Realtime Traffic Enhancement using Intelligent Route Optimization for Dynamic Logistics

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Abstract

Software defect prediction is a technique that may foretell when and where software errors will manifest. It should be the aim of every software development project to provide a product devoid of bugs. Software defect prediction (SDP) is a crucial aspect of software repair that involves predicting potential code locations for problems. Software of excellent quality need to be bug-free. Software metrics are assessments of the program or its needs that are either quantitative or qualitative in nature. The Lévy flying patterns of various birds and fruit flies, together with the flight patterns of some cuckoo species, served as inspiration for Cuckoo Search (CS), a population-based algorithm that was developed relatively recently. Computer science satisfies the requirements for global convergence. Among the many supervised learning methods that do not need parameters, KNN stands out. This study provides a social metaphorical overview of Stochastic Diffusion Search (SDS) to show how SDS distributes resources. Using a new probabilistic approach, SDS solved the problems of best-fit pattern recognition and matching. Using interactions amongst basic agents, SDS is a distributed computing paradigm that employs multiagent population-based global search and optimization. An optimization approach that combines CS and SDS methods is suggested in this work. This hybridization proposal seeks to improve the cuckoo bird's search strategy for the ideal host nest by using the global search strategy solution of the SDS algorithm. So, to find the best spot for the cuckoo egg, the SDS approach would be used. One possible explanation for PC2's superior performance when compared to other classifiers is its greater recall values. Specifically, KNN outperforms Radial Bias Neural Network (2.20% improvement) and Naive Bayes (7.54% improvement) classifiers.

Keywords: Stochastic Diffusion Search; Cuckoo Search; Software Defect Prediction; K Nearest Neighbor; Naïve Bayes; Radial Bias Neural Network

1. Introduction

Using ITS [1] for-accident prediction and prevention on Indian highways is the main goal of this research. Because of the improvements to traffic safety and efficiency, the number of unintentional fatalities and injuries will go down. With such in mind, a system for predicting highway traffic accidents is created and referred to as an emergency prediction mechanism (ESPM). To testing the road accident prevention procedure, we have also created a road accident prediction (RAP) [2] scheme and a bandwidth efficient acknowledgment-based multicast protocol for highway (BEAM-HW) scenario [3].

The roadside device in this setup gets updates from passing cars and information on traffic flow from sensors placed along highway lanes. Vehicles [4-7] equipped with on-board sensors relay their status to a unit stationed on the road. A new Four Lane Sensor Grid (FLSG) [8] is developed and implemented to provide the roadside device with data on traffic flow. The roadside unit in FLSG receives signals from sensors buried in the roadbed, which detect and relay the presence and motion of cars. After receiving the status report and traffic flow data, the roadside unit fixes the thresholds and extensively investigates the data for abnormalities.

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An abnormal condition is determined (i.e., the likelihood of a road collision is forecast) when either the vehicle status or the traffic flow data is abnormal, according to the roadside unit. If it anticipates an unusual event, the roadside unit immediately creates an emergency warning message and sounds an alarm, alerting all nearby cars and roadside units. A Road Accident Prevention (RAP) system is created and implemented for the four-lane highway highways in India to achieve the second aim [9]. Using a broadcast strategy for immediate emergency warning message transmission, the RAP scheme takes care of the preventative process after the ESPM framework warns about a successful highway road accident prediction.

To prioritize the distribution of the EWMs, this strategy employs a new mechanism. Three zones, one for low risk, one for high risk, and a non-risk zone make up the highway road section in the RAP system. Each vehicle using the highway road section has its own unique risk factor, which is calculated in addition to the danger zones. Normally, a vehicle's risk factor is set to low, but its set to high if it is heading towards the prospective accident site (PAS) or if it is in the high-risk zone. Each vehicle is assigned a unique EWM reception priority that is determined by its risk factor and the danger zone it is located in. Vehicles with a higher EWM receiving priority get the EWM [10-11] immediately. Along with the function, the BEAM-HW protocol includes an acknowledgment mechanism that guarantees the transmission of EWMs to the cars that are part of the present multicast group.

2. Related Work

When an emergency warning message must be sent to a group of vehicle nodes in the present network, the procedure is called multicast. With multicast, the network may limit the transmission of data that is not essential. By using this method, the EWM will only reach the specific recipients and not everyone. This method is covered in the articles.

