EVALUATION OF THE ENVIRONMENTAL EFFECTS OF CONNECTED AUTONOMOUS VEHICLES IN TRAFFIC INCIDENT SCENARIOS ON UNINTERRUPTED FACILITIES

by

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ABSTRACT

EVALUATION OF THE ENVIRONMENTAL EFFECTS OF CONNECTED AUTONOMOUS VEHICLES IN TRAFFIC INCIDENT SCENARIOS ON UNINTERRUPTED FACILITIES

Traffic incidents can occur due to both human errors and the inadequacy of road networks. These incidents can cause not only material damage but also loss of life. In case of an incident, it causes the vehicles in the traffic network to stay on the road longer and consume more fuel. The increase in fuel consumption increases the emission of CO2 (Carbon Dioxide), which is an effect of climate change. To reduce the negative effects of incidents on the environment, incident detection, and real-time traffic management methods are important. In this thesis, an uninterrupted road network was created utilizing SUMO traffic simulation to evaluate the environmental effects of incidents. This road network was evaluated over different scenarios with the integration of incident detection algorithms which are California and Standard Normal Deviation and real-time traffic management algorithms which are VSL and LCS. Environmental results were obtained by analyzing these different scenarios. Two types of vehicles were used: human-driven and connected autonomous vehicles. 11 different percentages of autonomous vehicles in increments of 10 from 0 to 100 were based on the research. It was seen that the increase in the use of connected autonomous vehicles in countries such as Turkey, which provide their electricity needs from non-renewable energy sources, harms the environment. In the countries that provide their energy sources mostly from non-renewable sources, the scenario with the least CO2 emissions in the CAL-LCS and CAL-VSL scenarios was achieved in conditions with 40% connected autonomous vehicle traffic. Finally, a relationship of up to 80% was found between CO2 and speeds two by using KNN and Decision Tree Regressor models.

ÖZET

TRAFİK KAZA SENARYOLARINDA BAĞLANTILI OTONOM ARAÇLARIN KESİNTİSİZ YOL AĞLARI ÜZERİNDEKİ ÇEVRESEL ETKİLERİNİN DEĞERLENDİRİLMESİ

Trafik kazaları hem insan hem de yol ağlarının yetersizliğinden kaynaklı ortaya çıkabilmektedir. Bu kazalar sadece maddi hasar vermenin yanında can kayıplarına da neden olabilmektedir. Kaza durumunda trafik ağındaki araçların daha fazla yol üzerinde kalmalarına ve daha fazla yakıt tüketimine neden olmaktadır. Yakıt tüketimindeki artış iklim değişikliğinde etkisi olan karbondioksit salınımını artırmaktadır. Kazaların çevreye olumsuz etkilerinin azaltılabilmesi için de kaza tespit ve trafik yönetim algoritmaları önem arz etmektedir. Bu tez çalışmasında kazaların çevresel etkilerinin değerlendirebilmesi için SUMO trafik benzetimi vasıtasıyla katılımsız bir yol ağı oluşturuldu. Bu yol ağı Kaliforniya ve SND kaza tespit ve VSL ve LCS trafik yönetim yöntemlerinin entegrasyonuyla farklı senaryoları üzerinden değerlendirildi. Bu farklı senaryolarının analizi yapılarak çevresel sonuçları elde edildi. İnsan sürücülü ve bağlantılı otonom araç olmak üzere iki araç çeşidi kullanıldı. 0'dan 100'e 10'ar artışlarla 11 farklı otonom araç yüzdesi araştırmada temel alındı. Araştırma sonucunda Türkiye gibi elektrik ihtiyacını yenilenemez enerji kaynaklarından sağlayan ülkelerde otonom araç kullanımdaki artışın çevreye olumsuz etkiye neden olduğu görüldü. Enerji kaynaklarını çoğunlukla yenilenemez kaynaklardan sağlayan ülkelerde CAL-LCS ve CAL-VSL senaryolarında CO2 salınımının en az olduğu durum %40 bağlantılı otonom araç trafiğine sahip koşullarda elde edildi. Son olarak, KNN ve Decision Tree Regresör modelleri kullanılarak CO2 ve ortalama hız arasında %80'lere varan bir ilişki tespit edildi.

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LIST OF SYMBOLS

h	Hour
k	Density
m	Meter
q	Flow
s	Second
t	Time
v	Speed
W	Watt

LIST OF ACRONYMS/ABBREVIATIONS

AV	Autonomous Vehicle
AVP	Autonomous Vehicle Percentage
CAL	California
CAV	Connected Autonomous Vehicle
CO	Carbon Monoxide
CO2	Carbondioxit
DR	Detection Rate
FAR	False Alarm Rate
HC	Hydrocarbon
KNN	K-Nearest Neighbors
LCS	Lane Control Signals
MTTD	Mean Time to Detect
NOX	Nitrogen Oxides
PMX	Particulate Matter
SND	Standard Normal Deviation
SUMO	Simulation of Urban Mobility
VSL	Variable Speed Limits

1. INTRODUCTION

Traffic incidents can hinder transportation activities [1]. To avoid this situation with the least damage, the traffic can be managed more efficiently by informing the users in that transportation network by detecting the incidents quickly. Incident detection algorithms such as Standard Normal Deviation (SND) and California can detect whether there is an incident in the traffic network using traffic parameters. The SND algorithm examines the status of predetermined traffic control parameters. If there is a sudden change in these situations, it gives an incident status warning. This algorithm can use different traffic parameters. For example, it can detect incidents by examining sudden changes in traffic parameters such as density, speed, and flow [2]. The California algorithm, on the other hand, uses the occupancy from two consecutive sensors placed in the road network and compares it with the predetermined threshold value. If any unusual situation is observed, it gives an incident warning to the system [2]. After the detection of traffic incidents, using real-time traffic management methods, vehicles may be diverted to a new route or they can change their speed or lanes if they are in the incident area. Lane control signals (LCS) and variable speed limits (VSL) are some of these real-time traffic management methods. With the LCS, the user is informed with the help of signals to change the lanes of the users inside or outside the incident zone. By considering these warnings, the size of the affected area can be shortened and the time spent in traffic can be reduced [3]. With VSL, congestion that may occur can be prevented by requesting the speed of users who are in or outside the incident area to be adjusted, and thus the density of the network can be improved [3].

Greenhouse gas emissions such as CO2. CO, HC, CO, NOx, and PMx emitted from motor vehicles are one of the most important air pollutants [4]. In a study, it was pointed out that carbon monoxide is one of the pollutants that cause the most air pollution [5]. The amounts of these pollutants and CO2 gas, causing climate change, are dependent on the time spent by the vehicles in traffic. In this thesis, the emissions of these gases to the environment in case of an incident, with incident detection algorithms and real-time traffic management were investigated through the SUMO traffic simulation program.

Some of the problems caused by traffic incidents are the increase in fuel consumption, the time users spend in traffic, and the emission of gases such as CO2 [6,7]. This thesis, it is aimed to look at the improvements in traffic flow in terms of environmental factors, taking into account different percentages of connected autonomous vehicles. The scenarios also included the integration of SND and California incident detection algorithms with VSL and LCS real-time traffic management methods algorithms in the presence of connected autonomous vehicles. Simulation studies of different scenarios were carried out by integrating the SUMO traffic simulation program with 'TRACI' in the Python software package.

2. LITERATURE REVIEW

In this section, studies on the use of autonomous vehicles in real-time traffic management methods and the environmental effects of autonomous vehicles in traffic incidents will be discussed.

