Earliest Deadline Based Scheduling to Reduce Urban Traffic Congestion

Asif Ahmad, Rabia Arshad, S.A.Mahmud, G.M.Khan and H.S. Al-Raweshidy, *Senior Member, IEEE,*

***Abstract*—One of the major problems, caused by the traffic congestion, owes its existence to the unwanted delay experienced by the priority vehicles. The evaluation of two scheduling algorithms as adaptive traffic control algorithms has been proposed here to reduce this unwanted delay. One of these algorithms is the earliest deadline first (EDF) while the other is the fixed priority (FP) algorithm. The performance of both the algorithms as adaptive traffic lights control algorithms is evaluated for isolated traffic intersections. A comparative study is performed here, where the performance of these algorithms is compared against a fixed static traffic lights controller. Moreover their performance is also compared against each other. Conclusive results from the simulation of the algorithms reveal that the number of stops, average delay and mean trip time of the priority vehicles is significantly reduced by the implementation of these algorithms. Furthermore it has been shown that the overall performance of the EDF is much better than the FP in terms of improvement of different performance measures for congestion reduction of Priority vehicles.**

***Index Terms*—Earliest deadline First (EDF), Fixed Priority (FP), Intelligent Transportation System (ITS), SUMO (simulation of urban mobility), Adaptive Traffic Light Control**

I. INTRODUCTION

REDUCTION of vehicular traffic congestion, a very hot area of research in recent times, has many direct and indirect effects on the economic and social growth of countries. Among the many problems caused by congestion one is the excessive and unwanted delay experienced by many vehicles. This delay becomes more pronounced in cases where a high priority vehicle, having an early deadline for reaching its destination, needs to be serviced. These vehicles include ambulances, carrying critically ill patients, as well as the security vehicles of law enforcement agencies that need to reach their destination on time. The Intelligent transportation system (ITS) based traffic streamlining techniques are gaining excessive attention, nowadays. ITS refers to intelligent and operationally advanced techniques for traffic management and regulation. It works by making transportation smart and forming an intelligent communication network oriented framework for the efficient handling of the traffic and consequently reducing the congestion [1]. ITS includes a large number of different techniques but the most important ones are the Global Positioning System (GPS), Dedicated Short Range Communications (DSRC), wireless networks, mobile telephony, radiowave and infrared beacons. Also in the list are roadside camera recognition, sensing technologies, inductive loop detection and Bluetooth detection. Among all these ITS techniques, the advanced transportation management system is an area garnering a lot interest. The latter encompasses management of traffic applications focusing on control devices - like traffic signals, ramp metering and dynamic highway message signs [1]. These control devices communicate with vehicles by setting up a communication framework for the information exchange. They collect important traffic data and take timely and necessary decisions for traffic management and control.

Asif Ahmad, Rabia Arshad, S.A.Mahmud and G.M.Khan are with the Department of Electrical Engineering, NWFP University of Engineering and Technology, Peshawar,Pakistan. Hamed Al-Raweshidy is currently the Director of The Wireless Networks and Communications Centre (WNCC) at Brunel University, London, UK. E-mail: asif.eng007@gmail.com, rabia.arshad@nwfpuet.edu.pk,
sahibzada.mahmud@nwfpuet.edu.pk, gk502@nwfpuet.edu.pk, Hamed.Al-Raweshidy@brunel.ac.uk

This work focuses on the development and usage of adaptive traffic signal control in order to do away with the fixed time traffic control. The idea is to utilize the intuitive and smart traffic signals as the control devices for traffic management. In the adaptive control, the duration for which a traffic light remains green or red depends on the information collected regarding the state of traffic and vehicles at that particular time. This information may be collected via some specialized sensors and technologies. The contemporary research [2][3][4], regarding the use of dynamic adaptive control, reveal that very effective results can be achieved, in the context of controlling the traffic congestion, as opposed to the fixed time traffic control, since the latter does not take into account the traffic state and may lead to unnecessary delays. The adaptive control of traffic lights, on the other hand, has the potential of reducing the traveling time of vehicles manifold. The major contribution of this research is to evaluate scheduling algorithms particularly the Earliest Deadline First(EDF) and the Fixed Priority(FP) algorithms for the adaptive control and management of traffic lights in order to reduce congestion by improving the performance parameters like waiting time, overall travel duration and servicing of priority vehicles.

The rest of the paper is arranged as follows. Section II gives a detailed literature review of the techniques adopted to reduce urban traffic congestion. Section III gives details regarding the architectural considerations while applying the Adaptive control algorithms. Section IV elaborate the simulation setups and the results of the implemented algorithms. While a conclusion is presented in section V.

II. RELATED WORK

The adaptive traffic lights control (TLC) has long got the attention of the researchers and one can find references as old

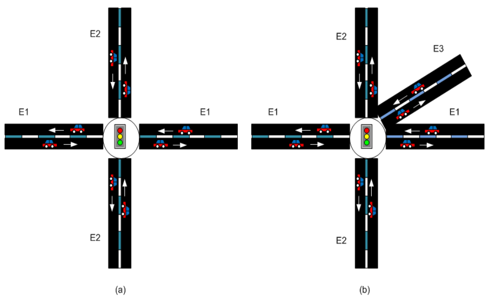


Fig. 1. (a) Simple four Arms Traffic Intersection (b) Complex Traffic Intersection

as [5], [6] wherein the proposed exhaustive algorithm (EA) controls the duration of traffic lights, in a particular direction, in such a way that the switching of green light occurs when the served queue becomes empty. The main advantages of EA include no car waiting time during the whole EA cycle and minimization of time wastage during the green period. The major drawback behind the use of EA is that it is efficient only when applied to short queues. The interval reacting algorithm (IRA) [7] takes decisions based on the interval between two successive vehicles following a green way or a green direction. The interval between successive vehicle is monitored vigilantly at traffic intersections and the light is switched whenever the interval exceeds a set threshold value or whenever the duration of a green light reaches its saturation point. The IRA is also good for short queues, only.

Recent literature [8][9] demonstrates that the adaptive control of traffic lights can be efficiently achieved by the effective use of wireless sensor networks (WSN's). The sensors are deployed at lanes forming an entrance and an exit to different intersections. These sensors collect the information of the vehicles entering and leaving an intersection and communicate it to the nearby traffic controlling servers or agents most probably installed at the intersection. A decision regarding the traffic signal is taken based on the information statistics of the traffic collected from all the sensors of the intersection lanes. This decision is communicated to the traffic signal controller in order to decide the duration of a certain light remaining green or red.

Many different ITS based techniques and algorithms have been proposed for intelligently managing the adaptive TLC. One such technique involves the time-space model and is known as cycle and split optimization technique [2]. This optimization is used to set the timing of traffic signals at an isolated intersection. The cycle length is adjusted according to the state of the residual queues at the end of each cycle, while the splits are adjusted depending on the minimization of delay per cycle. By using the concept of time-space diagram for each traffic intersection, the duration of green lights can be aptly managed in order to minimize the residual queue lengths at the end of each cycle.

The adaptive TLC techniques of [10][3] are based on the reinforcement learning (RL) and relies on the Q-learning algorithm with function approximation [11], State-Action, Reward-State Action (SARSA) [12] and the Policy Gradient Actor Critic algorithm [13]0. The traffic light decisions of all RL algorithms are based on the congestion level information (low, medium or high) updated on each lane and do not require accurate queue length information. A neural network [4] is used to predict Q values for each control decision, based on the number of waiting vehicles and the time since the traffic lights last changed.

An adaptive algorithm [14] exploits fuzzy logic for managing the traffic lights at isolated traffic intersections. Using the urgency demand, the fuzzy logic controller controls the signal timings according to the observed changes and updates its traffic light phase information that may be the extension/termination of a particular phase or the selection of some other sequences. The Particle Swarm Optimization (PSO) algorithm of [15] works by optimizing the mean delay and average number of stops at adjacent intersections. A fuzzy logic controller, also installed at each junction, assists in the initial phases of PSO algorithm. PSO has been found effective in optimizing signal timings and its implementation does not require any complicated hardware.

Another technique employed to optimize traffic signal timings is the Genetic Algorithm based approach proposed in [16]. The total number of vehicles in the lanes and the weights allotted to each road are the important parameters which optimize the signal timings. Another adaptive TLC approach is the Longest Queue Maximal Weight Matching (LQ-MWM) approach [17]. This algorithm tends to reduce the average delay of vehicles through isolated intersections by making all queues stable. The maximal weight matching algorithm controls the timing of traffic signals so as to significantly reduce queue sizes and, as a consequence, increase the traffic management throughput and minimize the average latency experienced by the vehicles.

Some advantages and disadvantages of the techniques discussed in this section are detailed in Table I

III. Adaptive TLC: Architectural Considerations

The EDF and FP algorithms are being applied to two types of traffic signal intersections. One is the simple traffic intersection in which there are four edges, where each edge contains two way lanes for the commuting traffic. The other architecture is a complex traffic signal intersection having more than four edges (see Figure 1).

For the application of the two algorithms, wireless sensors are deployed on each lane. One of the sensors on each lane is used for detecting the vehicles entering the queue and the other sensor on each lane is used for detecting the vehicles leaving the queue. The sensors thus form the entry and exit to a queue. Each vehicle will be able to convey its information including its deadline to the traffic controller via a road side unit using a suitable wireless communication technology e.g. Zigbee. The information being communicated to the controller includes the following information par rapport a queue:

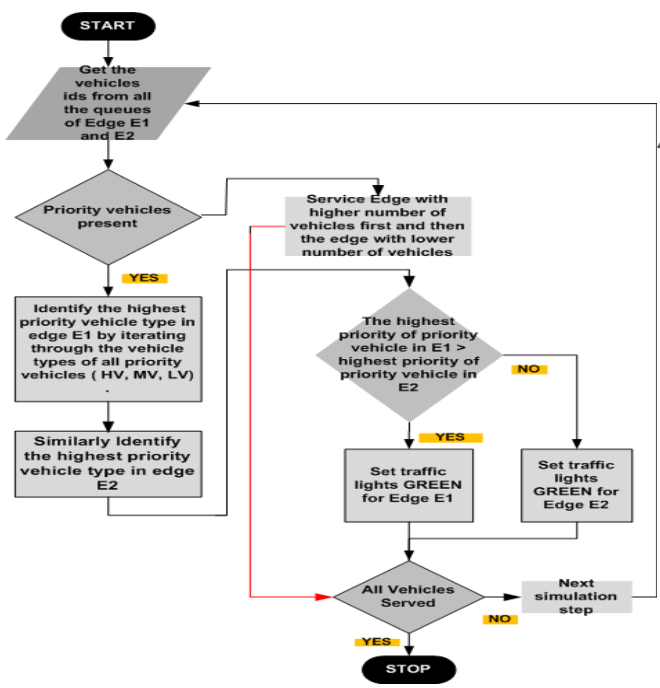
- the number of vehicles,
- type of each vehicle,
- the time spent by each vehicle and
- the initial assigned deadline of each vehicle.