[12] used GPS to create a system that can determine the relative positions of moving cars depending on their journey directions. Multicast of alarm packets during emergencies is the primary use case for this technology. This system employs a multicast technique to prevent network traffic congestion caused by the sending of too many alarm messages in a highway scenario. The processing of context information causes the CMED protocol [13-15] to have a larger computational cost than other protocols. Multicast tree creation also contributes to the longer execution time of this protocol.

To determine how well VANET's multicast audio communication works for safety applications, [16] conducted a study. The writers tested how well the messages might be multicast from vehicles to RSUs. They simulated using the LScube project's client-server software stack. It is planned to apply this method to the highway scenario once it was developed and tested for the VANET urban scenario. The findings demonstrate the viability of using the simple IEEE 802.11b standard for the multicast transmission of safety information, including weather forecasts. [17] created a viable method for geographical multicasting using VANET called the ROVER protocol, which stands for robust vehicular routing. Vehicles inside the relevant zone received traffic updates via multicast transmissions under this protocol. The authors used Jist/SWANS and a 10-kilometer highway with 6-lanes-for-43-vehicles (three in each direction) to model the procedure.

With different vehicle densities and zones of importance in mind, the simulation was run to evaluate the ratio of packet delivery time and packet delivery ratio. A reactive protocol, ROVER executes multicast as needed. The research shows that, in certain cases, the multicast method is more suited to EWM distribution than the broadcast method. By using the multicast method, just the cars that are meant to receive them are notified of emergency warning messages, without disturbing the vehicles that are further away. This decreases the overall amount of message transactions occurring inside the network and helps to preserve bandwidth [18]. It is possible to use either a broadcast or multicast strategy to transmit the emergency warning messages, according to the literature.

You may choose between broadcast and multicast depending on the kind of necessity. It is important that the emergency warning message be sent to all nearby cars if they approach the potential accident location. In this case, a broadcast strategy might work well. If, on the other hand, a subset of the surrounding cars covered by the RSU travels towards the potential accident scene while the remainder of the vehicles avoid it, then a multicast strategy is appropriate.

The literature study made it quite evident that most current methods for predicting and avoiding highway vehicle accidents are created and developed independently. Currently, there is no solution on the market that can forecast and prevent highway traffic accidents simultaneously [19]. Because of their interdependence, it is well knowledge that these systems are highly connected. The prediction system is essential to the preventive system's ability to carry out its duties, and the inverse is true. Because of this, the suggested approach is tailor-made for predicting and preventing accidents on India's four-lane highways. The preventative system will direct or help cars to avoid accidents if they are projected to occur on highways. [20].

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3. Proposed Framework

The Emergency Situation forecast Mechanism (ESPM) that has been presented is a framework for the forecast of highway traffic accidents. The ESPM conducts the prediction of an emergency in three stages, which include reporting, monitoring, and predicting, as seen in Figure 1.

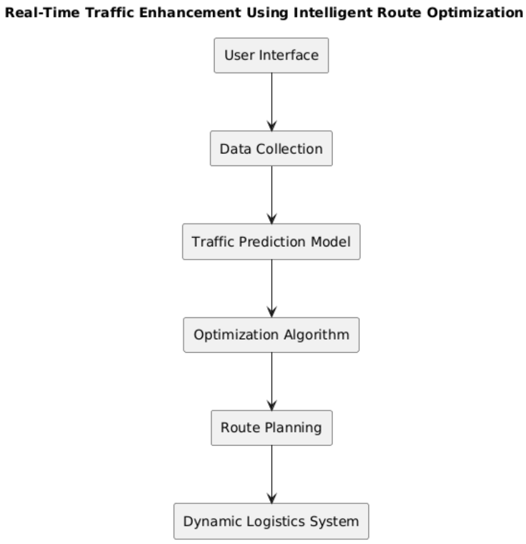

Figure 1. Block Diagram of Proposed work

Participating in the processes that are included in the stages of reporting, monitoring, and prediction are the cars, a highway road with four lanes, and the infrastructure that is located along the pavement. When it comes to the reporting phase, the cars that are taking part will transmit a Status Report (SR) to the Roadside Unit (RSU) that is located nearby. During the monitoring phase, the RSU is responsible for monitoring the flow of traffic within its range by looking at the data that is sent by the sensors that are located on the highway road. In the prediction phase, the RSU is responsible for making predictions about emergencies by using the SR and the TF analysis as a basis. Conservation of the Flow of Traffic