2.1. Studies on Autonomous Vehicles in the Literature

While the use of autonomous vehicles has become quite widespread in some countries, its use in some countries remains quite small. Some of the theoretical studies on autonomous vehicles can be applied to real life, but some of them can only remain in theory. The reason why these studies remain in theory is not due to the inadequacy of the research but the unsuitability of the usual conditions, technological inadequacies, and so on. In a study, using the comparative multi-criteria analysis, autonomous vehicles used in public transportation were examined in terms of traditional transportation, namely with a driver, in terms of travel comfort, usability, punctuality, environmental friendliness, travel cost, duration, and reliability. In this research, although the use of autonomous vehicles in public transportation creates some problems, it has been revealed that it has a positive effect on the environment, traffic, and users in general terms [8]. The use of autonomous vehicles in public transport may cause some problems. These problems are delays in the coordination of vehicles, faulty situations, and other possible situations. What kind of action should be taken against these possible situations is discussed in another study. In this research, importance is given to the conditions related to how autonomous vehicles used in public transportation can be coordinated, travel frequency, where the stops should be, what route autonomous vehicles should follow, and operating times, and they have shown that these conditions can be solved in theory by applying a different approach method [9]. Another study conducted in the literature focused on ride-sharing and investigated what could happen if autonomous vehicles were used in public transportation. In the research, a method was proposed, and this method focused on how autonomous vehicles would perform on public transportation systems. By using this proposed method, it has been theoretically shown that the use of ride-sharing together with autonomous vehicles leads to a significant improvement in the fixed cost, that is, the operating cost and the more widespread use of this system in transportation is directly proportional to the increase in the performance of the system [10]. In another study, the study carried out by Lam and others in 2014 was updated by the same team, and in addition, a new system was proposed for autonomous vehicles used in public transportation by making the admission control and timing caused by the journey sharing in the journeys from point A to point B. While conducting the research, attention was drawn to two main problems. The first of these two problems is the configuration of possible and economical routes to meet the demands of vehicles in the integration of autonomous vehicles into public transportation. The other problem is to put forward the set of demands to maximize the profit when the usual situations are evaluated in a general framework. The coordinators of this research showed that it is possible to reach a solution and result in theory for these two problems by using the linear mixed integer program [11].

When we look at the use of autonomous vehicles in our daily lives, they can take the place of both personal vehicles and public transportation vehicles. When this situation is examined practically in the literature, the use of autonomous vehicles differs from country to country in the world. While the use of autonomous vehicles is more intense in public transportation in some regions, it can be concentrated in personal vehicles in some regions. Considering the use of autonomous vehicles in public transport, it seems that there are exemplary uses in Switzerland, Finland, and Australia. The use of autonomous vehicles in public transport in these countries has been evaluated from different perspectives. Some research was carried out based on the data obtained from these countries about feelings and thoughts, travel perceptions, and experiences of using shuttle buses and service vehicles by determining certain stops and routes in the city. The antecedents considered in the studies are passengers' sense of confidence when traveling in driverless public transport, their concerns, and whether their prejudices against autonomous vehicles will change due to some media reports. Therefore, stated that they did not experience any safety problems, and the majority of passengers said that they trust autonomous public transportation vehicles [12–14]. In a study conducted on Singapore-focused autonomous public transport, the integration of the country of Singapore against autonomous vehicles was examined and the possible effects and consequences of this integration were investigated. In this research, instead of regions where public transportation is used intensively, regions with less traffic flow in public transportation were selected as pilot regions and a proposal was prepared and presented for these routes to serve autonomous vehicles. In the results obtained from the research, it has been revealed that the use of autonomous vehicles in public transportation has the potential to reduce the operating costs of the vehicles, increase the quality of the integrated system, and financial sustainability, and a more efficient journey for passengers than transportation services [15]. In a study conducted on shuttle voyages, the development process of the voyages and the regions in which these voyages are used or can be used in the case of autonomous vehicles are examined. One of the important issues highlighted in this research is that the average speed of autonomous shuttle services is 25 kilometers per hour in many countries, campuses, airports, and various other centers and routes, that is, in areas with low traffic. The research has shown that these autonomous shuttle vehicles are used in some regions as pilot areas, either for scientific activities or postal transportation services. It has been seen that autonomous shuttle services can be used in many areas of daily life and it is an undeniable fact that autonomous vehicles will take place more in our lives in the future [16].

In the previous section, the use of autonomous vehicles in the world is increasing day by day, based on the studies in the literature. In Turkey, there are studies on the use of autonomous vehicles in public transportation. In addition, there are studies not only in use but also in production. Fourth level electric autonomous bus production started at the partnership of KARSAN Automotive Industry and Trade Inc. with ADASTEC, the importance of autonomous vehicles in our country and that this sector may become a significant market in the future [17]. In addition to the production news, an important contribution of the studies carried out on the use of autonomous vehicles in our country to the literature has been examined in the master's thesis. In this thesis, artificial intelligence applications and autonomous driving systems were evaluated. In the thesis, it is listed where the driving systems of autonomous vehicles can be applied, and by drawing attention to autonomous public transportation, it is explained how these vehicles will play a role in transportation and traffic in the future [18]. In another master's thesis conducted in our country, autonomous and shared vehicle systems were examined. The vehicle assignment problem has been solved in line with the determination and estimation of the demands on shared autonomous vehicles, which is the focus of this thesis [19]. The opinions of the drivers about autonomous vehicles and their opinions on the participation of autonomous vehicles in traffic were taken, and based on this research, many samples made positive statements about autonomous vehicles, and some samples expressed their concerns [20].