In the proposed environment, each edge in an intersection is being served as a whole, rather than serving individual

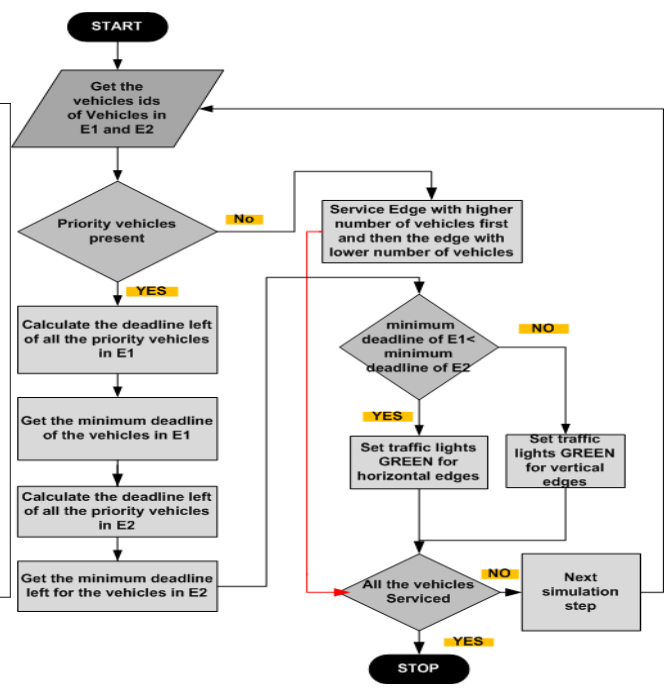
TABLE I

ADVANTAGES AND DISADVANTAGES OF FORMERLY PROPOSED TECHNIQUES

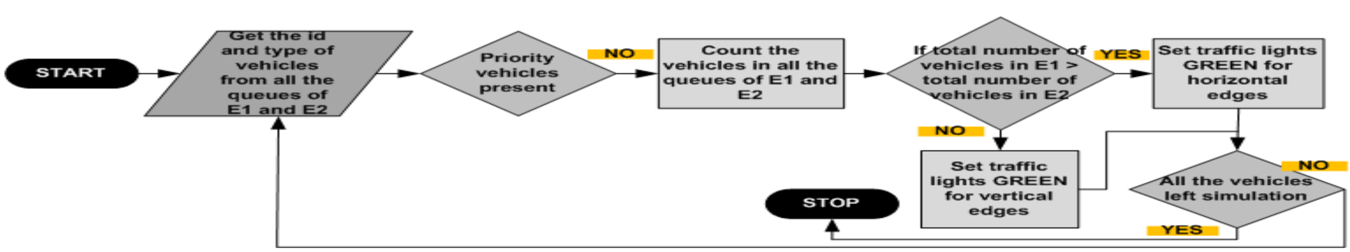
Method	Advantages	Disadvantages
[2] Neural Network based Traffic signal control	1. Online learning Capability at different Stages 2. Can effectively monitor traffic for large networks	1. Complex Design 2. Complexity of real time implementation as well as difficulty in off-line parameter optimization
[8] WSN based Traffic Light Control	1. A real time testbed presented along with simulation to determine system feasibility 2. Tested on multiple traffic intersections 3. Follows international standard for traffic lights operation 4. Self Configurable and operates in real time to detect traffic states and exchange information	Wrong choice of topology or deployment can lead to detection of vehicles on one intersection leg, that belong to a different intersection leg
[9] WSN traffic signal control while using vehicle numbers forecasted in an in intersection	The proposed model realizes flow and velocity of vehicles for a single intersection	Extensive simulation not performed
[10] Two reinforced learning TLC algorithms proposed	Both algorithms require only coarse information regarding traffic congestion (i.e. low, high or medium) rather than detailed traffic parameters	The use of the proposed techniques is limited to simple smaller networks only and the practical implementation for larger networks is not feasible
[14] Fuzzy Logic based traffic controller	A flexible form of fuzzy logic controller whose parameters can be tuned effectively offline	Tested on a simple singles intersection and the simulations are not as extensive as the ones discussed in current proposed research
[15] Partcle swarm optimization algorithm for optimized traffic control	1. Provides flexible means to deal with imbalanced and varying traffic demands 2. Significantly reduces average traffic delays	Simulations performed on a single traffic junction only
Earliest Deadline based Scheduling (Proposed Technique)	The total number of stops, average delay, and mean trip time of priority vehicles is reduced compared to a Fixed Priority (FP) based scheme	Heavily dependant on the mechanism,accuracy, and reliability of data exchange between the Road Side Modules and the Vehicles



(a) Fixed Priority Flow Diagram



(b) Earliest Deadline First Flow Diagram



(c) Non-Priority vehicles Servicing Flow Diagram

Fig. 2. FP, EDF and Non-Priority Algorithmic Flow Diagram

lanes separately. In the considered intersection for algorithmic application the opposite edges are coupled as is the norm nowadays with traffic lights utilization. For example, when one horizontal edge(see Figure 1(a)) is being served then its opposite horizontal edge is also served.

A. Fixed Priority (FP) Implementation Considerations

For the FP algorithm, the vehicles are partitioned into four distinct fixed priority classes, namely:

1) high priority vehicles (HV),
2) Moderate priority vehicles (MV)
3) low priority vehicle(LV) and
4) the no-priority vehicles(NV).

When applying the FP algorithm, the lane within an edge having the highest priority vehicle is served first. As mentioned previously, in reference to Figure 1, the edges are coupled and if the traffic along one edge is being serviced, the traffic along its coupled opposite edge is also being served.

The FP algorithm is static in nature, as it processes the tasks according to the fixed priorities starting from highest to the lowest. Thus when applied to the intersections of Figure 1, the algorithm will first serve all the lanes having HV type vehicles. It will then service lanes with MV type vehicles and then provide service to the lanes containing the LV vehicles. The priorities of the vehicles will always remain fixed. The FP algorithm is demonstrated in the form of a flowchart in Figure 2(a).

B. Earliest Deadline First (EDF) Implementation Considerations

The EDF, as the name suggest, prioritizes processes according to their deadlines. For the application of the EDF algorithm, the HV type vehicles are assigned the smallest absolute deadline, the MV type vehicles are assigned the intermediate absolute deadline and the LV type vehicles are assigned the lowest absolute deadline. The NV type vehicles are not assigned any deadline. The algorithm then serves the queues having vehicles with the earliest deadline first. The priority of a given vehicle may change, depending on its already consumed time in reaching its current location, i.e. the priorities of the vehicles are relative to the time they spent commuting. The serving of a lane thus also becomes dependent on the total time spent by all the vehicles contained in the lane. This demonstrates the dynamic nature of the EDF algorithm as the priority of the vehicles it serves changes at each instant of time. The flow of the EDF algorithm at the intersections considered in Figure 1 can be realized from the flowchart shown in Figure 2(b).

Consideration has been given to a special case, when all the lanes contain NV type vehicles only. In such a case, the algorithm will get the total number of vehicles in all the lanes and service the edge having the most number of vehicles. The same case will be applied when all the lanes contain the same priority vehicles. The flow of the algorithm in such a case can be observed in the flowchart of Figure 2(c).

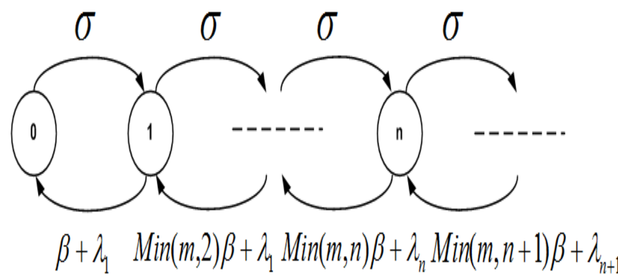


Fig. 3. Markov Model M showing the State Transition Rate

1) Mathematical Model for EDF: The mathematical model for EDF can be determined with the help of the method proposed in [18]. For the EDF model for traffic simulation, consider a system of K intersections (indexed $k = 1, 2, \dots, K$), serving Q queues (indexed $q = 1, 2, \dots, Q$), with N vehicles (indexed $n = 1, \dots, N$) currently traveling in the system. Let the priority vehicle rate (traffic intensity) be defined as ϵ and let λ_n be the rate of missed deadlines. Each vehicle is assigned a deadline β_n based on its type. Let $\mathbb{R}_{>0}$ denote the set of positive real numbers, then for a time t, we associate a real number $\sigma \in \mathbb{R}_{>0}$ with each vehicle in the system, such that $\omega(t, \sigma)$ defines the probability that a vehicle misses its deadline during the time frame $[t, t + \sigma]$. where σ defines the increment in seconds from time t after which a vehicles misses its deadline.

Let us define the rate of missed deadlines as

$$\lambda_n(t) = \frac{\omega(t, \sigma)}{\sigma} \tag{1}$$

Assuming that the system is at an equilibrium statistically,

$$\lambda_n = \lim_{\sigma \to 0} \lambda_n(t) \tag{2}$$

λ_n defines a steady state loss rate, in the presence of n vehicles (both the moving and those waiting at intersections) in the system. By deriving a Markov Chain Model M (see Figure 3) for the system, it can be seen that in the presence of n vehicles traveling from intersection to intersection, the number of vehicles can be decreased by 1 based on the fact that either a vehicle reaches its destination (at the rate $Min(m, n)\beta$ or misses its deadline(at the rate λ_n).