$$\sum_{j\in\mathcal{N}(i)} f_{ij} - \sum_{k\in\mathcal{N}(i)} f_{ki} = 0 \quad (1)$$

where f_{ij} is the flow from node i to node j, and $\mathcal{N}(i)$ is the set of nodes adjacent to i. Link Capacity Constraint

$$f_{ij} \leq c_{ij} \quad (2)$$

where c_{ij} is the capacity of the link from node i to node j. Travel Time Function

$$t_{ij} = t_{ij}^{0}\left(1 + \alpha\left(\frac{f_{fj}}{c_{ij}}\right)^{\beta}\right) \quad (3)$$

where t_{ij} is the travel time on link (i, j), t_{ij}^{0} is the free-flow travel time, and α and β are parameters.

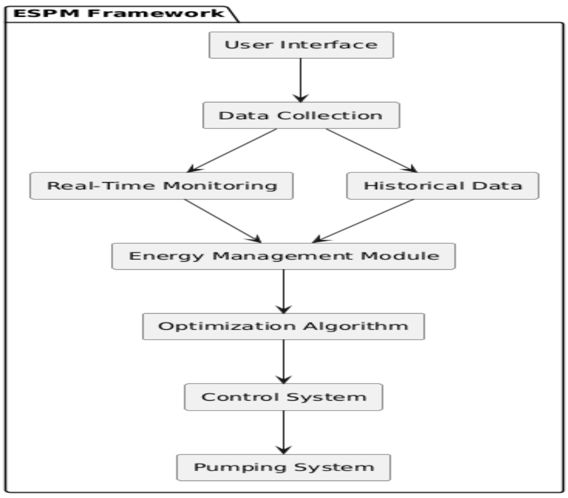

Figure 2. Overall structure of ESPM framework

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The ESPM architecture may be broken down into three distinct stages, which are the reporting, monitoring, and prediction phases at large. During each phase, a certain job is given to it. In pseudocode 1, the definitions that are used inside the ESPM framework are shown.

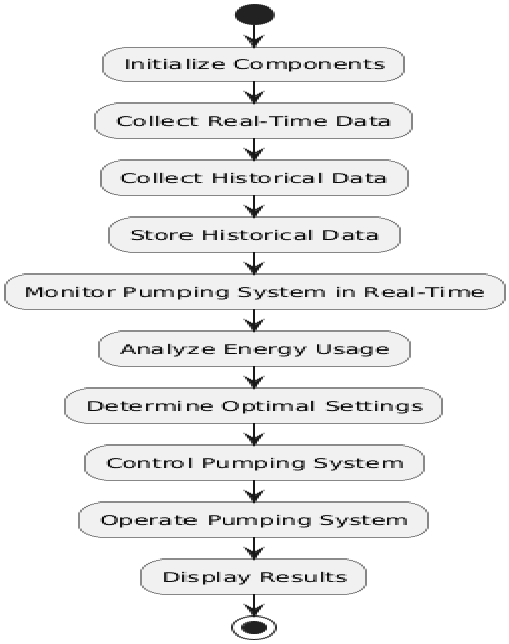

Figure 3. Flowchart of working Model

The working of reporting, monitoring and prediction phases of the ESPM framework are discussed in the following sections.

3.1 Reporting Phase

The reporting phase begins when a vehicle reaches the coverage area of the RSU. At regular intervals, the vehicle sends a state Report (SR) to the RSU, in which it provides information about its current operational state. In reference to Figure 3, the status report includes the characteristics of the vehicle, which include the vehicle ID, location, speed, and yaw-rate of the vehicle.