2.2. Studies on Incident Management and Traffic Management using Autonomous Vehicles

It is the area of traffic management to provide the necessary assistance and service safely without disrupting the traffic flow in incidents or other adverse situations that may occur while the vehicles are moving. Traffic management has been studied in many areas in the literature and its effect on autonomous vehicles has been one of the remarkable issues in recent years. A systematic review of proposed methodologies on autonomous vehicles for smart intersection management systems has been made in a study and the shortcomings of research conducted in this area and possible future research topics are discussed. The articles published from 2008 to 2019 were considered and a thematic analysis method was applied to analyze the data obtained. This analysis method allowed us to identify the main challenges of the presented methodologies and to identify new approaches in this field [21]. The developments in autonomous vehicles and the features of these vehicles have a great potential to be transformed into non-stopping traffic flows by improving the stopped traffic due to the traffic density at the intersections. In this direction, a new autonomous vehicle traffic coordination system called DASH has been proposed in a study. DASH can continuously process various types of large volumes of vehicle information, resolve timing conflicts for all vehicles arriving at the intersection, and generate the optimal itinerary for each vehicle in real-time to safely and highly efficiently guide vehicles passing through intersections. This proposed method has been evaluated in different intersection types and different traffic flow scenarios, and the practicality and efficiency of the system have been revealed by conducting the necessary experiments [22]. Another study utilized connected autonomous vehicles (CAVs) to design a more efficient traffic management system for single-lane roundabouts. Using the proposed system, optimal coordination of CAVs will be ensured to analyze the roundabout, the efficiency will be maximized and the average control delay will be minimized. Therefore, it was concluded that the system guarantees higher efficiency with a lower average control delay compared to the operation of conventional vehicles [23]. In another research, it is aimed to synthesize an autonomous transportation system operation that improves vehicle flow rates and transit delays by integrating traffic management and data network mechanisms. In the research, it has been shown that traffic management is possible with the data network mechanism and the proposed method has yielded efficient results for autonomous vehicles [24]. In one study, the problem of safe and efficient intersection crossing traffic management of autonomous and connected road traffic was examined. The efficiency of the proposed method in this study, the improved computational efficiency of the improved algorithm, was verified through simulations using an open source traffic simulator called urban mobility simulation (SUMO). The overall output and computational efficiency of the improved algorithm can also be compared with an optimized traffic light control algorithm [25]. In a study, an optimal lane management strategy was designed for corridors with heterogeneous traffic demand for driver, autonomous, and connected autonomous vehicles, and the effects of autonomous and connected autonomous vehicles on system performance were examined by modeling the congestion that may occur in the traffic network using the macroscopic network basic diagram. It has been seen that the implementation of an optimal lane management strategy will reduce the delays experienced by the proportional use of autonomous and connected autonomous vehicles in the network [26]. Another study proposes a traffic flow management model based on a new two-stage approach for autonomous vehicles to optimize traffic in congestion situations. These models are Intelligent Redirection Techniques with Deep Reinforcement Learning. Considering the proposed approach, it demonstrated improved performance efficiency compared to traditional settings using pre-timed signals and without redirection, while the two-stage approach improves overall traffic flow while reducing delays and minimizing lengths of long traffic queues [27]. In another study, the writer examined measuring the effects of autonomous driving on the level of traffic management and suggested developing an autonomous driving model that enables human-controlled and autonomous vehicles to be used with only minor modifications [28]. In one study, a cell transmission model-based system was investigated with an optimal dynamic traffic assignment model, focusing on a traffic management application in which autonomous vehicles are already available. This model can show the model on a single connection and a grid network by determining the optimal lane configuration in small space-time intervals. In another study, investigations were made on the optimal timing of autonomous vehicle arrivals when traveling from one intersection to another in the traffic network. In this research, a mixed integer linear program was designed and computational control node assignment was made for each intersection, and position and speed information was regularly obtained from each vehicle. The approach proposed in this research is applied to an intersection, and it has been found that it has a better effect on traffic flow and fuel economy of vehicles compared to traditional intersection control scenarios [29]. In one study, they examined a trajectory-based traffic management problem to manage traffic in a road facility dedicated to autonomous vehicles (AV). The proposed model has been formulated as a mixed integer program that can be solved using ready-made solvers, and a special algorithm has been developed to increase computational efficiency. It has been seen that trajectory-based traffic management can create optimal trajectories for more than one vehicle at the same time [30]. Another study proposes a method for a simulation-based traffic management system that could be particularly successful in the era of connected and autonomous vehicles (CAVs). The most important aspect of this method is that it can evaluate traffic conditions for different traffic control strategies using fast traffic simulations and neural networks. At the same time, meta-heuristic algorithms were used to find optimal traffic control strategies in this research. It shows that the establishment of such a traffic management system may be technically feasible and particularly successful during the CAVs period when it will be possible to collect the necessary traffic data and make accurate traffic forecasts [31]. To examine the contribution of research that contributes to autonomous traffic management in the literature, a study reveals that many issues related to autonomous vehicles are open to discussion and basic research difficulties. This research lists and examines six main research topics and research problems on autonomous vehicles [32]. Another study focused on improving the final public transport stage system with autonomous vehicles, especially traffic control techniques, and presented a technique that does not require the transfer of passengers to other fleets by rearranging the vehicles. In addition, a method is proposed to automatically switch to a temporary work schedule for continuous migration service to ensure fault tolerance of the system against failure of the central server. It has been shown that the proposed method in the research can provide an efficient public transportation network with autonomous vehicles [33]. Another study addresses this new traffic management paradigm by proposing a route server that can handle all traffic in a city and balance traffic flows taking into account current and future congestion conditions. It shows that the proposed traffic prediction equation, combined with frequent updating of traffic conditions in the route server, can provide significant improvements in terms of average travel speeds and travel times, which are indicators of both lower congestion degrees and improved traffic fluidity [34].

Traffic incident management is defined as the systematic, planned, and coordinated use of human, institutional, mechanical and technical resources to reduce the duration and impact of incidents and increase the safety of drivers, casualties, and incident responders. These resources are also used to increase highway operating efficiency, safety, and mobility by systematically reducing the time to detect and verify that an incident has occurred; Implementing the appropriate response, and safely clearing the crash location while managing the affected flow until full capacity is restored. In most metropolitan areas, incidental delay accounts for 50 to 60 percent of total congestion delay [35]. According to the US Department of Transportation's National Highway Traffic Safety Administration (NHTSA), 94% of serious traffic incidents are due to human error [36]. The FHWA estimates that 25% of congestion is caused by traffic incidents, and about half of these are incidents [37]. Autonomous vehicles eliminate the influence of the human factor in the occurrence of a traffic incident. Autonomous vehicle tests are carried out worldwide in real traffic conditions. In traffic incidents with autonomous vehicles that occurred during this period in the US state of California, the effectiveness was analyzed and it was determined that the most important difference in collision type was rear collisions. That is, the share of such collisions among traffic incidents in incidents with AVs (64%) is higher than the incidents involving only CAVs (28.3%). This difference assumes that the drivers of CAVs are not accustomed to the driving style of AVs in the convoy. AVs strictly comply with traffic regulations and do not: speed, aggressively drive inexperienced, slow reaction times, carelessness, and other miscellaneous AV drivers' shortcomings [38]. The reduction in deaths and injuries is one of the most frequently cited benefits of technology. Analysis of incident data shows that even semi-autonomous collision avoidance technology such as forward collision warning systems and automatic braking in existing vehicles reduces the frequency of incidents [39]. Evidence shows that AVs, especially equipped with V2V technology, can reduce congestion by increasing vehicle capacity on highways reducing traffic incidents, and smoothing traffic patterns. With the full adoption of autonomous vehicles, it is expected that incidents related to certain factors, such as operating under human influence, will decrease and thus reduce congestion by significant margins. Vehicle-to-Vehicle link (V2V) technology in the form of Cooperative Adaptive Cruise Control (CACC) can further reduce congestion. It is estimated that with the widespread use of CACC, time gaps between vehicles can be safely narrowed, which will increase traffic congestion. Additionally, highway traffic flows, lane junctions, and intersections will be coordinated and smoothed with more laminar queues and fewer stop-and-go [40, 41]. Many of the congestion-reducing improvements depend not only on automated driving capabilities but also on collaboration capabilities through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. Even without V2V-V2I communication, significant congestion reduction can occur if the security benefits are realized alone. Combining connected and autonomous technologies allows computer-based vehicles to "know" the conditions of the road network ahead, re-route according to updated information (for example, lane closure), and alert vehicles behind an incident to avoid an obstacle. Non-recurring congestion is often caused by events. With AVs (Level 0 and above), drivers or vehicles themselves can make smarter route choices based on weather and traffic data received by the vehicle in real-time to avoid recurring congestion. With the increasing adoption of AVs, travel time reliability is expected to increase as non-recurring delay-inducing events will decrease. The addition of wireless connectivity will increase the operational efficiency of CAVs by providing real-time road information such as traffic signal staging and timing information, downstream traffic event alerts, and future traffic queue information. In a Transportation Cyber-Physical System, traffic congestion relief is achieved through incident management systems with simultaneous benefits in terms of economic savings, energy savings, and improved environmental conditions and health and safety aspects. With the implementation of traffic incident management planned intervention can be achieved. Regularly updated data in terms of incident site management and traffic control and rapid clean-up and recovery activities can alleviate post-incident congestion. Therefore, it is very important to develop and evaluate a dynamic steering application that can support a traffic incident management scheme. When it comes to reliability, all four common sensors of AVs have security shortcomings, such as radars and sonar can be jammed with electromagnetic waves. When these two transmit signals, one can use an energy source that emits waves of the same wavelength from a different range or a different angle. In the case of lidar, special devices can be used to create slight noise to squeeze the lidar. AVs use camera data for highly accurate image detection and recognition; however, a recent study has proven that simple physical elements or invisible attack patterns can be used to mislead artificial intelligence [42].