The concept of steady state rate λ_n was introduced by Barrer [19] for determining the relative deadlines in a deterministic case. The case of EDF, being discussed in this research, follows the Deadline till end of Service(DES) for which λ has been derived in [20]. The model M(Figure 3) solution along with the probabilities of the system in equilibrium can be derived by letting the steady state probability that n vehicles are present at the intersection be ψ. The balance equations for a system model in the state of equilibrium are

$$0 = \begin{cases} -\sigma\psi_0 + (\beta + \lambda_1)\psi_1, & if\ n = 0 \\ \\ \sigma\psi_{n-1} + (\sigma + Min(m, n)\beta + \lambda_n)\psi_n \\ +\ (Min(m, n + 1)\beta + \lambda_{n+1})\psi_{n+1}, & if\ n > 0 \end{cases} \tag{3}$$

Solving for the equilibrium conditions given in equation 3, one get equation 4

$$\psi_n = \frac{\sigma^n}{\prod_{j=1}^{n}(\lambda_j + Min(m,j)\beta)} \tag{4}$$

The normalized condition after derivation becomes,

$$\sum_{n=0}^{\infty} \psi_n = 1 \tag{5}$$

Using equation 4 and 5, it can be derived that

$$\psi_0 = \left(1 + \sum_{n=0}^{\infty} \frac{\sigma^n}{\prod_{j=1}^{n}(\lambda_j + Min(m,j)\beta)}\right)^{-1} \tag{6}$$

The probabilities for the vehicles missing their deadlines can now be obtained from the expression in equation 7

$$\beta_{dead} = \frac{\sum_{n=1}^{\infty} \psi_n \lambda_n}{\sum_{n=0}^{\infty} \psi_n \sigma} = \frac{\sum_{n=1}^{\infty} \psi_n \lambda_n}{\sigma} \tag{7}$$

Equation 7 shows the average rate of deadlines being missed by the average arrival time of vehicles in an intersection.

C. Adaptive TLC Communication Architecture

The proposed communication architecture at each intersection consists of Road Side Modules (RSM), In-Vehicle Modules (IVM), Synchronization Modules (SM), Decision Module (DM), and a Data logger (DL). All of these modules communicate using the Zigbee communication framework in the 2.4 GHz frequency band. At each leg of an intersection, at least one RSM and one SM are present. The SM module acts as a coordinator for the IVM modules (IVM modules act as End Devices). Each intersection has its unique intersection ID and each leg of an intersection has its unique road ID. The IVM modules operate on a certain default radio frequency channel termed as DRFC. Each SM module also operates using the DRFC. When an IVM module passes through the SM module, it communicates with the SM module and gets the intersection ID, road ID and in some cases, a channel ID from it. The channel ID indicates to an IVM module, the particular radio frequency channel an RSM is using for that particular leg of the intersection. The IVM module can then switch to that particular radio frequency channel in order to communicate with the RSM. When the IVM module switches its channel to communicate with the RSM, it sends the required information(number of vehicles, type of each vehicle, time spent by each vehicle) to the RSM including its deadline to reach a certain destination. Once the IVM module communicates with the RSM, it switches back to the DRFC. When it encounters the SM module at the exit leg of the intersection, it gets information about the intersection ID, road ID and channel ID again. It compares the intersection ID with its previously stored intersection ID. A positive match indicates that it has already communicated at the entry leg of the intersection with the required RSM and therefore, does not switch its channel again. The RSMs at each leg of an intersection use a different radio frequency channel to avoid interfering with one another and also the possibility of detecting IVMs from different intersection legs than theirs once they come in the transmission range of one another. The RSMs at each leg of an intersection periodically send data to the DM module at the intersection that includes the deadlines of IVMs. The DM module then makes decisions based on the proposed algorithm to schedule the traffic flows of each queue/ intersection leg. The DL module is equipped with a GPRS/EGDE/HSPA radio to send the data collected at each intersection to a traffic control and monitoring center. In our proposed architecture, we have considered two scenarios based on the roles assigned to each of the participating modules present at an intersection.

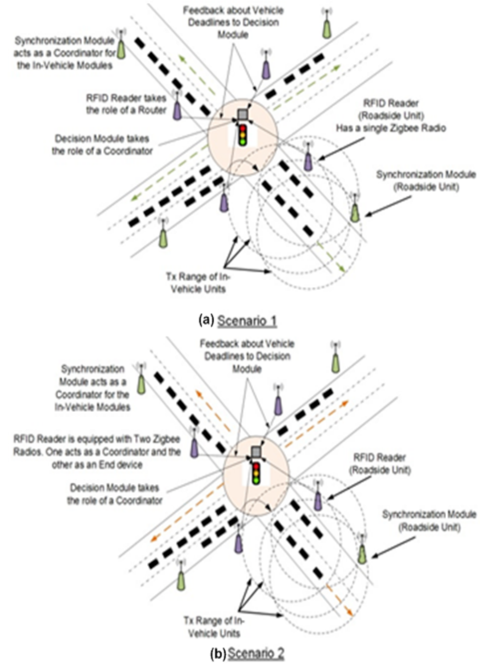


Fig. 4. Communication Scenarios for WSN Implementation

1) Scenario 1: In the first scenario (Figure 4(a)), each RSM is equipped with a single Zigbee radio and operates on a distinct channel compared to the rest of the RSMs deployed at the same intersection. The SM module at each intersection leg is responsible for indicating to the IVMs, the particular channel on which the RSM at that intersection leg is operating. The IVM then switches its radio frequency channel to the channel of the RSM and communicates with it. The SM takes on the role of the coordinator; the RSM takes on the role of a router, and the DM module acts as a coordinator, and the IVM module acts as an end device. The communication between the IVM modules with the SM and the RSM is contention based i.e. Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) is used. The communication with RSMs and the DM module is contention free i.e. Time Division Multiplexing (TDMA) is used. The reason for using CSMA/CA based channel access for communication between IVM modules and the SM and RSM modules is that since the IVM modules are mobile, achieving synchronization and allocation of time slots in case of using TDMA will be difficult.

2) Scenario 2: In the second case (Figure 4(b)), each RSM is equipped with two Zigbee radios, each operating on a different radio frequency channel. One radio is tasked to act as a coordinator for the IVM modules, while the second radio is assigned the role of an end device to communicate with the DM module. Therefore, each radio of the RSM module dedicatedly communicates with the IVM modules and the DM module on different channels. The SM module again takes on the role of a coordinator and the DM acts as a coordinator. Each RSM in the second scenario uses the CSMA/CA access mechanism to communicate with the IVM modules as well as with the DM module. The radio of the RSM that communicates with the IVM operates on the DRFC. Therefore, no channel switching is required in scenario 2 by the IVM.

The main advantage and the reason behind the consideration of scenario 2 is the use of dedicated radios in the RSM for communication with IVM modules and the DM module. A complete superframe is assigned by one radio to accommodate the requesting IVM modules to communicate with the RSM that helps in reducing the probability of missed vehicles. Furthermore, at any time instant (within the time slot duration assigned to a particular RSM), the information collected from IVM modules can be sent to the DM module for decision making.

The communication aspects of the proposed solution were analyzed by integrating SUMO with the OPNET Modeler. The integration of SUMO with OPNET Modeler was based on the details given in [21]. However, the details of the communication aspects taken into account, and the respective evaluation are considerably exhaustive and therefore, to be detailed in a separate treatise on the subject.

IV. Simulations and Results

The simulations of both the algorithms are carried out for the two types of intersections shown in Figure 1. However most simulations are carried out keeping in view the simple four-edged intersection.

A. Simulation Setup

For the simulations of EDF and FP, as adaptive TLC algorithms, the SUMO (Simulation Of Urban Mobility) traffic simulator had been adopted [22]. SUMO is a microscopic traffic simulator and provides better evaluation of the two mentioned algorithms. In order to code the 2-D traffic networks and vehicle routes, XML scripting had been employed, as SUMO works proficiently with the XML files while efficiently managing simulations of large traffic networks [23]. SUMO has an added advantage, that it supports different vehicle types [22]; tailor made for the proposed scenarios of diverse vehicle types. The simulator sends the traffic statistics to the python-based controller which takes a decision regarding the serving of the lanes following a client/server model, where SUMO acts as the server and the controller is the client. The controller uses its EDF or FP algorithm to schedule the queues at any given intersection.

1) Relationship between SUMO and XML coded scripts: SUMO is used to carry out static as well as adaptive traffic lights simulation. XML scripting files are used to generate 2-D road network, vehicles and their routes. The XML files are then integrated to produce a single SUMO configuration or simulation file which is responsible for running the overall simulation. Figure 6 shows the overall flow of the relationship between SUMO and XML coded files. The overall simulation process required to start simulation in SUMO consists of the following four basic steps as evident from Figure 6 and are listed below

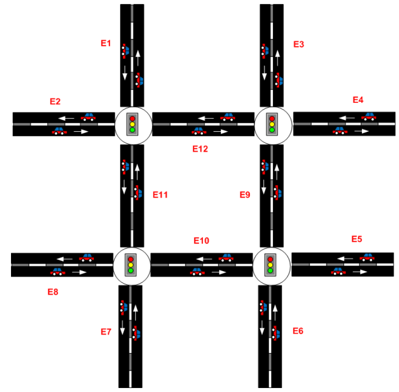


Fig. 5. Network containing Simple Intersections

- Generation of road network
- Generation of road traffics (vehicles and their routes)
- Deployment of induction loops
- Integration into SUMO configuration file

In the first phase, SUMO road network is generated using XML scripting files. One of the XML file is used to define all the nodes in the network. Nodes or junctions can be described as the positions (x-y coordinates) in the traffic network from where vehicles depart into simulation and the positions to represent traffic intersections. Another XML file is used to define all the roads in the network. The graphical visualization of road network in SUMO is generated by running the NETCONVERT application, on command line. NETCONVERT converts the road network definitions, described in network configuration file, into 2-D SUMO road network and stores all the necessary parameters of network in the final XML file which is the output file generated by NETCONVERT application.

In the second phase, vehicles along their particular routes are to be setup on the road network. Flow XML file is used to define vehicles, their types (normal, priority etc), their routes and the number of vehicles on a particular route. Route of the vehicle is defined from source edge to destination edge. The acceleration, deceleration and maximum speed of the vehicles are also defined in the flow XML file. Then the route configuration file integrates the SUMO road network and flow XML file. The DUAROUTER (Dynamic User Assignment Router), an application of SUMO runs on command line to build the vehicle routes on the principle of best optimal path selection from source edges to destination edges and stores all the vehicles demands information in route XML file. Route XML file is the output file generated by DUAROUTER application.