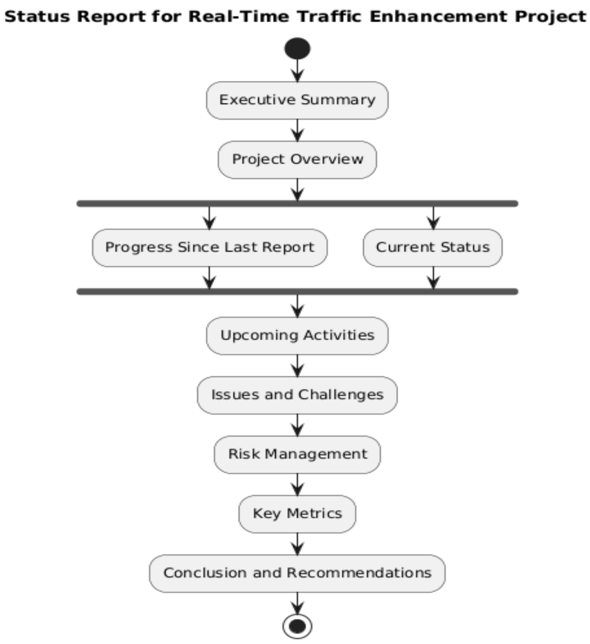

Figure 3. Components of status report

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$$t_{ij} = t_{ij}^0 \left(1 + \alpha \left(\frac{f_{ij}}{c_{ij}}\right)^\beta\right) \quad (4)$$

where t_{ij} is the travel time on link (i,j), t_{ij}^0 is the free-flow travel time, and α and β are parameters. Route Choice Probability

$$P_{ij} = \frac{e^{-\lambda t_{ij}}}{\sum_{k \in N(i)} e^{-x_{ik}}} \quad (5)$$

where P_{ij} is the probability of choosing link (i,j), and λ is a sensitivity parameter. Objective Function for Minimizing Total Travel Time

$$\min \sum_{(i,j) \in \mathcal{L}} f_{ij} t_{ij} \quad (6)$$

where $\mathcal{L}$ is the set of all links. Shortest Path Problem

$$\min \sum_{(i,j) \in P} t_{ij} \quad (7)$$

where P is a path from the origin to the destination. Dynamic Traffic Assignment

$$\frac{df_{ij}}{dt} = R_{ij}(t) - S_{ij}(t) \quad (8)$$

where $R_{ij}(t)$ is the rate of vehicles er ↓ ring link (i,j), and $S_{ij}(t)$ is the rate of vehicles exiting link (i,j).

$$\min \sum_{k \in K} \sum_{(i,j) \in \mathcal{L}} c_{ij} x_{ijk} \quad (9)$$

where x_{ijk} is 1 if vehicle k travels from node i to node j, and 0 otherwise. Demand Satisfaction Constraint

$$\sum_{j \in \mathcal{N}(i)} f_{ij} = d_i \quad (10)$$

where d_i is the demand at node i. Time-Dependent Travel Time

$$t_{ij}(t) = t_{ij}^0 \left(1 + \alpha \left(\frac{f_{ij}(t)}{c_{ij}}\right)^\beta\right) \quad (11)$$

Load Balancing

$$\sum_{i \in \mathcal{N}(j)} f_{ij} = \sum_{k \in \mathcal{N}(j)} f_{jk} \quad (12)$$

Fuel Consumption Model

$$FC_{ij} = \gamma f_{ij} t_{ij} \quad (13)$$

where FC_{ij} is the fuel consumption on link (i,j), and γ is a fuel efficiency parameter to an Access Point (AP) attached in the RSU.

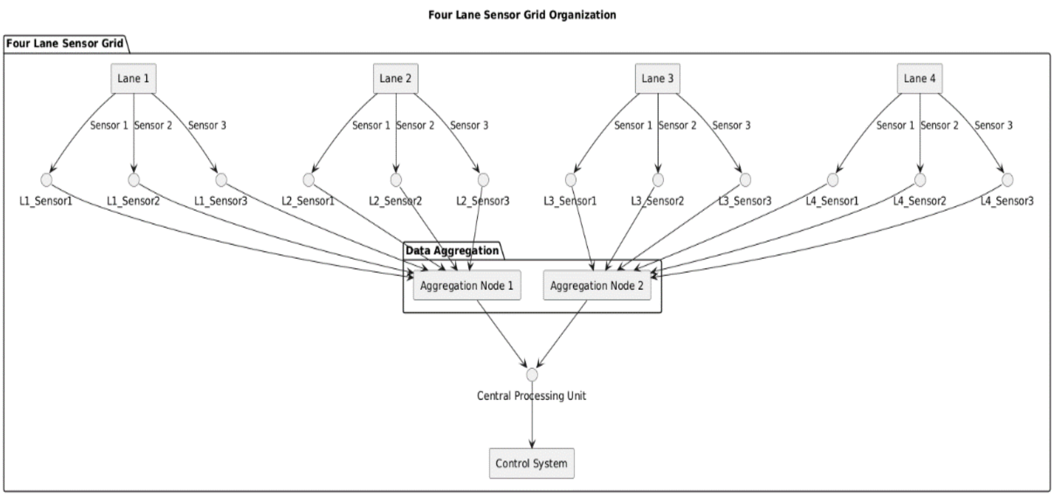

Figure 4. Organization of Four Lane Sensor Grid

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In the Indian four-lane express expressway, lanes 1 and 2 are fixed with travel speeds ranging from sixty kilometers per hour to ninety kilometers per hour, respectively, in real time. The first and second lanes are symmetrical to the fourth and third lanes, which are in the other direction. In the FLSG, the width of each lane is 3.6 meters, and the total width of the four lanes, including the highway barrier, is 17 meters.

