals at urban road junctions are sometimes static in nature and vehicles are to wait for a fixed time in the road junctions even if other sides of the junction are free or have comparatively fewer vehicles. Thus vehicles on one side of the junction may experience longer waiting times though other side may be less number of vehicles causing increased congestion on the road junctions. Therefore, if optimization is done for the waiting times, the dynamic signal can be assigned to junctions depending on number of vehicles in each side. This paper emphasizes a comparative study of dynamic traffic control signals at city road junctions using different methods with working principles, equipment and technology with typical applications. This paper also proposes a hybrid model to compute the Dynamic Green Signal time for the vehicles waiting in queues on urban road junctions which ensures efficient traffic flow at road junctions.

Key Words: Urban Traffic Control, Mobile Area Networks, Urban Traffic Management, Congestion Control, Pressure Based Dynamic Control, Hybrid Traffic Control.

I. INTRODUCTION

Urban Traffic Management is used to minimize congestion on roads and minimizing waiting time for commuters. But, traffic situations in urban areas are dynamic in nature and it is difficult to predict the traffic condition at a point of time. The traffic complexity increases on city roads due to the increase in population and also easy ownership of vehicles. Traffic congestion on urban roads cannot be controlled only by creating sufficient infrastructure but also creating proper control measures. Creation of new roads, widening existing roads, creating flyovers, and bridges etc are some possible solutions for mitigating such problems. Sometimes creation of infrastructure facilities are not also possible due to different reasons. In such situations, intelligent logical measures to control the urban traffics has a great role in mitigating traffic congestion on urban roads. The modern control measures like Intelligent Transport System (ITS) which used Information and Communication Technology (ICT) has a great role in urban traffic management. Mobile Phone Networks (MPN) a readily available network also have an important role in collecting the commuter information on urban roads.

Mobile Phone Networks can be mapped on Urban Traffic Networks and mobility data of the urban traffic commuters can be collected easily for proper route planning. The mobility of the Commuters can be recorded from the transition record from one mobile tower to another. Thus the mobility data can be collected in real time basis and same can be used to understand the mobility pattern of the commuters. Compared to other traffic monitoring tools—such as magnetic loop detectors, pneumatic road tubes, piezoelectric sensors, wireless sensor networks, GPS systems, and vehicular ad-hoc networks—the use of mobile phone networks offers a comparatively economical and scalable solution. Since the infrastructure already exists, it requires minimal additional deployment effort while still providing valuable real-time traffic insights. Consequently, leveraging mobile network data can serve as an effective and sustainable strategy for improving urban traffic management.

II. RELATED WORKS

Urban traffic control and congestion management have long been studied using mathematical and graph-theoretical frameworks. Early foundational work by Beckmann et al. [1] Studies in the Economics of Transportation (1956), represented one of the earliest models which uses economics and optimization techniques for analyzing the traffic behavior. Expanding on this foundation, Sheffi [2] presented mathematical programming approaches for urban transportation networks, providing computational techniques for equilibrium analysis and route choice modeling which can be used with present Intelligent transport Systems for minimizing traffic congestions. Describing maximum flow, minimum-cost flow, and shortest-path algorithms, Ahuja et al. [3] systematically developed a method which helps in traffic routing, signal timing optimization, and congestion mitigation strategies. Sometimes localized bottlenecks influence the global network performance. Daganzo [4] contributed to understanding congestion propagation by modeling queue spillovers within transportation networks, demonstrating how localized bottlenecks can influence global network performance. Mahmassani [5], proposed dynamic traffic assignment models using time-dependent edge weights. These models present real-world variations in road traffic conditions and also enables adaptive traffic control strategies. Based on distributed and parallel control mechanisms Wang [6] introduced intelligent transportation system