In the third phase, induction loops or detectors are deployed on each lane. Detector XML file is used to define road side induction loops on each lane. Two induction loops are deployed on each lane (directing towards traffic intersection),

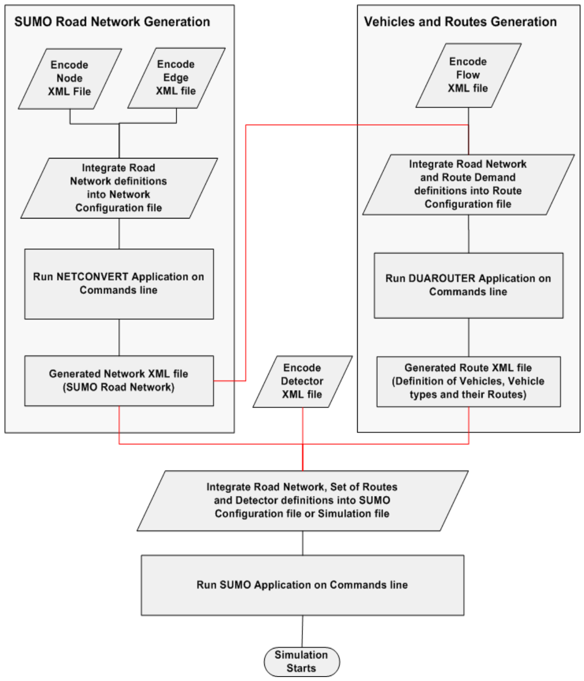


Fig. 6. Flow diagram depicting the generation of road network, vehicle Routes and the deployment of roadside detectors in SUMO using XML coded files

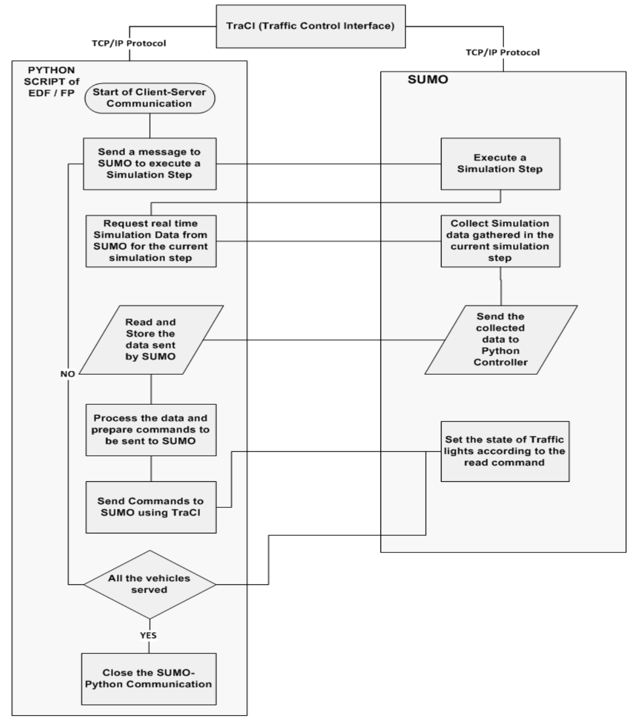


Fig. 7. Flow Diagram depicting the flow of Data between Python Controller and SUMO using TraCI (Traffic Control Interface)

one for detecting the vehicles entering the queue and the other for detecting the vehicles leaving the queue. Detector XML file is referred to as additional XML file in SUMO which is directly integrated in SUMO configuration file.

In the final phase, a SUMO configuration file by integrating SUMO road network, set of routes and definition of detectors is built. TraCI (traffic control interface) is an application of SUMO which allows dynamic interface of traffic in SUMO with python controller encoding scheduling algorithms. TraCI is used to establish a client server communication between python controller and SUMO using the remote port number which uniquely identifies a particular simulation file simulating a defined scenario.

2) Flow of data between SUMO and Python Controller: The adaptive traffic lights simulation of the two proposed algorithms, EDF and FP, can only be achieved if python script or controller encoding scheduling algorithms and SUMO establish client server communication. This communication can be achieved only by using special application of SUMO, TraCI (Traffic Control Interface). TraCI allows the duplex communication between python controller and SUMO using TCP/IP protocol in which python script acts as a client and SUMO acts as a server. The step by step duplex communication between python controller and SUMO has been depicted in Figure 7.

B. Important Parameters associated with Different Networks during Simulation

The important parameters associated with each network scenario are:

- Number of lanes per each edge
- Number of edges per each signalized traffic intersection which describes the complexity of traffic intersections
- Number of adaptive traffic lights intersections which describe the static and dynamic lights (lights which are implemented with adaptive control algorithms).
- Intensity of priority vehicles out of total traffic intensity
- Initial deadlines spanning of LV, MV and HV types vehicles and
- Length of each edge.

The last two parameters, initial deadlines spanning and edge length, have been fixed throughout the simulations in all the scenarios. Length of each edge has been fixed to 500 meters while the longest route in all the scenarios consist of four edges, therefore initial deadlines spanning remain same in all the scenarios. Intensity of priority vehicles describes the percentage of EDF or FP vehicles out of total traffic intensity. The two parameters including percentage of priority vehicles and initial deadlines spanning are specifically associated to EDF implementation while intensity of priority vehicles and initial fixed priority fashion are specifically associated with FP implementation.

The parameters including length of each edge, number of lanes per each edge, number of intersections and complexity of traffic intersections are the network parameters which define the network infrastructure. In all the scenarios number of intersections are also fixed to four while their complexities can vary from simple to complex in different scenarios. Simple intersection consist of simple four arms/edges intersection while complex intersections can have varied numbers of arms/edges per intersection oriented at different angles in plane.

TABLE II
A COMPARATIVE TABLE SHOWING THE PARAMETER CHANGES IN DIFFERENT NETWORK SCENARIOS

SCENARIOS	Changing number of Lanes per each edge	Network Containing Complex Intersection	Changing Intensity Of Priority Vehicles	Hybrid Signalized Traffic Intersections
Lanes per each edge Changing	(1, 2 and 3)	2	2	2
Edge Length (meters)	500	500	500	500
Traffic Intersections	4	4	4	4
Complexity of Traffic Intersections	Simple	Complex	Simple	Simple
Percentage of Adaptive Traffic Intersections (%)	100	100	100	Changing (0,25,50,75,100)
Intensity of Priority Vehicles out of total Traffic Intensity (%)	14	14	Changing (14, 30 and 50)	15
Initial Deadlines Spanning (seconds) of LV, MV and HV vehicles respectively	240, 250 and 260	240, 250 and 260	240, 250 and 260	240, 250 and 260

The comparison of all the parameters associated to different scenarios has been depicted in Table II

To study the effect of number of lanes per edge on the performance evaluations of scheduling algorithms, all other parameters except number of lanes are fixed to their optimum values as shown in table B. As described earlier, the optimum deadlines spanning are 240, 250 and 260 seconds for LV, MV and HV types vehicles respectively. In the same way the optimum intensity of priority vehicles are kept 14% of the total traffic intensity (the reason for this optimum priority vehicles intensity are described as, "effect of changing intensity of priority vehicles"). Similarly to study the effect of any other parameter (in other scenarios including traffic intersections turn into complex, changing intensity of priority vehicles and changing number of adaptive traffic intersections) on performance evaluation of scheduling algorithms, all other parameters except the parameter under study are kept constant as depicted in table B.

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C. Simulation Network 1: Network Containing Simple Intersections

A simple intersection network scenario is given in Figure 5, where all the edges (roads) have a fixed length of 500 meters. The trip time, of a particular vehicle, along the longest route had been fixed at 163 seconds, in the absence of traffic congestion. A latency amounting to 48% of the congestion-free trip time, had been assumed in the case of congestion. For the EDF simulation, an initial deadline spanning 240, 250 and 260 seconds, from the start time, had been assumed for all HV, MV and LV type vehicles, respectively.

For the sake of simplicity, four traffic intensities were assumed, namely:

1) the low traffic intensity of up to 400 vehicles amounting to 0.8 vehicles per second,
2) the medium traffic intensity of up to 600 vehicles, i.e. 1.2 vehicles per second,
3) the high traffic intensity of up to 800 vehicles equivalent to 1.6 vehicles per second and
4) the very high traffic intensity of more than 800 vehicles, that is 2.0 vehicles per second.

Simulations were performed for a number of different scenarios by changing the number of lanes of the intersecting edges. The ensued results were evaluated in terms of:

- the mean waiting steps,
- mean trip time,
- average speed and
- deadlines missed by the priority vehicles.

The maximum speed of vehicles on each edge in SUMO has been set to a default value of 12.3 meters/second. This maximum speed can be set to any value other than default. Our simulations have assumed the default maximum speed of 12.3 meters/second on all the edges. The vehicles following the longest route consisting of four edges, for instance the vehicles traveling from edge E2 towards E6, cover 2000 meters distance $(500x4 = 2000)$ with maximum speed of 12.3 meters/second if traffic congestion is assumed to be zero. The ideal trip time for such vehicles following the longest routes in the absence of traffic congestion (maximum speed) can be calculated by the formula, $Triptime = \frac{longestroutelength}{maximumspeed} = \frac{2000}{12.3} = 163secs.$ The 163 seconds trip time is the ideal time which can be achieved by vehicles following longest route in the absence of congestion. However as the number of vehicles along the longest routes increases, the waiting steps of the vehicles increases as a result of close proximity of vehicles and speed of the vehicles decreases. In other words traffic congestion reduces the speed of the vehicles and consequently increases their trip time. Vehicle's traveling with maximum speed is possible only if all the static lights are green and the intensity of vehicles are kept to such a minimum level that the distance between two vehicles do not decelerate the vehicles, which is the ideal case.

To determine what range of trip times can be acceptable with practically few numbers of stops, the basic criteria is to vary the intensity of vehicles (start from very low, zero number of stops) along the longest routes and examine the number of stops for each intensity. If the number of stops is acceptable, determine the mean trip time of that traffic intensity which has maximum number of acceptable stops. This highest trip time of the vehicles along the longest routes with maximum acceptable number of stops is to be chosen as the deadline

TABLE III
MEAN TRIP TIME AND WAITING STEPS OF DIFFERENT INTENSITIES OF VEHICLES GENERATING WITHIN SAME INTERVAL OF 500 SECONDS

Traffic Intensity	Mean Trip Time (secs)	Mean Waiting Steps (secs)
20	163	0
100	164	1.08
150	173	4.84
180	223	15
200	240	20
210	260	45
250	280	60

TABLE IV
PERCENTAGE REDUCTION IN WAITING STEPS FOR DIFFERENT TRAFFIC INTENSITIES AS COMPARED TO STATIC(%)

Algorithms	No of Lanes	Percentage Reduction in waiting steps for Intensities			
		Low (400)	Medium (600)	High (800)	Very High (1000)
EDF	1	83	70	55	20
	2	86	82	50	21
	3	90	71	56	15
FP	1	70	60	49	15
	2	79	70	47	10
	3	81	57	36	10

TABLE V
MEAN WAITING STEPS COMPARISON FOR DIFFERENT VEHICLE TYPES

Algorithms	Vehicle Types	Initial Fixed Priority	Mean Waiting Steps
EDF	HV	High	67.44
	MV	Intermediate	71.66
	LV	Low	72.2
	NV	None	-
FP	HV	High	53.71
	MV	Intermediate	78.7
	LV	Low	94.27
	NV	None	-

that should be achieved by the vehicles.