In the simulation experiment, it is assumed that the length of each block in each lane is six meters, and the minimum and maximum speed limits of the lanes are set to be between sixty and ninety kilometers per hour. Therefore, the period for transmitting the SR has been set at 0.24 seconds, which is the least period that can be calculated given the speed constraints that have been discussed above. (A period of 0.36 seconds is the maximum allowed). It is generally agreed that the size of FLSG is 24 blocks, in other words, M x N. Furthermore, the number of blocks may also be expanded, and the number of lanes can be dynamically increased up to a maximum of eight lanes.

At regular intervals, the RSU looks at the flow of traffic within its range. By using both historical and current traffic data, it is possible to make predictions about the flow of traffic and the position dynamics of cars in VANET. Because there are on-road traffic accidents, off-road events, and the lack of traffic data in all links of a network owing to the absence of traffic sensors in most highway routes, it is not feasible to anticipate traffic flow by just analyzing the data from the past.

For the RSU to be able to receive data on traffic from sensors that are installed in FLSG, it is configured in such a manner. By using the information provided by these sensors, the RSU will be able to determine whether a vehicle is present inside a certain section of the FLSG highway. In the same manner, the RSU will get the data on the traffic that has been observed from all the sensors in the form of a Grid Position (GP) attribute. If the sensor detects and reports the presence of a vehicle, the GP value will be predetermined to be 1. In every other case, the GP value is maintained at 0. In this manner, the RSU is able to get the GP value by using the traffic data that is supplied by the sensors that are located in the FLSG.

4. Results and Discussion

The findings provide evidence about the effectiveness and performance of the Emergency scenario Prediction Model (ESPM) framework for emergency scenario prediction. To measuring the effectiveness of ESPM, the prediction accuracy taken into consideration regarding vehicle density is chosen. To provide evidence that the ESPM methodology can make accurate predictions, simulation tests are carried out for the three various situations that are listed below.

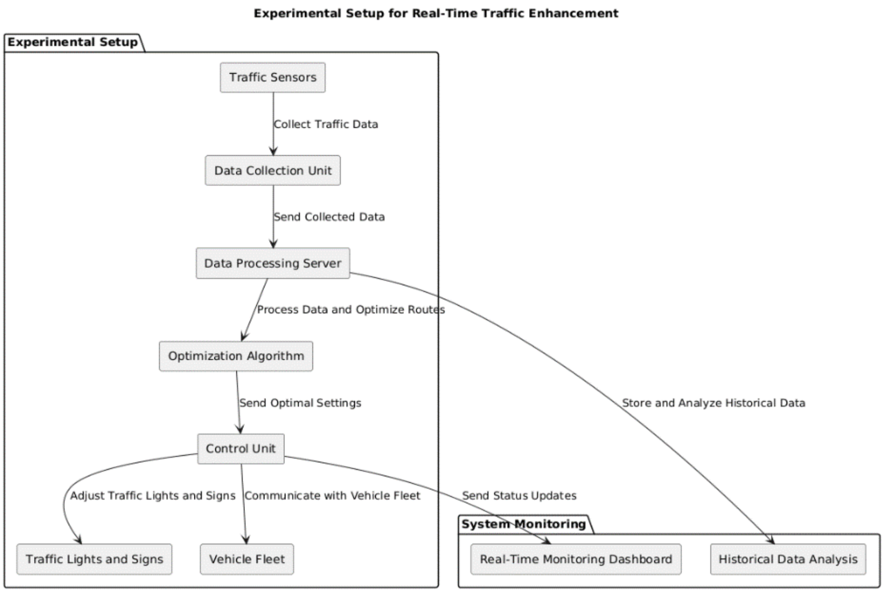

Figure 5. Experimental setup of proposed work

For the first scenario, the vehicle experiences an abnormal deceleration, which is an abrupt stopping of a moving vehicle.