architectures, emphasizing network-wide coordination of traffic signals through graph-based state representations. Graph-theoretical analysis has also been applied to structural properties of urban road networks. Porta et al. [7] utilized centrality measures such as betweenness and closeness to identify critical intersections influencing congestion patterns. Batty [8] explored scaling properties and spatial graph structures in urban systems, linking network topology with traffic performance and city growth. Newman [9] further formalized complex network theory concepts—including modularity and community detection which are increasingly applied to segment urban road networks into manageable sub regions for decentralized traffic control. Recent advances in machine learning have incorporated spectral graph theory into traffic prediction. Kipf and Welling [10] introduced graph convolutional networks (GCNs), enabling learning over graph-structured data. Building upon this concept, Wang et al. [11] applied graph convolutional techniques to traffic flow prediction which significantly improve forecasting accuracy by capturing spatial-temporal correlations among interconnected road segments. Beyond conventional transportation models, researchers have increasingly explored network resilience and robustness through the lens of complex network theory. Cohen and Havlin [12] studied the vulnerability and percolation characteristics of networks, offering useful insights into how the failure of strategically important nodes can seriously weaken network performance. In urban traffic systems, this perspective is especially important because disruptions at major intersections or links may spread across adjoining routes and result in wider traffic instability. Overall, prior studies indicate that graph-based approaches provide a strong theoretical and analytical basis for urban traffic management. When concepts such as equilibrium modeling, flow optimization, dynamic network behavior, centrality analysis, spectral learning, and resilience assessment are combined, traffic systems can become more effective in forecasting congestion, adapting control measures, and maintaining stable operation under varying conditions. An innovative contribution in this area was presented by M. R. Singha and B. Kalita, who introduced an approach for studying urban traffic using communication network structures. Their work connected mobile phone communication patterns with the corresponding urban road network in order to investigate mobility trends and congestion characteristics [13]. The study showed that mobile communication data can be used as a meaningful alternative source for understanding traffic movement in cities. In another related investigation, the same authors expanded this idea by examining the role of mobile phone networks in traffic management applications [14]. They pointed out that telecommunication systems can provide valuable large-scale information for observing traffic conditions and strengthening intelligent transportation solutions. This is particularly beneficial in urban areas where direct traffic sensing infrastructure is insufficient or costly. The prediction of traffic volume has also received considerable attention in transportation studies. Tom Thomas, Wendy Weijermars, and Eric van Berkum [15] developed an urban traffic forecasting approach based on a single time-series model. Their findings showed that past traffic observations can be effectively utilized to estimate future traffic volume, thereby supporting traffic planning, congestion reduction, and operational management. The introduction of artificial intelligence methods has further improved urban traffic control research. Asad Salkham, Raymond Cunningham, Anurag Garg, and Vinny Cahill [16] proposed a collaborative