Number of simulations has been performed for network of Figure 5 having two lanes per each edge with varying low traffic intensities along the longest routes (four edges) only. Table III tabulates the mean trip time of the vehicles along with their mean waiting steps. As evident from table A, zero waiting steps (maximum speed) results in trip time of 163 seconds which is in agreement with mathematical derivation of trip time presented before.

Table III suggests that as the number of vehicles increases, mean waiting steps along the longest routes increases and consequently mean trip time also increases. This is due to the face that all the vehicles enter in to the simulation within same generation interval of 500 seconds. Keeping the same generation interval, increasing number of vehicles results in decreasing distance between two successive vehicles and hence results in increasing number of stops. The traffic intensities including 20, 100 and 150 vehicles are almost the ideal cases. However number of stops increases after traffic intensity of 150. For traffic intensities of 180 and 200 vehicles, the mean waiting steps increases up to 20 seconds but these numbers of stops are acceptable. If one chooses the maximum acceptable mean waiting steps to be 4.84 seconds and choose the corresponding trip time of 173 seconds as the deadline to be achieved by the vehicles, then very few percentages of vehicles will achieve deadlines by the implementation of scheduling algorithm (EDF) because it is very difficult to reduce congestion level to such a small extent equivalent to waiting steps of 4.84 seconds. So the trip time of 240 seconds corresponding to 20 seconds waiting steps can be better chosen as the optimum deadline to be achieved by the priority vehicles (one should not relate these results with any other results presented in the paper because the results presented in table A have been collected for vehicles following the longest routes only). At traffic intensities of 210, 250 and afterwards, the congestion increases above acceptable level and the corresponding trip times cannot be chosen as deadlines to be achieved.

In short a latency amounting to 48% of the congestion free trip time (163 seconds), have been assumed in the case of congestion. For the EDF simulation, an initial deadline spanning 240, 250 and 260 seconds, from the start time, have been assumed for all HV, MV and LV type vehicles, respectively. Though the deadlines have been set according to the longest route criteria however the same initial deadlines have been set for vehicles following the shortest routes with an added advantage that vehicles following the shortest routes can easily achieve deadlines. Moreover as the length of edges in all the scenarios presented in this paper is same, therefore the initial deadlines spanning remain the same in all the scenarios.

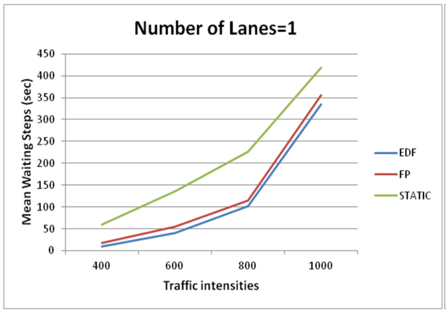
1) The mean waiting steps of the priority vehicles: Figures 8(a),(b) and (c) plot the mean waiting steps for the simple network as a function of the traffic intensity, with the number of lanes per edge being one, two and three, respectively.

It must be mentioned here that the results compiled here are irrespective of the number of lanes as our main purpose is to compare the performance of the adaptive algorithms against the static algorithm to reduce the mean waiting steps. This is because increasing the number of lanes brings about an improvement in the mean waiting steps by all three algorithms by the same percentage. This can be observed from table IV, which gives the percentage reduction in waiting steps experienced by priority vehicles as compared to static algorithm for different lane scenarios.

With a single lane, in comparison to the static control algorithm, the EDF algorithm reduced the mean waiting steps of priority vehicles by 83% for low traffic intensity, 70% for medium traffic intensity, 55% for high traffic intensity and 20% for very high traffic intensity; the same comparison of the FP algorithm yielded a reduction of 70% for low traffic intensity, 60% for medium traffic intensity, 49% for high traffic intensity and 15% for very high traffic intensity.

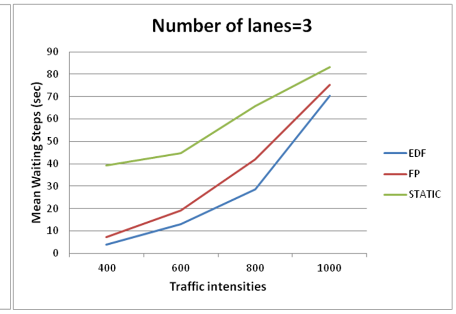
Along the same lines, when the lanes were doubled (Figure 8(b)), the EDF algorithm improved further by 86% for low traffic intensity and by 82% for the medium traffic intensity in comparison to the static algorithm. The FP algorithm reduced the waiting steps of priority vehicles, par rapport the static algorithm, by 79% for low traffic intensity, 70% for medium traffic intensity, 47% for high traffic intensity and 10% for very high traffic intensity. Barring the low intensity case, the reduction is lower than that of the single-lane version . Generally, the EDF outperformed the FP algorithm, especially at high intensities.