Within the context of this scenario, a moving vehicle, which is referred to as a vehicular node, is first compelled to come to a complete and total halt by bringing its speed down to zero kilometers per hour in an instant, and the response within the system is observed. Following the receipt of the SR from the various vehicular nodes, the RSU node will report an irregularity within the allotted time, and it will be seen that the prediction was successful.

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Ten runs are performed in the simulation, during which the vehicle density is progressively increased from 120 vehicular nodes to 160 vehicular nodes, and cars in both lanes are brought to an abrupt halt at random. To determining the accuracy of predictions and the overall performance of ESPM, the response of both the vehicular nodes and the RSU node is monitored. About Figure 6, it has been observed that the Prediction Accuracy (PA) versus Vehicle Density (VD) for both one and two Abnormal Behaviors (AB) are more than 92 percent.

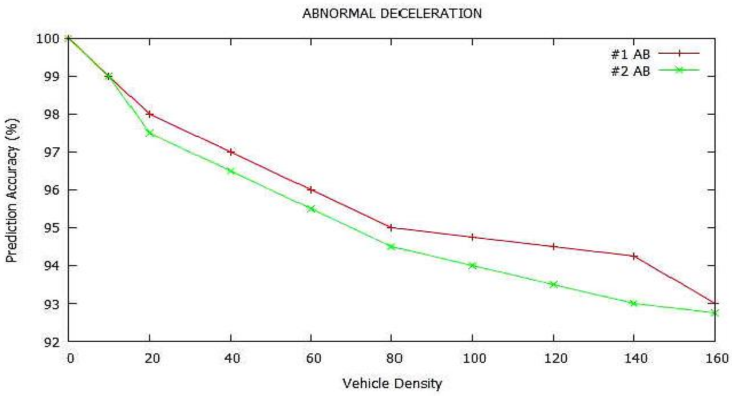

Figure 6. Comparing the accuracy of predictions with the number of vehicles in scenario 1

Scenario 2: The car is accelerating at an abnormal rate because of a rapid rise in speed.

Within the context of this scenario, which includes a vehicular node that is situated in two lanes and is required to increase its speed to surpass the maximum limit of ninety kilometers per hour, the behavior of the system is being studied. Following the receipt of SR from the related vehicular node, the RSU node notifies the relevant vehicular node of an irregularity within the specified period. This occurs within the stipulated period. To continue along the same lines, the speed of the vehicular nodes in two lanes is increased, and the reaction of the RSU node is measured. To accommodate each following run, this simulation is carried out 10 times, with the vehicle density being gradually raised each time. This is shown in Figure 7, which shows that the behavior and responsiveness of vehicular nodes, in addition to the number of RSU nodes, are continuously monitored for the purpose of performance assessment in terms of prediction accuracy.

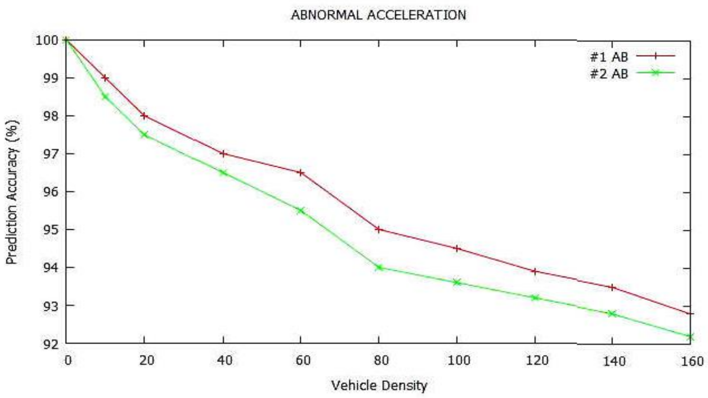

Figure 7. The accuracy of the prediction in relation to the number of vehicles in scenario 2

According to the findings of the simulation, the accuracy of the forecast is increased to a level that is more than 92 percent in both one and two abnormal behaviors (AB). Figures 8 and 9 show reveal that the accuracy of the prediction in scenario 2 for two deviant behaviors is somewhat lower when compared to scenario 1. This is something that may be seen.

Abnormal lane change (inner to outer and outer to inner) is occurring in the third scenario.