2.3. Studies on Incident Detection Algorithms

The data obtained by the incident detection algorithms from the traffic network can be extremely large. Analyzing this data are only possible with highly equipped technological tools and complex algorithms, which can increase the cost of traffic management. To prevent this situation, the data must be filtered. In some studies in the literature, these filtering methods are included in incident detection algorithms, and efficient results can be achieved with less and more precise data [43, 44]. In a study, three-based vehicle recognition technology is discussed to examine automatic incident detection methods. It has been shown that automatic vehicle identification automatic incident detection algorithms reach close results with automatic incident detection methods [45]. In incident detection methods, data can be obtained from more than one place. One of them is Bluetooth sensors. In a study, investigations were made on how the data obtained from these sensors were used in incident detection algorithms. The method proposed in the research was evaluated as a case study in Tel Aviv, and the performance of the system showed high performance [46]. Only one of the incident detection algorithms may not be used in traffic management, there are cases where more than one incident detection algorithm is used in single traffic management at the same time. A hybrid incident detection algorithm was created by combining research machine learning and time series analysis. This hybrid algorithm was found to detect incidents in a shorter time than other algorithms [47]. In a study, incident detection applications in existing smart transportation systems were compared. It is accepted that the main factors are used to evaluate the current practices. To evaluate the effectiveness of incident detection algorithms, a certain section of the road network has been considered by using the automatic data processing system. Quality calculations were made for the six analyzed algorithms and the algorithm proposed by the authors, and the need for multiple uses of algorithms to identify events on the path was demonstrated [48]. Another study examines a range of incident detection technologies to identify a recommended combination of approaches for use in the Utah Department of Transportation's (UDOT) Advanced Traffic Management System (ATMS). The technologies reviewed are computer-based automatic Event Detection, Video Image Processing (VIP), and detection by mobile phone calls. Three performance measures were used in the incident detection technology analysis: detection time, detection rate, and false alarm rate. This project was originally designed to include rigorous testing of several computer-based algorithms. However, the project's Technical Advisory Committee redirected this study to take a closer look at the impact of mobile phones on incident detection [49]. Users need to detect incidents in traffic. By using incident detection in traffic management, users can be informed and possible delays can be minimized and a safe transportation network can be obtained when possible. These incident detection algorithms determine where and when the incident happened and transmit the necessary data to the necessary places [50].

In a research conducted in the literature, a survey study was conducted on whether the methods used in automatic incident detection algorithms are included in traffic management centers. It was concluded that the existing incident detection algorithms were not sufficient both now and in the future in line with the answers given by the samples [51]. Considering other studies, particle swarm optimization and least squares regression can be used as methodologies used for incident detection algorithms. In these studies, it is possible to determine the instantaneous incident detection that occurs in the traffic network by examining the data taken from the traffic network and creating a new model [52, 53]. In another study, the effects of vehicles on incident detection management were examined by using deep learning methods consisting of convolutional neural networks and generative competitor networks, and incident detection can be made with correct incident detection algorithms and traffic congestion can be reduced [54,55]. Another study focused on traffic sensors used in traffic management and showed that most of the data used in incident detection algorithms include inductive loop data. Since the data used from these loops in traffic management do not work with a simple method, a traffic sensor that can work with a simpler method has been proposed [56]. In a study, an automatic incident detection algorithm has been developed to detect the events that occur on the main roads and cause traffic delays. The data to be used in the developed algorithm were collected in two ways; sensors and connected vehicles. Data integration technology has been used to obtain incident-incident or incident-no-incident information as a single outcome using travel time data collected from connected vehicles and sensors using V2I technology [57]. In a study conducted on autonomous vehicles, a new approach has been proposed for the incident detection problem by using the SADAVS dataset. In this study, it was seen that the proposed method, using both the fusion technique and the deep learning method, showed high performance. In addition, this research can contribute to the collision problems of autonomous vehicles [58]. In one study, a method is proposed for automatic highway incident detection in mixed traffic environments, considering connected autonomous vehicles. This study also developed highway incident detection to provide fast and reliable incident event detection. It was seen that connected autonomous vehicles achieved useful and efficient results for automatic incident detection [59].

2.4. Studies on the Environmental Effects of Traffic Incidents

Traffic incidents have become an indispensable part of daily life. Although precautions are taken, it is very difficult to prevent incidents completely. To prevent incidents, there are methods such as traffic management and incident management, as well as some algorithms. Incidents also cause both material and moral damage. Among these material damages, environmental effects have taken an important place. For example, in the event of an incident, traffic disruptions occur and most vehicles have to spend more time in traffic. Therefore, it causes more fuel consumption and more emissions of pollutants. In the literature, there are studies on the relationship between incident events and environmental impact as a sub-title of traffic and environment relationship. One study calculated fuel consumption, traffic performance, and emissions by focusing on road transport and adding all possible traffic-related problems (such as traffic incidents) on a given street. In this study, necessary investigations were made using VISSIM, a traffic simulation program, and it was determined that it causes an increase in fuel consumption and emissions due to traffic incidents and the increase in stop-starts causes both physical and moral damage [60]. In another study, the relationship between the environment and traffic incidents was analyzed with data from certain highways in Texas. In addition, environmental factors that may cause incidents were examined in the study. It has been revealed that conditions such as time of day, viewing perspective, and lighting conditions are the antecedents in determining the incident type. In addition, it was concluded that the 5-minute occupancy in the traffic network tired the traffic density in the lane and caused an incident [61]. Several scenarios were analyzed using DTALite, a mesoscopic traffic model, on emission and energy levels in a regional road network. In this study, it has been seen that there is a 2% reduction in emissions and energy consumption by using advanced traveler information systems. In addition, another result obtained in this study showed that the change in road type affects the emission and energy levels [62]. In another study, the decrease in fuel consumption of the use of smart transportation systems application was compared with the environmentalist construction in road construction. In this research, a road network was used in the South Carolina region in the USA as a case study, and, it was revealed that the amount of savings obtained from the application of intelligent transportation systems are more than the green road construction design [63]. In one study, measurements were obtained from a tunnel at a time when the weather conditions were cold and extreme, during the evening traffic incidents and rush hour. Air velocity, CO concentration, air temperature, and PM concentration are obtained from these measurements. With the proposed method in the study, it was seen that the place where the incidents occurred had a direct effect on the CO concentration and air velocity, but it was seen that there was no direct relationship with the air temperature [64]. Another study used a model called MEET to examine the impact of incident events on carbon dioxide emissions by taking real-time data from a road in Rio de Janeiro. It has been shown that incidents in the traffic network increase the increase in carbon dioxide rate by 22% [65]. In another study, traffic incidents of a 14-kilometer road network in a region were created with different locations and durations by using the traffic simulation program Aimsun. Fuel consumption and carbon dioxide data were obtained, and it was revealed that traffic incidents cause an increase in fuel consumption and carbon dioxide emissions [66]. In another study, substances such as CO2, CO, and PM10 resulting from vehicle emissions were compared with vehicle types in traffic. In the research, it has been revealed that the presence of more efficient and new technology vehicles in the traffic network is inversely proportional to the emission of these substances [67]. When the studies in the literature are examined, the lack of studies on the relationship between traffic incidents and environmental effects through autonomous vehicles makes this thesis one of the values that make it unique.