When it came to the three lanes per edge situation (Fig-

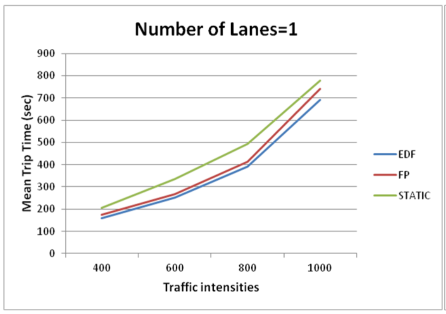


(a) Mean Waiting Steps $Lanes = 1$

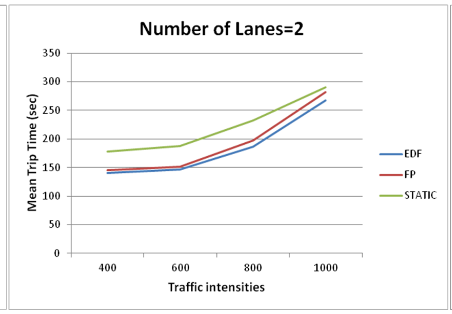
(b) $Lanes = 2$



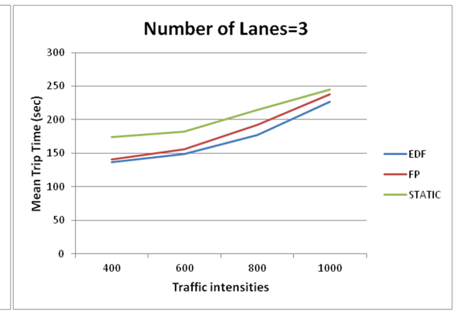
(c) $Lanes = 3$



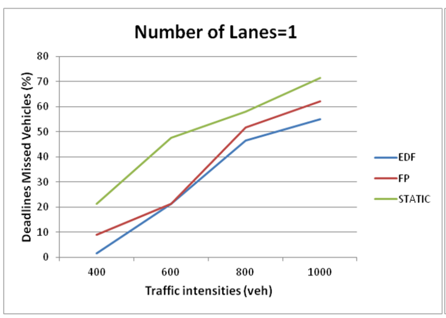
(d) Mean Trip Time $Lanes = 1$



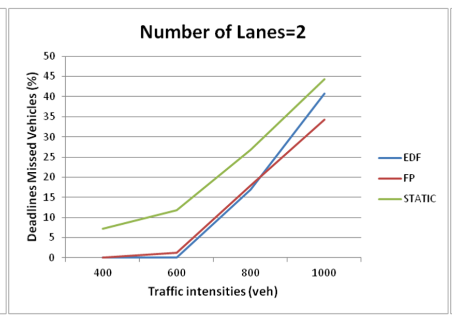
(e) $Lanes = 2$



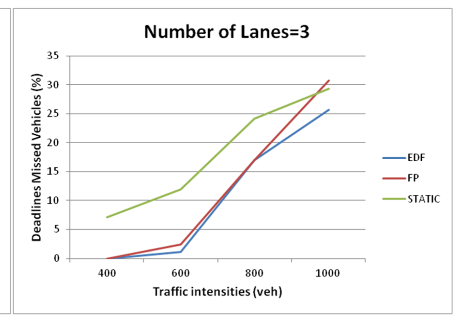
(f) $Lanes = 3$



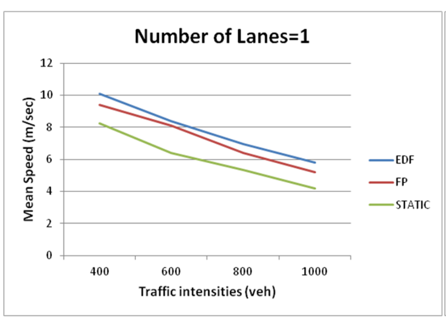
(g) Deadlines Missed $Lanes = 1$



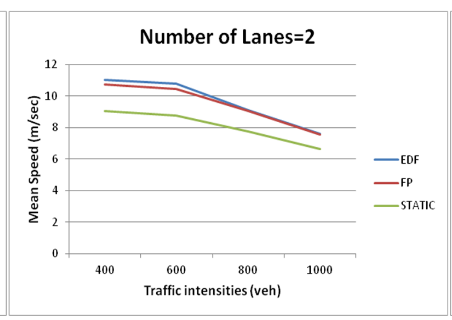
(h) $Lanes = 2$



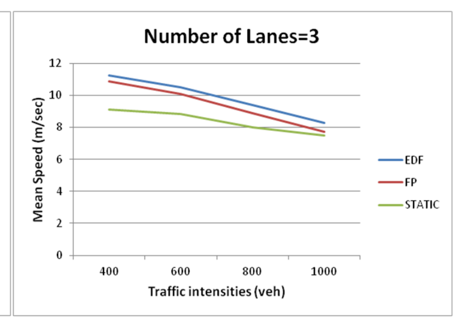
(i) $Lanes = 3$



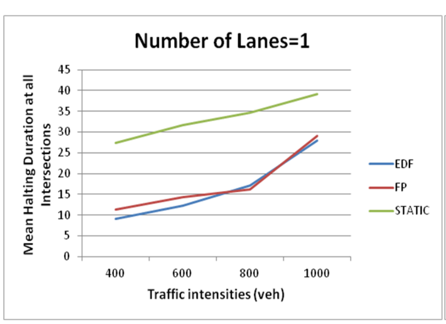
(j) Mean Speed $Lanes = 1$



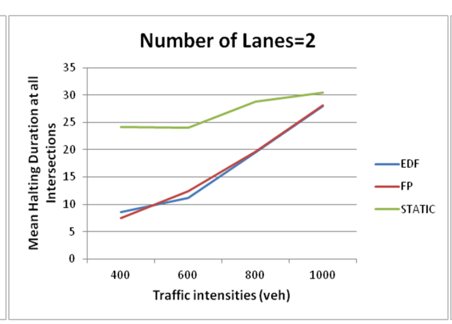
(k) $Lanes = 2$



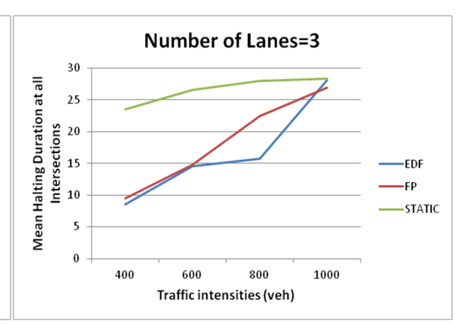
(l) $Lanes = 3$



(m) Mean Halting Durations $Lanes = 1$



(n) $Lanes = 2$



(o) $Lanes = 3$

Fig. 8. Performance Evaluation for Priority Vehicles with Different number of Lanes per Edges for Network with Simple Intersections

ure 8(c)), the EDF algorithm reduced the waiting steps of priority vehicles by 90% for low traffic intensity, 71% for medium traffic intensity, 56% for high traffic intensity and 15% for very high traffic intensity. The FP algorithm under performed, comparatively, and the waiting steps of priority vehicles were found to be reduced by 81% for low traffic intensity, 57% for medium traffic intensity, 36% for high traffic intensity and 10% for very high traffic intensity. Table V reveals that simulation of fixed priority algorithm results in low mean waiting steps experienced for highest priority vehicles. In comparison, the MV and LV type vehicles experience more waiting steps. With the EDF algorithm, the average waiting steps had been almost the same irrespective of the priority of vehicles.

As compared to static control algorithm the two adaptive TLC algorithms, EDF and FP, reduce the waiting steps of priority vehicles dramatically. The reason for such dramatic reduction is obvious from the fact that the static control algorithm does not take into account priority vehicles found on the roads. It can also be observed that increasing the number of lanes increases efficiency of the two algorithms in comparison with static control algorithms.

As far as the inter se comparison of EDF and FP is concerned, the former outperforms the latter as is being evident from Figures 8(a), (b) and (c), the main reason being that EDF is a dynamic algorithm in which the deadlines change at each interval of time as against the static priorities in FP.

It can be concluded that FP and EDF produce efficient results when the traffic intensity is not very high. At very high traffic intensities however, performance degradation can be seen. Although the mean waiting steps still remain smaller than the static flow algorithm. This is because increasing traffic intensity over the same generation interval of 500 seconds (all vehicles are generated and departed in the simulation within this time) causes the vehicles to depart into simulation very closely one after the other, thereby decreasing the gap between vehicles leading to more waiting steps for priority vehicles.

2) Mean Trip time of Priority vehicles: Another important performance measure for testing the viability of the algorithms is the average trip time of the priority vehicles. The average trip time has also been evaluated at different number of lanes per edge at an intersection. Figure 8(d), (e) and (f) show that the FP and EDF strategies greatly reduce the trip time for the priority vehicles. Furthermore, it can be seen that EDF performs better than FP when reducing the average trip time for priority vehicles.

It is evident from the figures that for low and medium traffic intensities, the mean trip time remains the same for both the FP and EDF algorithm based controllers. A comparative analysis of the mean trip time of the adaptive algorithms with the static algorithm with respect to an increase in the number of lanes shows that the mean trip time is independent of the number of lanes. This is concluded by studying the percentage reduction in the mean trip time of priority vehicles when compared against the static algorithm under high traffic intensity and with different number of lanes. Considering the single lane scenario, it was found that the EDF algorithm reduced the mean trip time of priority vehicles by 21% for high traffic intensity while FP algorithm reduced the time by 16% when compared against the static algorithm. By increasing the number of lanes to two, EDF reduced mean trip time by 20% and FP reduced trip time by 15%. While considering a three lane scenario, it was found that the EDF algorithm reduced mean trip time by 18% while FP reduced mean trip time by 11% for the same traffic intensity as compared to static.

TABLE VI
MEAN TRIP TIME OF DEADLINE MISSING VEHICLES

Algorithms	Deadlines Missed Vehicles	Mean Trip Time Of deadlines missed vehicles
EDF	40.71%	432.49 secs
FP	34.28%	519.29 secs

3) Deadlines missed by priority vehicles: One important performance measure for evaluating the performance of the EDF and the FP is to study the percentage of deadlines missed by the important priority vehicles. Figures 8(g), (h) and (i) show these percentages for priority vehicles traveling in edges with one, two and three lanes respectively.

With the implementation of the EDF and FP algorithms on the traffic lanes, the number of missed deadlines reduced by 60% with low and medium traffic intensities and by 25% with high and very high traffic intensities in comparison to the static control. From the three figures, it is also evident that the EDF behaves better than FP, as the former operates on the deadlines of the vehicles while the latter only serves the vehicles based on their initial assigned priority. Figure 8(h) however shows some contradictory results in which the FP outperforms the EDF for very high traffic intensities. This behavior can be explained by taking into context the mean trip time of the vehicles which missed their deadlines in table VI. The table shows that although the vehicles traveling on EDF operated intersections miss their deadlines as compared to the FP operated intersections, yet their mean time is still considerably reduced in comparison to the FP operated intersections.

From Figure 8(g), (h) and (i), it is also clear that that increasing number of lanes has no affect on comparative deadline missed vehicles percentage but the analysis of the two dynamic algorithms for comparison with static has been taken to be independent of the number of lanes.

4) Average speed of priority vehicles: Typically, the speed decreases when the traffic intensity increases irrespective of the control strategy. Figure 8(j),(k) and (l) plot the average speed of priority vehicles with respect to various traffic intensities on the basis of EDF, FP and static control algorithms for 1, 2 and 3 lanes per edge, respectively. It can be readily observed that the EDF algorithm reduces the waiting steps of priority vehicles and hence causes their speed to increase. The three figures reveal that the two adaptive TLC algorithms increase the speed of priority vehicles more as compared to static traffic light control algorithm. However in comparison to FP, the EDF causes the priority vehicles to maintain higher speed. Moreover increasing the number of lanes also increases the speed of priority vehicles.

5) Traffic congestion at different intersections: At different traffic intersections, the congestion is measured in terms of mean halting duration of all the vehicles (priority and non

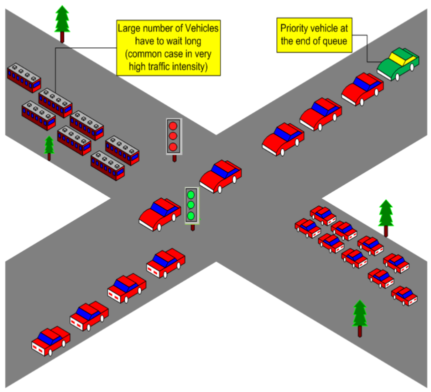


Fig. 9. Scenario of a Fixed Priority Vehicle at distance from the Intersection

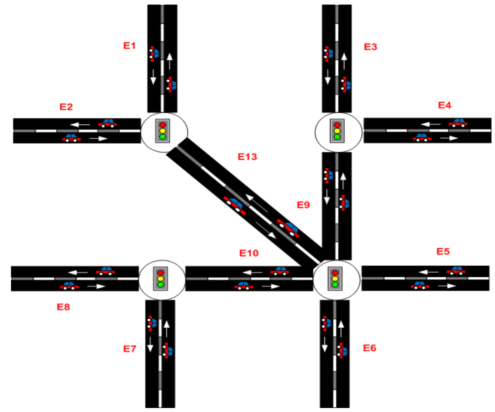


Fig. 10. Network containing Complex Intersections

priority) near that intersection. Though the scheduling algorithms, EDF and FP only serve the priority vehicles, they do reduce the overall traffic congestion at traffic intersections. Figures 8(m), 8(n), and 8(o) plot the mean halting durations of all the vehicles at all intersections at various intensities for the three algorithms involving 1, 2, and 3 lanes per intersection edge. The halting durations at individual intersections are not presented here. Instead, the overall halting durations at all the intersections are depicted. These are obtained by taking the mean of halting durations of individual intersections for all the intersections considered.

From the figures it is also clear that the congestion is reduced by 50% when FP and EDF are applied at the traffic intersections. As evident from the three figures, the graph lines of EDF and FP algorithms are not following a uniform or but dominating each other at several points. This random behavior has been detailed as follows.