reinforcement learning framework for optimizing urban traffic signals. Their model allowed multiple learning agents to cooperate in adjusting signal strategies dynamically, which led to more efficient movement of traffic in complex city road networks. Researchers have also examined the economic and operational consequences of congestion. S. O. Fadare and B. B. Ayantoyinbo [17] investigated the effects of road congestion on freight transport within metropolitan regions and concluded that congestion creates serious inefficiencies in logistics and goods movement. In a similar context, Adekunle J. Aderamo and Tolu I. Atomode [18] analyzed congestion at urban intersections and identified important contributing factors, including excessive traffic demand, poor signal coordination, and inadequate roadway facilities. Another relevant contribution was made by Kenedy Aliila Greyson [19], who studied the prediction of traffic jam locations using inlet and outlet flow parameters. The work proposed analytical techniques for identifying areas with a high likelihood of congestion, helping traffic authorities take preventive action before delays become severe. Accurate and timely traffic data are essential for any effective traffic management strategy. Guillaume Leduc [20] reviewed a wide range of road traffic data collection methods and explained their importance in transportation planning. The study discussed several approaches, including manual counting, sensor technologies, GPS-based monitoring, and automated traffic data acquisition systems, all of which support better traffic analysis and decision-making. Advanced analytical methods have likewise been used to process traffic flow information. Hu Chunchun, Luo Nianxue, Yan Xiaohong, and Shi Wenzhong [21] proposed a traffic data mining and evaluation method based on fuzzy clustering. Their research demonstrated that clustering techniques can be used to classify traffic states, recognize congestion patterns, and interpret large and complex traffic datasets more effectively. The use of wireless sensor networks has also enhanced traffic monitoring systems. Ryota Ayaki, Hideki Shimada, and Kenya Sato [22] introduced a sensor data collection mechanism based on mobile relay nodes, which improved the efficiency of communication in distributed monitoring environments. Such methods are valuable for building scalable and economical traffic observation systems. The rapid expansion of mobile communication technologies has created additional possibilities for mobility analysis. Xielin Liu, Feng-Shang Wu, and Wen-Lin Chu [23] examined the spread of mobile telephony and the factors influencing its adoption. Their findings indirectly suggest that the increasing penetration of mobile devices provides a rich source of data for studying human mobility and travel behavior at a larger scale. Studies conducted at the regional level are equally important for understanding local transport problems. Bhaskara Tejaswi E and Ashish Verma [24] analyzed the public transportation system in Guwahati and reported several structural as well as operational weaknesses that reduce the efficiency of urban transport services. Their observations are useful for designing city-specific traffic improvement strategies. From the surveyed literature, it is clear that extensive work has already been carried out in areas such as traffic forecasting, intelligent control, congestion assessment, data mining, and sensor-supported monitoring. Even so, there is still a clear need for further investigation into the integration of mobile communication network data with graph-theoretical traffic models. Such integration has the potential to produce more scalable, efficient, and data-driven solutions for monitoring urban mobility and managing congestion more effectively.