3. THEORY

In this section, the theory related to selected incident detection algorithms, real-time traffic management methods, and environmental models for transportation pollutants and their analysis tools will be discussed.

3.1. Incident Detection Algorithms

Incident detection algorithms are significant where traffic incidents and traffic jams occur frequently. In a study, it was observed that density due to traffic incidents increased with the delay of the intervention [68]. For this reason, it is of great importance that incident management be carried out quickly on the roads that are used intensively and harm the lives of many people. For the incident management to intervene quickly, the incident must be detected very quickly. At this point, incident detection algorithms come into play. With the rapid and accurate detection of an incident, the response time is reduced and the time interval when the incident occupies the traffic becomes smaller. Therefore, the active use of incident detection algorithms will provide great benefits. There are many incident detection algorithms in the literature. However, in this thesis, Standard Normal Deviate (SND) Algorithm and California Algorithm were used.

3.1.1. Standard Normal Deviate (SND) Algorithm

Standard Normal Deviate algorithm, as the name suggests, is a statistical incident detection algorithm that can be created with the mean value and standard deviation obtained from historical data [69]. This algorithm is a powerful algorithm based on statistically very basic principles. The equation of this algorithm is established by placing the mean value of a parameter that an unusual event in the normal flow of the road network will significantly affect and the preliminary measurement of the standard deviation of this value in the central limit theorem. This theorem is expressed as

$$SND = \frac{x(j,t) - \underline{\mathrm{x}}(j,t)}{s} > T_{SND} \tag{3.1}$$

where x(j,t) is the value of traffic control variable at j location and t time, $\underline{\mathrm{x}}$(j,t) is the mean value of traffic control variable at j location and t time, s is the standard deviation of traffic control variable at j location and t time and T_{SND} is the threshold value of the SND algorithm.

In this study, the traffic density variable is used in the SND system. Since density is the most reliable variable of traffic, this decision has been made considering that it will give high accuracy results. The no-incident case of traffic road networks was examined and the mean value and standard deviations of this course were examined. The distribution of the mean density in the scenario is given in Figure 3.1. As the road networks have mostly uninterrupted and flowing traffic, the average density value in this scenario is therefore low.

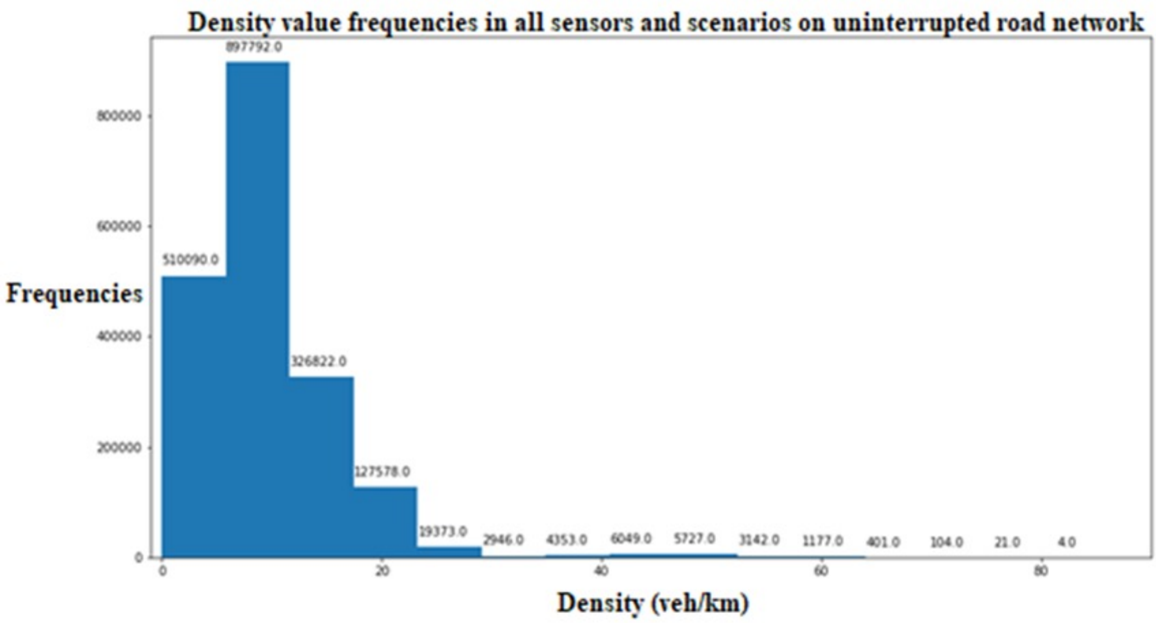


Figure 3.1. Density frequencies obtained from all sensors during normal cruising on the uninterrupted road network.

Then, the threshold value needs to be determined. Since every problem in the normal flow of traffic will only cause an increase in density, the statistical change in the TSND value will be examined with one-way tests. While determining the threshold value, a mixed data set created by using the data of the scenarios where traffic incidents occurred was used. The frequency distributions of the values in this data set were visualized and examined. The frequency distributions of the density value in the incident and no incident scenarios are given in Figure 3.2. When Figure 3.2 is examined, 30-35 vehicle/km density frequency in the road network has shown a noticeable increase with the addition of incident scenarios. The steps of this process are given:

- A data set with all scenarios were created.
- A new column was created by processing all density data with the SND algorithm.
- Density distributions in this column were examined and visualized.
- The threshold value was determined by examining the distribution; fine-tuning of the threshold value was achieved by cross-checking the iterations with data set.
- The threshold value was determined by observation and iteration.

The average density value for the road network, the standard deviation of this value, and the threshold value are given in Table 3.1.

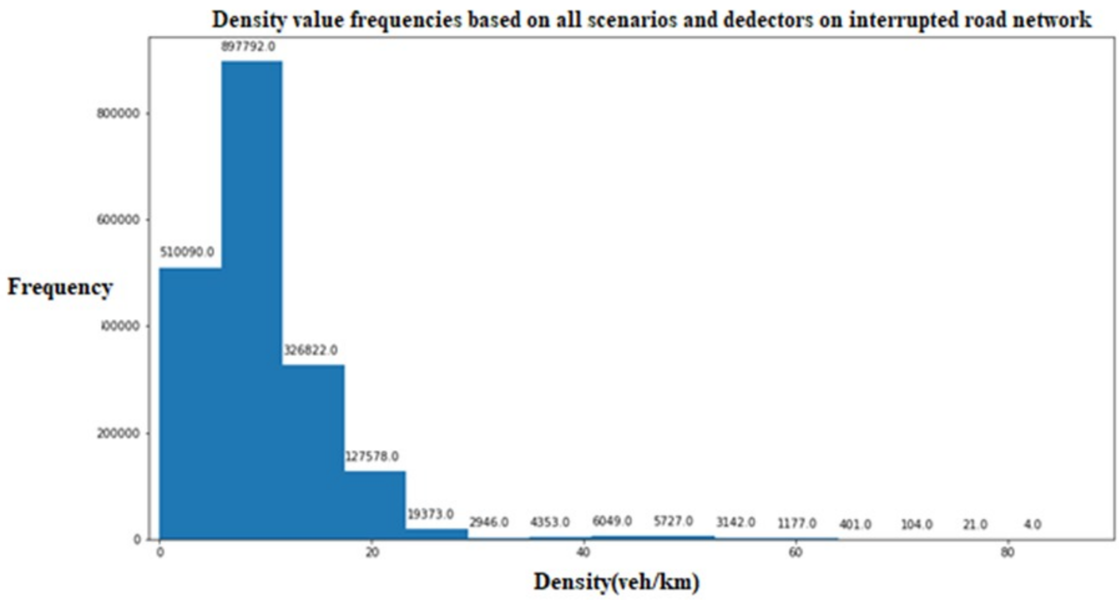


Figure 3.2. Density frequencies obtained from all sensors on the uninterrupted road network based on all scenarios.