For the purpose of this scenario, the vehicular nodes are manipulated such that they switch their lanes from inner to outer and vice versa throughout the course of the simulation. This scenario is broken up into two different situations, which are denoted by the numbers 3a and 3b. Changes in lanes from the inner to the outer and from the outer to the inner are represented by Scenario 3a and 3b, respectively. The first thing to note is that a vehicular node is permitted to make a regular inner to outer (ITO) lane shift, but it is compelled to do an abnormal inner to

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outer lane change, as described in section 3.3. In the second scenario, a vehicular node is permitted to make a regular outer to inner (OTI) lane shift, but it is compelled to do an abnormal outer to inner lane change, as described in section 3.3. This scenario is quite as the one stated in the first scenario. Following that, the response of the sensor nodes as well as the RSU node is taken into consideration. The RSU node uses the data it has received from the sensor nodes to determine what constitutes normal and abnormal lane changes within the time that has been provided. The RSU node is responsible for recording abnormalities and providing information about the effective prediction of an emergency scenario in the event of an anomaly.

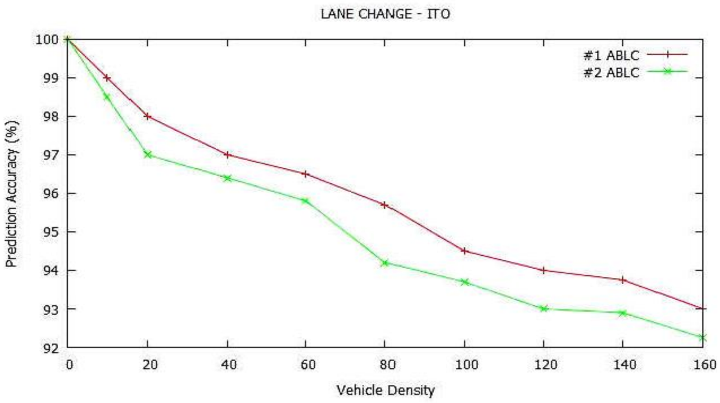

Figure 8. Prediction accuracy versus vehicle density for scenario 3(a)

The prediction accuracy of ESPM in this scenario is promising, this is shown in Figures 8 and 9 for Inner to Outer (ITO), and Outer to Inner (OTI) lane changes respectively. During simulation experiments, one and two Abnormal Lane Changes (ABLC) are induced to measure the accuracy of prediction. Figure 9 shows that the prediction accuracy in scenario 3a (ITO) is almost closer to 91 percent for both one and two abnormal behaviors respectively. On the contrary, the prediction accuracy of scenario 3b (OTI) is decreased when compared to the other as shown in Figure 9. The speed limit of inner lane is greater than the speed limit of outer lane and this leads to an increase in complexity of OTI lane change when compared to ITO lane change.

5. Conclusion and Future Scope

This framework predicts road accidents on the highway based upon both new coming vehicle status report and traffic flow existing in this stretch of lane. The new Four Lane Sensor Grid was a brand-new development to help produce traffic data for future research into how people move on roads. Moreover, the error rate of this framework is assumed larger as ESPM analyses with stateful vehicle and traffic flow information together while it may not work as a specific routing calculation. To develop and validate accident prediction, a case-specific roadway scenario in this study is constructed based on four-lane highway road. This case has sharp acceleration, rapid deceleration and abnormal lane change. At the end of simulation analysis, it has been concluded that ESPM framework is able to predict the probability within 0.20 seconds with an accuracy rate of about ninety-two per cent (%92) in case for different four-lane highway conditions Another chapter of the book deals with revolutionary road accident prevention (RAP) method for highway road accident prediction. This proposal aims to adopt a broadcasting technique for sending urgent warning messages among vehicular traffic with the objective of preventing vehicles from being trapped in accidents on roadways. In this RAP system, a precaution is implemented which depends on the forecasting data provided from ESPM framework. Based on this system, the four-lane highway routes are segmented into danger zones of different levels and a risk factor is heuristically calculated for vehicles with respect to their travel direction. According to the RAP topic, it assigns each vehicle a EWM reception priority and considers the danger zone as well as risk factor (metrics) in order. The EWM travels to vehicles of a higher reception priority and passes through the relevance zone on its way. The RAP utilizes the properties of VBN to deliver EWM to vehicles inside and outside its coverage area. It in turn extends the coverage of RAP system at a reduced infrastructure cost. According to the outcomes of our simulation experiment results, we conclude that this system correctly notifies EWMs in 93% of cars.

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