Many methods have been discussed in recent advances in technologies on intelligent traffic signal control which are emphasized on reinforcement learning and hybrid optimization techniques. A powerful approach like Deep reinforcement learning

(DRL) has also one of the approach for in real time and adaptive signal control techniques . These technique shows improvement over earlier techniques which reduces congestion [33] ,[35]. Moreover Hybrid models emphasized on maximum pressure control and learning-based approaches have also shows sizeable improvements in delays and queue reduction improvements [36], [38]. Again recent studies add in sustainability and multi-objective optimization on traffic control and management strategies [39], [40].

III. PROBLEM DEFINITION

Urban Road junctions may be junction of three roads, junction of four roads etc. Five road crossing junctions are rare in urban areas. So we shall take the example of four road junction to represent the problem. Consider an Urban Road Junction which is crossing point of four roads as follows:

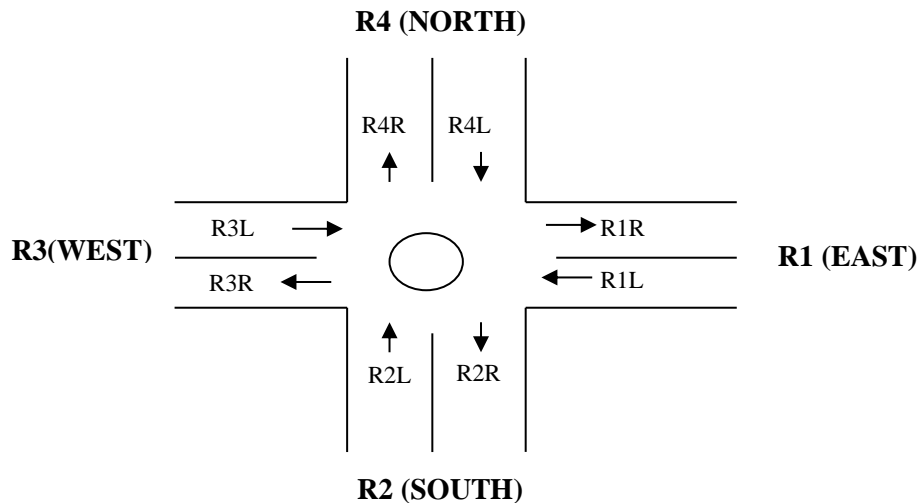


Figure-1 : Typical four road junction

There are four Road R1 (EAST), R2 (SOUTH), R3 (WEST) , R4 (NORTH) are crossing over the junction and the movement of the vehicles are represented using arrows at right and left side of the road segments. Now, Considering the movement of the vehicles through the road segment, all the Right side movement are always to be open and timing control is necessary for all left side road segments. If static timing is used for the left side junctions of the road segments then a total time of (say n) should be divided to the left side junctions equally or unequally to all. The total time n may also be dynamic depending on the time say morning, noon , evening etc.

The allotment of static time to the left side road segments may be useless if there is no traffic or little traffic is waiting to cross the junction. In such cases, all the waiting vehicles may cross the junction before the allotted time ends. So, the time will be considered a loss, because the same can be allotted to others who are waiting to cross the junction. So, in this situation dynamic traffic waiting time is necessary.

IV. DYNAMIC TRAFFIC SIGNAL CONTROL STRATEGIES

In city road junction’s automated signal control is done by assigning time to the vehicles who are to pass through the junction. The assignment of time to each flow of vehicles may be static and may not depend on the number of vehicles on each lane , however if the time for each flow of vehicles assigned dynamically the situation of the traffic flow may be improved, this system is known as Adaptive Traffic Signal Control (ATSC), which enables traffic lights to adjust the duration of green phases according to real-time traffic conditions. This intelligent traffic management approach improves operational efficiency by responding directly to vehicle demand at intersections, which helps reduce congestion, minimize waiting time, and enhance overall traffic flow in urban areas with fluctuating traffic volumes [25].

One widely used method in adaptive traffic signal control is the Maximum Pressure (MP) technique. This algorithm determines the optimal signal phase by comparing the queue lengths of incoming and outgoing traffic streams. The signal phase with the highest pressure value is selected, allowing the system to prioritize directions with greater traffic demand and maintain network stability [26][27]. The MP method is particularly effective because it uses only local traffic information and dynamically adjusts signal phases without requiring prior knowledge of traffic demand.

Another commonly applied strategy is actuated signal control, also known as gap-based control. In this approach, sensors such as inductive loop detectors or traffic cameras measure the time gap between successive vehicles approaching the intersection. When vehicles arrive at short intervals, indicating heavy traffic, the green signal is extended. Conversely, when the gap between vehicles becomes larger, the system terminates the green phase and switches to another traffic movement [28].

Recent advances in intelligent transportation systems have introduced Artificial Intelligence–based approaches, especially Deep Reinforcement Learning (DRL). In these systems, intelligent agents interact with the traffic environment and learn optimal signal timing strategies through trial-and-error learning. Over time, the learning algorithm improves the signal control policy, which leads to better traffic performance and reduced congestion under varying traffic conditions [29].

Fuzzy logic controllers are also widely used for adaptive signal control. Instead of relying on precise numerical thresholds,

fuzzy logic uses linguistic variables such as “low,” “medium,” or “high” traffic density to determine signal timings. This approach is effective in handling uncertainty and imprecision commonly present in real-world traffic data [31].

In addition, expert systems can be used to control traffic signals based on predefined rules developed by traffic engineers. These systems evaluate the current traffic conditions and apply appropriate decision rules to select the next signal phase and duration [32].