Table 3.1. Mean density values, standard deviations, and SND threshold values of the uninterrupted road network.

Road Network	Mean Density Value (vehicle/km)	Standard Deviation	SND Threshold Value
Uninterrupted	6.01	5.03	4.5

3.1.2. California Algorithm

California Algorithm is a comparative algorithm that uses predetermined thresholds to classify the current road condition. California Algorithm only needs density data from two adjacent sensors [70]. The algorithm calculates the density difference (DDF) between adjacent sensors and the relative density difference (RDDF) between adjacent sensors. In addition to these two data, the algorithm also uses densities obtained from subsequent sensors. DDF and RDDF equations are given as

$$DDF(x,t) = D(x,t) - D(x+1,t) \tag{3.2}$$

$$RDDF(x,t) = D(x,t) - D(x+1,t)D(x,t) \tag{3.3}$$

where DDF is the density difference, RDDF is the relative density difference, x is the sensor location and t is time.

The D(x,t) data represents the density value obtained from the x sensor at the data processing frequency t. If D(x+1,t) is the density value obtained from the (x+1) sensor at the data processing frequency t, it is shown as DD. The sensor in the (x+1) position refers to the next sensor from the sensor in the x position, and these two sensors are consecutive. California Algorithm calculates the DDF and RDDF values, takes the DD value from the sensors, and compares these inputs with the 3 predetermined threshold values, T1, T2, and T3. T1 is the maximum value of DDF under normal conditions. T2 is the maximum value of the RDDF under normal conditions. T3 is the maximum value of the temporal difference in the density value of the next sensor (DDRDF) under normal conditions [71]. DDRDF equation is expressed as

$$DDRDF(x,t) = D(x+1,t) - D(x+1,t+1) \tag{3.4}$$

where D is the density value, DDRDF is the relative density difference in the downstream sensor.

After comparing the thresholds and inputs, the algorithm decides if there are any exceptions in the path. There are 4 states defined by the California Algorithm [71]. The road is at state 0 when there is no incident, at state 1 when an incident is probable but no detected incident, at state 2 when an incident is detected, and at state 3 when an incident continues. The flow chart used by the algorithm in the decision-making phase is given in Figure 3.3.

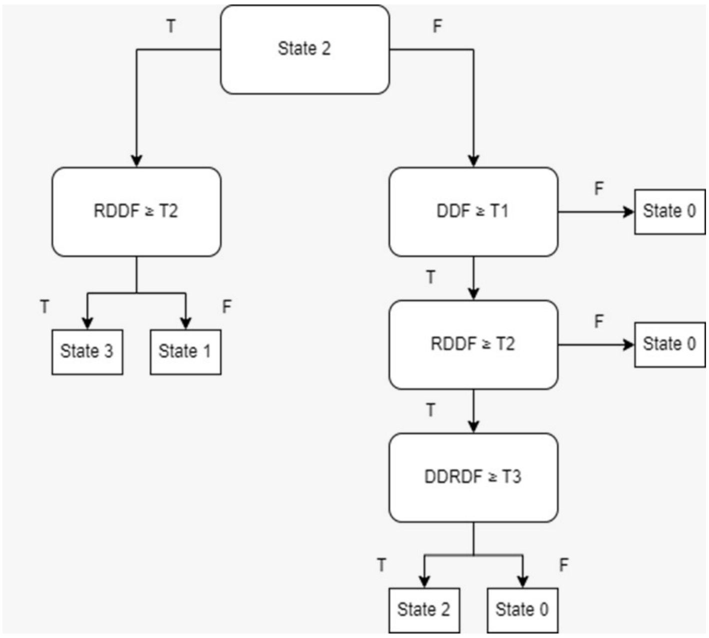


Figure 3.3. Decision Flow Chart of California Algorithm.

Threshold values calculated for use in the California algorithm are available in Table 3.2.

Table 3.2. Threshold values of the California Algorithm.

Threshold	Value
T1	17.242
T2	0.580
T3	-13.349

3.2. Real-Time Traffic Management Methods

Real-time traffic management methods are used to relieve and improve traffic conditions. There are many traffic management methods in the literature. In this thesis, lane control signals (LCS) and variable speed limits (VSL) methods were used.

3.2.1. Lane Control Signals (LCS)

Lane control signals (LCS) is a real-time traffic management method applied for the more stable and safe operation of lanes on highways. This aim is achieved by electronic traffic signs placed on the lanes informing drivers to change their lanes [3]. Since the use of these lanes will be closed to drivers in case of incidents such as an incident, police control, or roadworks occurring in any lane, the traffic density rises to very high levels due to dense lane changes that will take place in the incident area if no management is applied. With the implementation of the LCS management system, it is ensured that the drivers in the closed lane move to the other lanes at a regular and longer interval, and thus it is aimed to prevent congestion near an incident.

The LCS method applied on a 4-lane road can be seen in Figure 3.4. Marking the left lane with a cross indicates that this lane is closed to traffic due to the incident situation. The green arrows in the middle two lanes indicate that these lanes are open to traffic and that drivers can continue their journey in these lanes without changing lanes. The yellow diagonal arrow in the far right lane indicates that the drivers should switch to the neighboring lane in a short time [72].

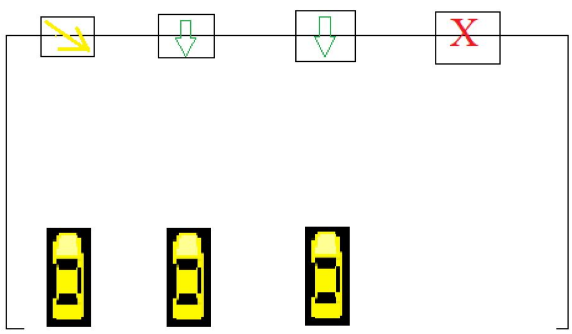


Figure 3.4. Representative LCS Management on a 4-lane road.

There are many benefits to be gained from the application of the LCS traffic management method. Some of these that can be given as examples of these benefits are listed as follows [3]:

- Reduction in the number and severity of secondary incidents caused by increased traffic density due to the incident situation.
- More stable vehicle speeds (preventing drastic increases and decreases in vehicle speeds due to traffic jams).
- Reducing traffic delays and consequent fuel and energy saving.
- Reduction of environmental impacts due to fuel and energy savings.
- Facilitating the transportation of vehicles that need to move quickly in emergencies such as ambulances, police, and fire trucks.

Simulation studies are required to observe the benefits to be obtained by applying the LCS traffic management method. At the same time, to what extent the use of autonomous vehicles within the scope of our study in the LCS method will affect the efficiency and benefits of this method will be seen.

Some variables need to be determined from the process of modeling the LCS traffic management method in the SUMO simulation environment. These variables are listed as follows:

- Control Distance (meter): The distance to be found between two electronic traffic signs
- Rate of Compliance of Close LCS: The rate at which autonomous and human-driven comply with the instructions shown on the electronic sign near the incident area.
- Rate of Compliance of Far LCS: The rate at which autonomous and human-driven vehicles comply with the instructions shown on the electronic sign, which is far from the incident area.