- In most of the scenarios, EDF reduces the halting duration more than FP. In case of EDF implementation, none of the queues have to wait for a long while to get serviced as opposed to the FP implementation where the duration of red light is quite large for a particular queue. This can be analyzed by taking into consideration a scenario in which a particular queue contains an HV type vehicle, then during FP implementation the remaining queues will be given red light so long as the HV type vehicle is not serviced. While in the same scenario if EDF is applied the remaining queues will not have to wait for so long to get serviced as the smallest remaining deadline will be the factor on which the queues will be serviced and this a continuously varying parameter.
- In some cases the fixed priority improves the congestion more than EDF however an overall analysis shows no major difference in their performance in terms of efficiency to improve traffic congestion. This behavior can be attributed solely to the halting durations experienced by non-priority vehicles. The calculation of halting durations not only take into account the congestion of priority vehicles but also congestion of non-priority vehicles, which are not served by either of the two adaptive algorithms. The non-priority vehicles may sometime experience more waiting steps and sometime less waiting steps causing the results of two algorithms to vary irregularly. It should be noted here that the priority vehicles experience much low halting duration near traffic intersections as compared to the non-priority vehicles which experience more waiting steps resulting in the increase of mean halting durations. Yet the mean halting durations for these adaptive algorithms are much lower then the mean halting durations resulting from the use of static control algorithm.
- The figures also reveal that at very high traffic intensity the performance of the two algorithms, EDF and FP, become close to the performance of the static algorithm. The reason is that in some cases when traffic intensity increases, a situation may arise where a priority vehicle is found at the end of a queue away from the intersection (Figure 9) and preceded by many non-priority vehicles. This can cause the priority vehicle to experience a long waiting time before it reaches the intersection and gets served. Such scenario is more common in very high traffic intensity as compared to other traffic intensities. At high traffic intensities, the halting durations at traffic intersection increase manifold and the performance of scheduling algorithms while curbing congestion coincides with the performance of the static algorithm. Note that the halting durations of priority vehicles are still low but the corresponding increase in halting durations of non priority vehicles becomes a cause of such undesirable situations.

D. Simulation Network 2: Network Containing Complex Intersections

The testing of FP, EDF and static control algorithms has also been carried out by making traffic intersections complex and changing the number of edges per intersection. The results discussed in this section have been compiled for the scenario, given in Figure 10, which contains a network containing complex traffic intersections. The number of lanes, per edge, had been fixed at two since the effect of the number of lanes is not being considered here. All the edges in the figure were assumed to have a fixed length of 500 meters except for edge E13 with a length of more than 500 meters. The vehicle generation interval was assumed to be 500 seconds for increasing number of vehicles during the simulation. The intensity with which priority vehicles were generated had been kept at 14% of the total traffic intensity.

In this section, not only a comparative study of the algorithms will be considered for the complex network, but also a comparative analysis of this network will be performed with the network considered in Figure 5. However, the analysis will be limited to two lanes per edge case only.

1) Mean Waiting Steps Of Priority Vehicles: The mean waiting steps of priority vehicles, as a function of traffic intensity, resulting from the implementation of EDF, FP and static algorithms on the scenario of Figure 10, can be observed from Figure 11(a). In comparison to the static control, the EDF and FP reduce the mean waiting steps of the priority vehicles by more than 50%. Furthermore the EDF, as can be viewed from Figure 11(a), tends to give better performance at scheduling than the FP.

Comparing the mean waiting steps of the two intersections[1], given in Figures 5 and 10, for double-lane edges (Figure 8(b) and Figure 11(a)) it is readily observable that FP, EDF and static control perform better at simple traffic intersections than at complex ones. This behavior can be attributed to the fact that the traffic at simple intersections is uniformly distributed and the traffic moving from edge E1 and E2 to other edges will be distributed via edges E11 and E12. While in the network of Figure 10, edge E13 is the only edge which provides a route for the traffic commuting from edge E1 and E2 towards all other edges. Therefore E13 is serving the traffic of both the edges E11 and E12 from Figure 5. This extra traffic flow on E13 (having the same width as all the edges) results in traffic congestion causing the priority vehicles to experience much more waiting steps, as compared to the simple network.

2) Mean trip time and average speed of priority vehicles: The respective trends of these two parameters, for the complex network of Figure 10, can be observed graphically in Figures 11(b) and 11(c). It can be seen that the mean trip time and the mean speed of the priority vehicles are markedly reduced using the EDF and FP algorithms. If we compare the results of the complex scenario (Figures 11(b) and 11(c)) with the results obtained for simple scenario (Figures 8(f) and 8(k)), it is evident that the results of the two networks are pretty much close to each other. However, due to the extra traffic congestion on E13, the mean trip time of priority vehicles increases in the complex network but still the priority vehicles maintain speeds comparable to those of the simple scenario.

3) Traffic congestion (mean halting durations) at different intersections: Both the simple and complex network scenarios contain four intersections but the difference lies in the number of edges connecting the intersections. The simple network has symmetric traffic intersections where all the intersections are constituted by four edges while the complex network contains asymmetric intersections with three of the intersections constituted by three edges and the fourth one by five edges. Figure 12 and Figure 13 plot the mean halting durations of vehicles near different traffic intersections of both the simple

[1]From here onwards the *simple* scenario/network refers to Figure 5 and the *complex* scenario/network refers to Figure 10

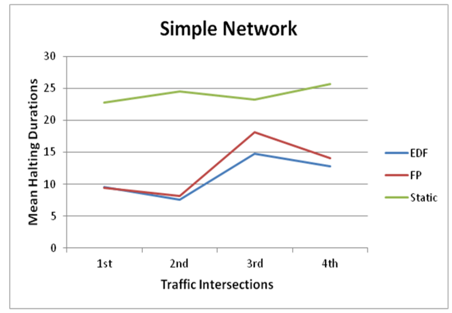


Fig. 12. Mean Halting Duration for Simple Intersections

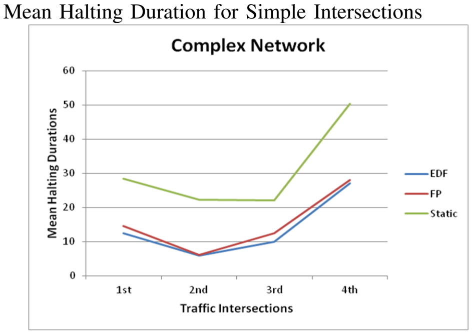
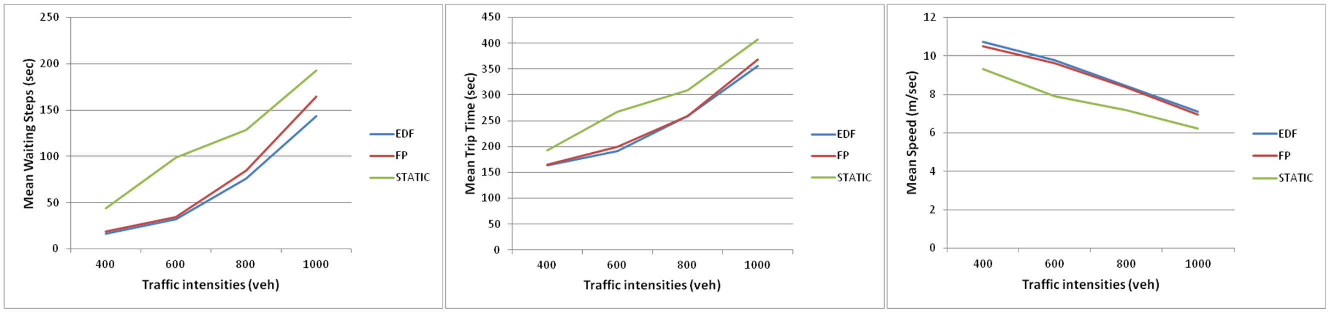


Fig. 13. Mean Halting Duration for Complex Intersections

and complex scenarios, respectively, having two lanes per edge with a medium traffic intensity of 600 vehicles. It is evident from Figures 12 and 13 that the mean halting durations near each of the four traffic intersections diminish considerably with the EDF and FP scheduling. The inter se performance of EDF and FP are close to each other. However, the EDF surpasses FP in terms of managing traffic congestions at all the traffic intersections of a particular network. The figures also show that using any of the adaptive control algorithms, the traffic congestions at the I1 (combining edges E1, E2 and others) and I2 (combining edges E5, E6 and others) traffic intersections are lower in case of the simple network, as compared to the complex network. However, the traffic congestions at I3 and I4 traffic intersections are low in the case of the complex network as compared to the simple network. This is because of the edge E13 in Figure 10 which replaced edges E11 and E12 of Figure 5. Such mean halting duration can be attributed to the reasons that

1) In the simple network, edges E11 and E12 are connected with the I3 and I2 traffic intersections respectively, whereas no such edges exist in the complex network.
2) The traffic congestion of vehicles on edges E11 and E12, near their respective traffic intersection, adds up to the mean halting durations at I3 and I2 intersections in the simple network while the congestion of edges E11 and E12 are not included in the mean halting durations at I3 and I2 intersections of the complex network as the two previously mentioned edges do not exist in the latter. This causes the traffic congestions at I3 and I2 traffic intersections to increase in case of the simple network as compared to the corresponding congestions in case of the complex network.



(a) Mean Waiting Steps of Priority Vehicles (b) Mean Trip Time of Priority Vehicles (c) Mean Speed of Priority Vehicles

Fig. 11. Performance Evaluation for Priority Vehicles for Network with Complex Intersections

The traffic congestions at I1 and I4 traffic intersections can be attributed to

1) The more traffic flow on edge E13 in the complex network, causing more waiting steps on edge E13. This increases the congestion on edge E13 which consequently increases the mean halting durations at I1 and I4 traffic intersections as compared to the simple network.
2) It can also be observed that there is much more traffic congestion at the I4 traffic intersection of the complex network as compared to congestion at other intersections in the same network. This is due to the fact that the I4 intersection combines five edges and most of the traffic flow occurs through this intersection.

E. Changing the intensity for priority vehicles

For all the aforementioned simulations the traffic intensity of priority vehicles, for all the testing scenarios, has been kept at a constant rate of 14% of the total traffic. However, it had been observed that changing the intensity of priority vehicles also affects the performance of EDF and FP algorithms. Three different intensity percentages (14%, 30% and 50%) had been selected to study the effects of changing traffic intensities. The network considered for the simulation of traffic with these three intensities is the network simple network of Figure 5.

1) Mean waiting steps of the priority vehicles: Figures 14 and 15 plot the mean waiting steps of priority vehicles as a function of varying priority vehicle intensities taken at 14%, 30% and 50% of the total traffic for traffic density of 600 (medium) and 800 (high) vehicles respectively. Number of lanes are kept at 2.

From the two plots in Figures 14 and 15, it is evident that the mean steps of the two adaptive algorithms when compared with static decrease as the intensity of priority vehicles increases for a fixed traffic intensity of either medium or high traffic density. For example Table VII gives the percentage reduction in waiting steps of priority vehicles, upon the implementation of EDF and FP algorithms as compared with static, for different intensities of priority vehicles at a traffic density of 600 vehicles.