V. COMPARATIVE STUDY OF DYNAMIC TRAFFIC SIGNAL CONTROL METHODS

Method	Working Principle	Technology Used	Equipment Required	Typical Applications	Reference	Courtesy
Maximum Pressure (MP) Control	Allocates green time based on queue length differences between incoming and outgoing lanes.	Queue estimation algorithms, adaptive signal control	Loop detectors, traffic cameras, signal controllers	Busy urban intersections and large traffic networks	Varaiya, P. (2013) Max Pressure Control of a Network of Signalized Intersections	IEEE Transactions on Automatic Control
Actuated (Gap-Based) Control	Signal phases change based on detected vehicle presence and time gaps.	Vehicle detection algorithms, sensor-based control	Inductive loop detectors, radar sensors, signal controller	Suburban roads and moderate traffic intersections	Gartner, N. (1983) OPAC: A Demand-Responsive Strategy for Traffic Signal Control	Transportation Research Record
Deep Reinforcement Learning (DRL)	AI agents learn optimal signal policies through interaction with traffic data.	Machine learning, neural networks, reinforcement learning	CCTV cameras, GPU servers, IoT sensors, communication network	Smart city traffic systems and research deployments	Wei, H. et al.(2019) IntelliLight: A Reinforcement Learning Approach for Intelligent Traffic Signal Control	ACM SIGKDD Conference
Image / Video Processing	Computer vision techniques detect vehicle count, density, and queue length.	Computer vision, AI-based image analytics	High-resolution cameras, edge processors, analytics software	Urban intersections and traffic surveillance	Buch, N., Velastin, S., & Orwell, J. (2011) A Review of Computer Vision Techniques for the Analysis of Urban Traffic	IEEE Transactions on Intelligent Transportation Systems
Fuzzy Logic Control	Signal timings determined using fuzzy rules based on density and waiting time.	Fuzzy inference systems	Traffic sensors, microcontrollers, controllers	Complex intersections with uncertain traffic flow	Pappis, C. & Mamdani, E. (1977) A Fuzzy Logic Controller for a Traffic Junction	IEEE Transactions on Systems, Man, and Cybernetics
Expert Systems	Knowledge-based rules developed by traffic experts control signal timing.	Knowledge base systems and rule engines	Traffic detectors, control servers, signal controllers	Traditional intelligent traffic systems	Niittymäki, J. (2002) Signal Control Using Fuzzy Logic	Transportation Research
Vehicle-to-Infrastructure (V2I) Control	Vehicles communicate with infrastructure to optimize signal phases.	V2X communication, IoT networking	Roadside units, onboard vehicle units, wireless communication modules	Connected vehicle environments and smart highways	Kenney, J. (2011) Dedicated Short-Range Communications for Vehicle Safety	IEEE Communications Magazine
Model Predictive Control (MPC)	Uses mathematical models to predict traffic and optimize signals over time.	Optimization algorithms, predictive modeling	Traffic sensors, computing servers, optimization software	Large coordinated traffic networks	De Schutter, B. & De Moor, B. (1998) Optimal Traffic Light Control Using Model Predictive	European Control Conference

					Control	
Hybrid Approaches	Combines multiple techniques such as AI, fuzzy logic, and vision systems.	AI, sensor fusion, IoT platforms	Cameras, IoT sensors, edge devices, central servers	Advanced smart city traffic management systems	Various recent ITS research combining AI and sensor fusion methods	IEEE Intelligent Transportation Systems Society

VI. THE PROPOSED METHODOLOGY

This work proposes a hybrid adaptive signal control framework that extends the classical Maximum Pressure method by incorporating real-time queue estimation and short-term traffic prediction into a unified cost function. This methodology is based on Hybrid Adaptive Pressure-Based Signal Control (HAPSC) system for urban road intersections. It integrates real-time traffic data, historical patterns, and short-term prediction to dynamically allocate signal timings.