The LCS traffic management method, which is activated after the detection of the incident carried out in the simulation environment, is carried out with 2 electronic traffic signs placed behind the incident location. The electronic traffic sign near the incident area is located at the sensor location before the incident area. The remote electronic traffic sign is placed as far back as the control distance from the close sign. Traffic management is carried out with the instructions given to drivers and autonomous vehicles through these two electronic traffic signs.

The values assigned to the LCS variables throughout the simulation studies are available in Table 3.3. Autonomous vehicles are modeled to comply 100% with the guidelines given on the LCS signs close and far from the incident area. Vehicles with drivers, on the other hand, are modeled to adapt 80% to the closest LCS to the incident area and 70% to the LCS farther away. The distance between 2 electronic traffic signs used in the implementation of the LCS traffic management method is 1500 meters.

Table 3.3. LCS variables that used in simulation studies.

	Variables	Values
Human-Driven - Autonomous	LCS Control Distance (m)	1500
Human-Driven Vehicles	Rate of Compliance of Close LCS	0.8
Human-Driven Vehicles	Rate of Compliance of Far LCS	0.7
Autonomous Vehicles	Rate of Compliance of Close LCS	1.0
Autonomous Vehicles	Rate of Compliance of Far LCS	1.0

The working flow chart of the LCS traffic management method is available in Figure 3.5.

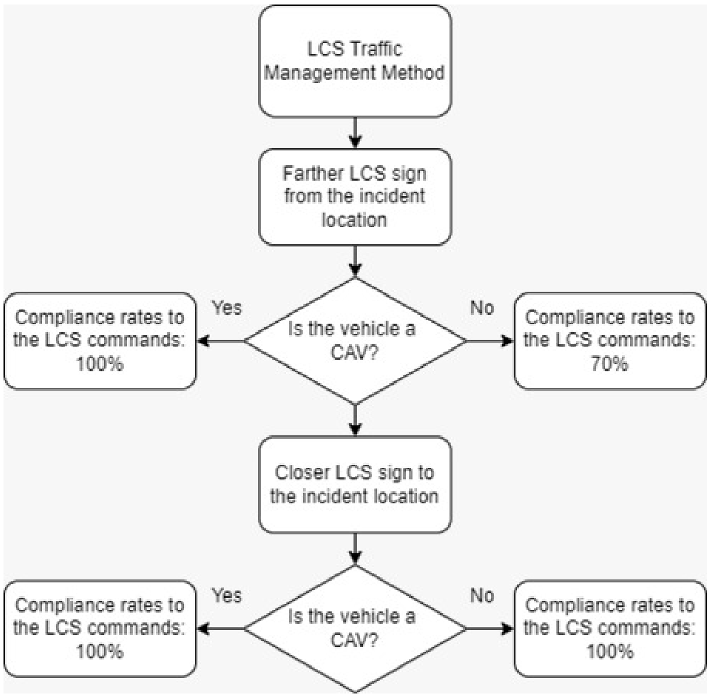


Figure 3.5. The working flow of the LCS traffic management method.

The assumptions made while integrating the LCS application into the simulation environment are as follows:

- The LCS application is activated 300 seconds after the incident. At the same time, the LCS application continues for 300 seconds after the incident is completely removed from the road network.
- Drivers can see electronic traffic signs from 30 meters away. After seeing the signs, they decide to comply or not to comply with the LCS guidelines within a maximum of 2 seconds.
- Autonomous vehicles comply with the LCS guidelines 100%, while self-driven vehicles comply with the near-incident LCS 80% and the incident-free LCS 70%.
- There are 2 electronic traffic signs in the LCS simulation scenarios carried out on both road networks. The first LCS sign is located on the first sensor before the incident location. The second LCS sign is located at the control distance from the first LCS sign. An illustration of LCS signage is available in Figure 3.6. The yellow lines represent the sensors and the distance between each sensor is 500

meters. The sensor location before the incident area is the point where the first LCS sign is. The second LCS sign is at a distance of 1500 meters, i.e. 3 sensors, from the first LCS sign.

- The values assigned to the LCS variables are the values that run the system optimally.

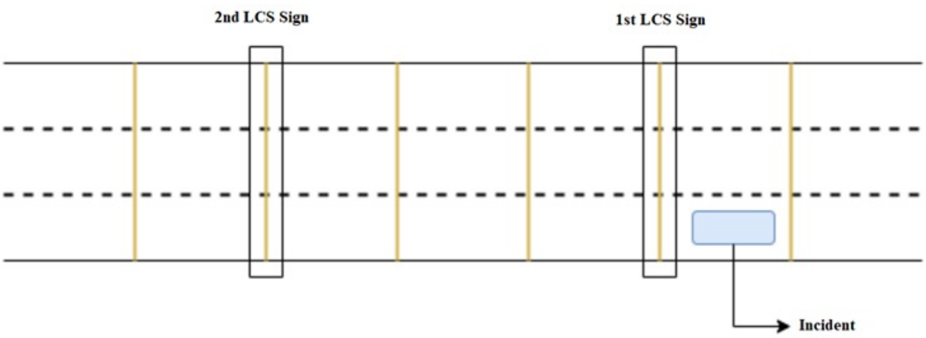


Figure 3.6. LCS sign locations.

3.2.2. Variable Speed Limits (VSL)

Variable speed limits (VSL) is a real-time traffic management method. It is aimed to reduce the speed of vehicles with the speed limits reflected on the electronic traffic signs behind the areas where there are traffic jams. By regulating vehicle speeds and reducing them to the desired speed limit, the number of vehicles arriving at the incident area is reduced from the moment the incident occurs until they are removed from the highway. In this way, the intensity of traffic jams due to incidents can be reduced and the control of these traffic jams and the evacuation process after the incident is removed becomes easier. At the same time, by reducing vehicle speeds, sharp deviations in vehicle speeds are prevented and more stable speeds are obtained.

In Figure 3.7, there is an illustration of VSL traffic management applied on a 4-lane highway with 3 lanes open to traffic. Within the scope of the application, it is expected that the speed of the vehicles will be reduced to 60 km/h [72].

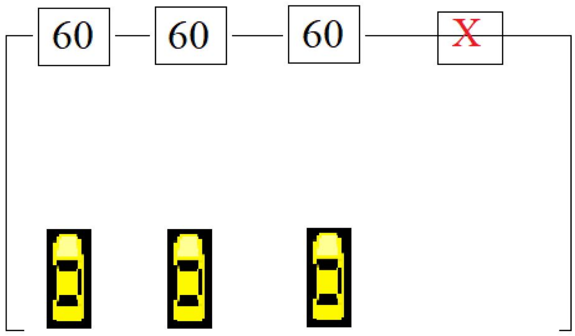


Figure 3.7. Representative VSL management implemented on 4-lane roads.

There are many benefits to be achieved with the implementation of the VSL traffic management system. Examples of these benefits are listed.

- The speed of vehicles advancing to the incident area is reduced, thereby reducing the number of vehicles arriving at the incident area. Thus, the number of vehicles within the shock wave limits and the traffic density values are reduced.
- By reducing vehicle speeds, deviations in speeds are reduced.
- With the more regular distribution of vehicle speeds, secondary incidents and safety problems are prevented.
- The shock wave boundaries are narrowed by reducing the high traffic density areas formed in the incident area and thus the length of the queues to be formed is shortened.

Simulation studies of the VSL method have been carried out to see the benefits to be obtained with the implementation of the VSL traffic management method concretely and to analyze how it performs compared to different traffic management methods such as LCS. In addition, VSL simulation studies were carried out in the presence of autonomous vehicles at different rates to see how much the performance of the system increases when autonomous vehicles are included in the VSL management system. Thus, it will be possible to see in which percentage of autonomous vehicles the VSL system works most optimally.