As the number of priority vehicles increases in the total traffic, the probability of finding more and more priority vehicles in the same lane increases. Consider the scenario of low priority vehicles found in edge1, which in case of EDF

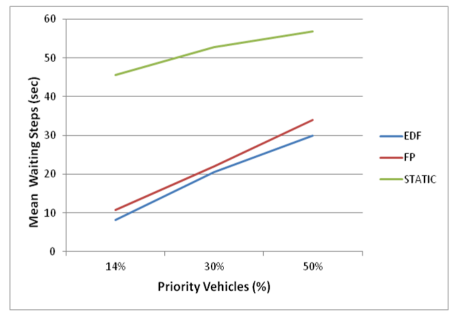


Fig. 14. Mean waiting steps of priority vehicles for different percentage of priority vehicles at medium traffic intensity (600 vehicles)

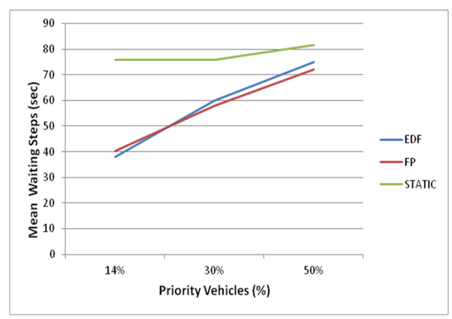


Fig. 15. Mean waiting steps of priority vehicles for different percentage of priority vehicles at high traffic intensity (800 vehicles).

are the vehicles with more remaining deadlines and in case of FP are the vehicles with low initial fixed priority. High priority vehicles are continuously entering edge2 (as the intensity of priority vehicles are high so more priority vehicles are coming one after the other). In this particular scenario the LV in Edge1 tend to wait until all the HV in Edge2 get served. For low intensity of priority vehicles, HV are few in number and the priority vehicles in vertical edge soon get serviced while on the other hand for high intensity of priority vehicles, HV vehicles

TABLE VII
PERCENTAGE REDUCTION IN WAITING STEPS FOR DIFFERENT INTENSITIES OF PRIORITY VEHICLES AS COMPARED TO STATIC (%)

Algorithms	Percentage Reduction in waiting steps for different intensities		
	14%	30%	50%
EDF	82	61	47
FP	76	58	40

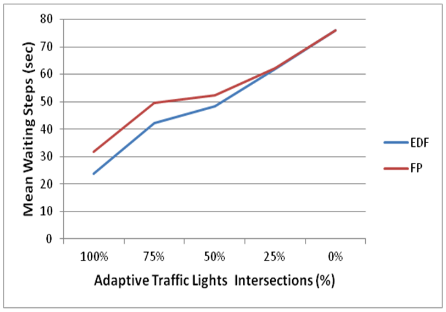


Fig. 16. Mean Waiting Steps at different Percentages of Adaptive Traffic Lights Intersections

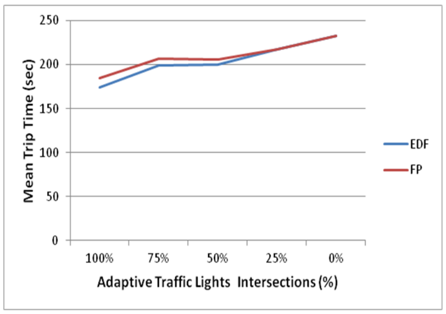


Fig. 17. Mean Trip Time at different Percentages of Adaptive Traffic Lights Intersections

in Edge2 are large in number resulting in LV in Edge1 to wait long and consequently the overall waiting steps increase. Such scenario of increasing waiting steps is a function of intensity of priority vehicles out of fixed total traffic intensity. Thus the performance of both EDF and FP algorithms becomes low as the intensity of priority vehicles increases. But still the performances of the two adaptive algorithms remains far better than static the algorithm.

Again comparing EDF and FP algorithms we observe that at a total traffic of 600 vehicles (Figure 14) EDF performance is better than FP while in case of high traffic of 800 vehicles (Figure 15), the FP outperforms EDF.

F. Simulation Network 3: Scenario of Hybrid Signalized Traffic Intersections

Rather than relying on a single algorithm, the implementation was also carried out in the hybrid form, i.e. some of the intersections were static while others being following the FP or EDF. The effect of this hybrid nature of traffic intersections (some intersections adaptive and some static) are being evaluated in this section.

Figures 16 and 17 plot the mean waiting steps and mean trip time of the priority vehicles resulting from implementation of EDF and FP algorithms at different numbers of adaptive out of a fixed number of traffic light intersections. These two figures show the simulations for a certain network having four traffic intersections. The two figures show that the mean waiting steps and the mean trip duration of priority vehicles are much improved by the implementation of EDF and FP algorithms if we make all traffic lights adaptive. However upon decreasing the fraction of adaptive traffic lights and replacing them by static lights, the performance measures for the commuting priority vehicles are affected. It is evident from the figures that the EDF algorithm produces good results as compared to FP algorithm but the two graph lines coincides at 0% adaptive traffic intersections. This is due to the fact that 0% adaptive intersections represent all static traffic lights and thus the two adaptive algorithms are not implemented on any of traffic intersections.

V. Conclusion

We presented a comparative evaluation of two scheduling algorithms for reducing the unwanted delay experienced by priority vehicles as a consequence of traffic congestion. These algorithms include EDF and FP, as the adaptive traffic light control algorithms. The simulation results showed that the two priority vehicle serving algorithms produce much better results as compared to fixed time control of traffic lights. The performance measures of priority vehicles such as the mean waiting steps, the mean trip time, the mean speed, deadlines achieved and the overall traffic congestion reduction are remarkably improved by the use of the proposed algorithms. Their main advantage becomes apparent while employing them at complex road networks and at heavy traffic intensities. Here the performance measures of priority vehicles significantly improve as compared to fixed timing algorithm. Furthermore the comparative study of EDF and FP algorithms conclude that EDF algorithm is more efficient than FP algorithm. It is also observed that increasing the number of lanes has no affect on the comparative performance of scheduling algorithms.

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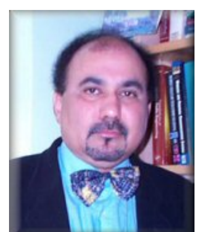
Asif Ahmad is studying for his degree in Electrical Engineering with majors in Communications from University of Engineering and Technology, Peshawar, Pakistan. He is also working as a Research Assistant in the Center for Intelligent Systems and Networks Research (CISNR) in the same University. He has experience in working with, and developing real world models and network protocols in various environments and simulators. His research interests include Intelligent Transportation Systems; Agent based intelligent algorithms, Fuzzy Logic, Wireless Network Protocols, and Communication in Smart Grids.

Rabia Arshad did her BEng in Computer Systems Engineering from College of Electrical and Mechanical Engineering, National University of Science and Technology Islamabad Pakistan in 2008. She completed her M.Sc from Center For Advanced Studies in Engineering, University of Engineering and Technology Taxila Pakistan in the year 2011. She has worked at the Center for Advanced Research in Engineering Islamabad Pakistan as a Design Engineer from 2008 to 2010. She is currently working as a Research Associate at the Center for Intelligent Systems and Networks Research (CISNR) in University of Engineering and Technology Peshawar Pakistan. Her research interests include Hardware Affine Fingerprint Recognition Algorithms, Massively Parallel Fingerprint Recognition Systems, Neuro-Evolutionary Techniques and Field Programmable Gate Array (FPGA) accelerated design and implementation of various operational entities in Smart Grids.

Sahibzada Ali Mahmud (M'08) did his B.Sc in Electrical Engineering from University of Engineering and Technology Peshawar. He was awarded a PhD scholarship and associated with the Wireless Networks and Communications Centre at Brunel University, West London, UK. He did his PhD in Wireless Communications and Networks in January 2010, and since then, is working as an Assistant Professor in Electrical Engineering Department of UET Peshawar. He is also the founder and Project Director of Centre for Intelligent Systems and Networks Research at UET Peshawar. His research interests include Scheduling for Real Time Traffic, Wireless Sensor Networks, Intelligent Transportation Systems, Communication in Smart Grids, M2M Communication, and Short Range Wireless Networks. He has served as a TPC member for conferences like IEEE ICC, IEEE PIMRC, IEEE WCNC etc. on several occasions, apart from reviewing for IET Communications and IEEE Communication Letters. He has worked on various funded projects including an EU funded project called "MAGNET BEYOND", and has published in various reputed journals and conferences.

G. M. Khan (M'09) did his B.Sc in Electrical Engineering from University of Engineering and Technology Peshawar. He was awarded a PhD scholarship and associated with the Intelligent Systems Research Group at University of York, UK. He is involved in a number of research projects in the area of Intelligent System Design, Smart Grid Technologies, Bio-Signal Processing, Intelligent Transportation Systems and Cotton purification processes using Image Processing Techniques. He has a working experience of more than Ten years in the Field. He is the major participant in research oriented project planning and development, and coordinating higher education activities. He is currently working as an Assistant Professor and Project Director at Centre for Intelligent systems and Networks Research at UET Peshawar.



Hamed Al-Raweshidy (SM) is Professor of Communications Engineering and has been awarded BEng and MSc from University of Technology, Baghdad in 1977 and 1980 respectively. He completed his Post Graduate Diploma from Glasgow University, Glasgow, UK in 1987. He was awarded his PhD in 1991 from Strathclyde University in Glasgow, UK. He has worked with The Space and Astronomy Research Centre (Iraq), PerkinElmer (USA), Carl Zeiss (Germany), British Telecom (UK), Oxford University, Manchester Met. University and Kent University. Professor Al-Raweshidy is currently the Director of The Wireless Networks and Communications Centre (WNCC) at Brunel University, London, UK. WNCC is the largest centre at Brunel University and one of the largest Communications Research Centres in the UK. He has published over 300 papers in International Journals and referred conferences. He is the editor of the first book in Radio over Fibre Technologies for Mobile Communications Networks and contributed chapters for 6 books. He is currently the "Editor-in-Chief" of Communication Networks Journal (USA). He has acted as Guest editor for the International Journal of Wireless Personal Communications. He is a member of several Journal Editorial Boards such as Journal of Communications and Mobile Computing and Journal of Wireless Personal Communications. Professor Al-Raweshidy acts as a consultant and is involved in projects with several companies and operators such as Vodafone (UK), Ericsson (Sweden), Andrew (USA), NEC (Japan), Nokia (Finland), Siemens (Germany), Franc Telecom (France), Thales (UK & France) and Tekmar (Italy). He is principal investigator for several EPSRC projects and European project such as MAGNET EU project (IP) 2004-2008. He has been able to attract over 3,000,000 from research projects.