The Mathematical Model

(a) Traffic Network Representation:

$$G = (V, E]$$

Where

V: set of junctions

E: set of incoming/outgoing lanes

(b) Queue Length Estimation:

$$Q_i(t) = \lambda_i(t) * \Delta t + Q_i(t-1) - \mu_i(t)$$

Where

$Q_i(t)$: Current Queue Length

$Q_i(t-1)$: Previous Queue Length

$\lambda_i(t)$: Arrival rate (vehicles per second/minute)

Δt : Time interval

$\mu_i(t)$: Departures i.e number of vehicles that cross the junction during time t

(c) Pressure Calculation:

$$P_i(t) = Q_{in}(t) - Q_{out}(t)$$

Where

$P_i(t)$: Pressure, represents **traffic imbalance**

$Q_{in}(t)$: Incoming Queue. i.e. Number of vehicles waiting to enter the intersection

$Q_{out}(t)$: Outgoing Queue i.e. Number of vehicles already present in downstream road

(d) Hybrid Cost Function:

$$C_i(t) = \alpha P_i(t) + \beta Q_i(t) + \gamma \hat{Q}_i(t+1)$$

Where

$Q_i(t+1)$: predicted queue (using short-term prediction)

α : Pressure Weight (Reactive Control), higher the α , the faster the response to congestion spikes

β : Queue Length Weight (Current State), higher β , reduces waiting time significantly

γ : Prediction Weight (Proactive Control), Higher γ , smoother traffic flow, less fluctuation

where $\alpha + \beta + \gamma = 1$

(e) Green Time Allocation:

$$T_i = (C_i / \sum C_j) * T_{cycle}$$

Where

T_i : Green Time for Lane i, i.e. duration for which signal remains green for movement i

C_i : Cost / Priority Value

$\sum C_j$: Total Cost of All Lanes

T_{cycle} : Total Signal Cycle Time

The Algorithm:

Input : Traffic data from sensors/mobile network

Output: Optimal signal timing

Step 1 : For each Road Segment (North, South, East, West)

Initialize cycle time $T_{cycle} = 100$ Sec

Step 2 : Arrival Rate λ_i (veh/sec)

Initial queue: $Q_i(0)$

Saturation flow (departure rate) $\mu \approx 1$ veh/sec

Weights: α, β, γ

Step 3 : For each time step t:

Calculate $Q_i(t)=Q_i(t-1)+\lambda_i(t)\Delta t-\mu_i(t)$

Calculate Pressure $P_i(t)=Q_{iin}(t)-Q_{iout}(t)$

Predict $Q_i(t+1) = Q_i(t)+\lambda_i(t)\Delta t$

Step 4: Taking $\alpha=0.3,\beta=0.4,\gamma=0.3$

Compute cost: $C_i(t) = \alpha P_i(t) + \beta Q_i(t) + \gamma \hat{Q}_i(t+1)$

Step 5: Allocate green time: $T_i = (C_i / \sum C_j) \times T_{cycle}$

Step 6: Assign Green Signal to each road sequentially based on the calculated T_i

Update Queues after each phase

Step 7: Repeat for next cycle

VII.SIMULATION RESULTS AND COMPARISION

Let us consider a four way junction as represented as figure-01 above. Now assume the traffic data for a particular situation as follows presented in the table:-

Road	Arrival Rate (Veh/Sec)	Initial Queue
North	0.8	35
South	0.7	25
East	0.5	20
West	0.6	22

Cycle Time =**100 Sec**

The Demand (traffic density) is calculated as follows)

Road	Demand (Veh/ Cycle)
North	$0.8 \times 100 = \mathbf{80}$
South	$0.7 \times 100 = \mathbf{70}$
East	$0.5 \times 100 = \mathbf{50}$
West	$0.6 \times 100 = \mathbf{60}$

Total Demand = 260 vehicles

So The Green time allocation as per the hybrid logic will be

Road	Green Time (Sec)
North	31 Sec
South	27 Sec
East	19 Sec
West	23 Sec

The Simulation results with comparison has presented below:-

Method	Avg Delay (sec)	Queue Length	Throughput (veh/hr)
Static Signal	120	48	900
Queue Based	85	34	1150
Pressure Based	68	28	1280
Hybrid Model (as proposed)	54	23	1420

So following are the findings as per the Simulation Results calculated above:

- (i) The North direction has the maximum green time i.e. 31 sec due to highest demand.
- (ii) The East direction gets the lowest allocation i.e. 19 sec

The improvement of the performance is as follows:-

Metric	Static Vs improved condition
Delay	Decreased by 55%
Queue Length	Decreased by 52 %
Throughput	Increased by 58%

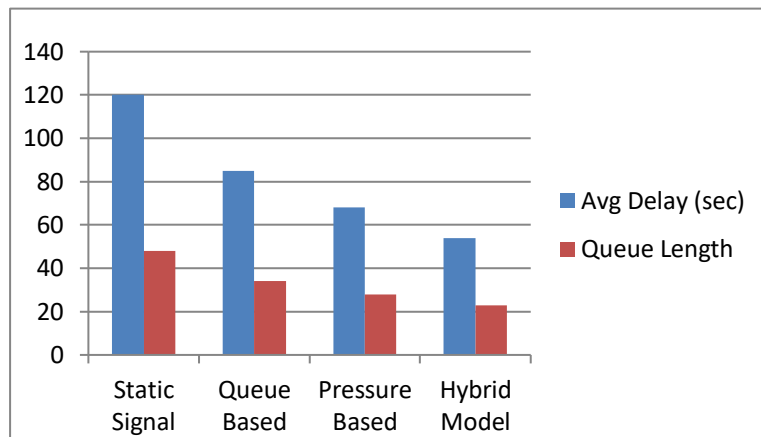
Comparison Graphs**(a) Average Delay Comparison Graph**

Figure 2. Average delay comparison among different traffic signal control methods.

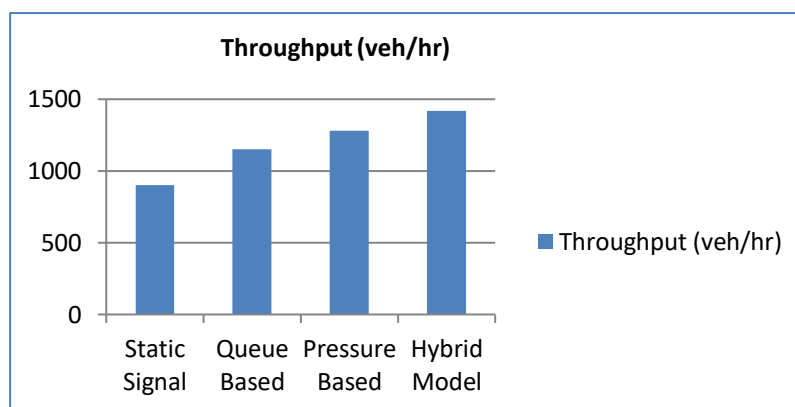
(b) Comparison of Throughput

Figure 3. Comparison of throughput among different traffic signal control methods.

VIII. FURTHER SCOPES AND CONCLUSION

Only physical infrastructure alone cannot solve the problem of congestion of city road. Efficient management of traffics using intelligent techniques are also essential to control the congestion problem on city roads. Traditional fixed time traffic signals sometimes worsens the situation leads to delays even if other sides are free in a traffic road junctions. Therefore Adaptive traffic signal control is inevitable in such situations.

In applying the Adaptive traffic signal control different techniques have been developed in producing dynamic control signal at the road junctions. The techniques includes Maximum Pressure control, fuzzy logic systems, actuated signal systems, expert rule based systems and many more. Recent frequent development of artificial intelligence and machine learning also have been studies and in discussion such as reinforcement learning, Model predictive control etc are also used to generate dynamic traffic signals at the road junctions. The real time traffic data as well as historic traffic data are used to consider such techniques place.

It also to be considered that, not only the the real time traffic data at a junction has been in consideration to generate the dynamic traffic signal but also traffic data generated at the nearby city road junctions should be one of the important consideration for generating dynamic traffic signal at city road junctions.

Thus, real time data at the junction, real time traffic data at nearby junctions, historic data should be analyzed with the artificial and machine learning techniques to general more accurate dynamic traffic signal at congested city road junctions.

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