Some variables need to be determined and assigned values from the process of modeling the VSL management method in the SUMO simulation environment. These variables are listed as follows:

- Control Distance (meters): The distance between the incident location and the signboard reflecting the VSL guidelines
- Compliance Rate: The rate of compliance of autonomous and driven vehicles with the target speed shown on the VSL signs
- Target Speed (km/hour): The speed limit at which vehicle speeds are desired to be reduced within the scope of the VSL application

VSL traffic management is carried out using an electronic traffic sign. It is activated after the detection of the incident created within the simulation studies, and the speed of the vehicles is reduced by reflecting the determined speed target on the electronic traffic sign. The signboard on which the VSL directives are reflected is located as far as the control distance from the incident area. Vehicles with drivers and autonomous vehicles adapt to the VSL system at different rates. The variables of the VSL system modeled in the simulation environment and the values assigned to these variables are available in Table 3.4.

Table 3.4. VSL variables that are used in simulation studies.

Variables	Values
VSL Control Distance (meter)	1000
Target Speed (km/hour)	50
Autonomous Vehicles Compliance Rate to VSL Directive	1.0
Human-Driven Vehicles Compliance Rate to VSL Directive	0.5

Autonomous vehicles comply 100% with the target speed directive reflected on the sign, while vehicles with drivers comply with 50%. The distance between the incident location and the VSL sign is taken as 1 kilometer. With the introduction of the VSL system, it is aimed to reduce vehicle speeds to 50 km/h. The flowchart of the VSL algorithm is provided in Figure 3.8.

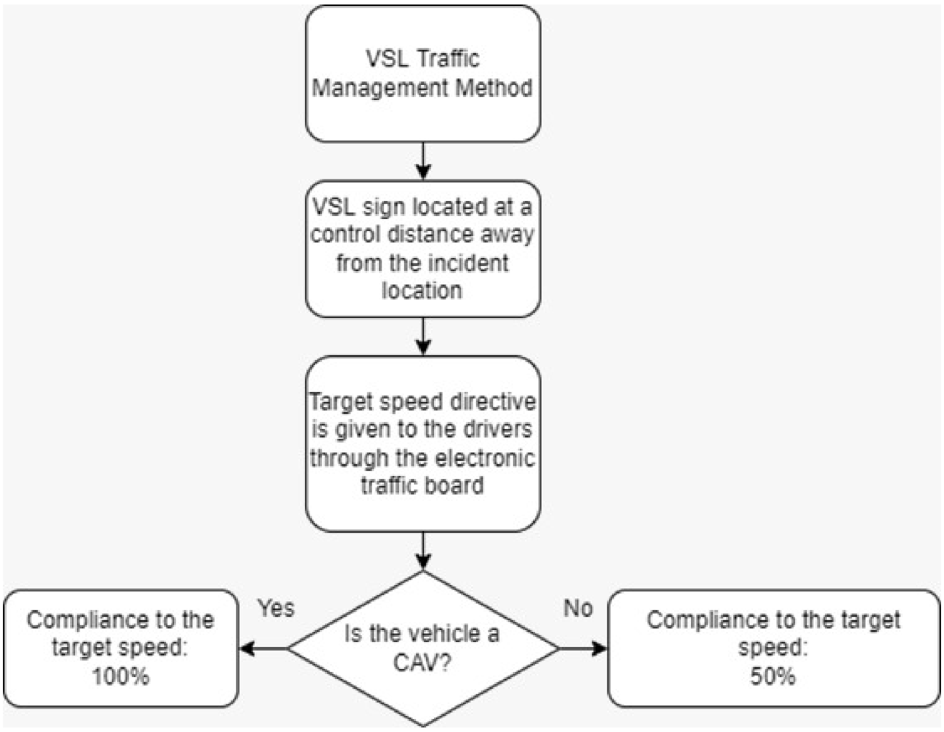


Figure 3.8. The flowchart of the VSL traffic management method.

The assumptions made while integrating the VSL application into the simulation environment are as follows:

- The VSL application is activated 300 seconds after the incident. At the same time, the VSL application continues for 300 seconds after the incident is completely removed from the road network.
- Drivers can see electronic traffic signs from 30 meters away. After seeing the signs, they decide to comply or not to comply with the LCS guidelines within a maximum of 2 seconds.
- Drivers that comply with the VSL directive reduce their speed to the target speed as quickly as possible.
- Autonomous vehicles comply with VSL guidelines 100%, while self-driven vehicles comply with 50%.

- The same target speed value is reflected for each lane on the electronic traffic sign.
- One electronic traffic sign is used in VSL simulation scenarios carried out on both road networks. The VSL sign is located 1000 meters behind the incident location. An illustration of the VSL signage location is available in Figure 3.9. The yellow lines represent the sensors and the distance between each sensor is 500 meters.
- The values assigned to the VSL variables are the values that run the system optimally.

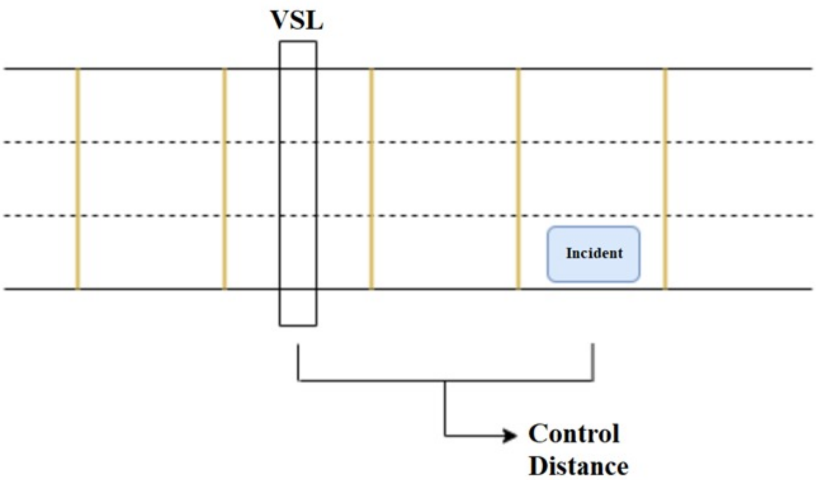


Figure 3.9. VSL Sign Location.

3.3. Environmental Models for Transportation Pollutants

With the SUMO traffic simulation program, the amount of emissions emitted by the vehicles to the environment can be calculated per step. While the SUMO is running, it can calculate the CO2, CO, HC, NOx, PMx, fuel, noise, and similar values emitted by each vehicle to nature. By keeping these values through the TRACI extension, the emission amounts and total emissions of each vehicle during the simulation can be accessed [73]. There are many emission calculations in the literature with the help of SUMO. In a study, two different scenarios were examined using the PHEMLIGHT and HBEFA-v2.1 models, which are SUMO emission models. In one of these scenarios, 100% liquefied natural gas (LNG) fuel was preferred, while in the other scenario 100%

conventional fuel was preferred. In this study, fuel consumption is given using SUMO emission models [74]. In another study, fuel consumption, CO2 emissions, and total delivery times were compared using SUMO using the route used by two different cargo trucks in their deliveries. It has been observed that the transportation of cargo with a single truck leads to a decrease in a certain amount of fuel consumption and CO2 emissions [75]. In another study in the literature, the emission models of HBEFA-v2.1, HBEFA-v3.1, and PHEMLight, which are emission models in SUMO, were compared. It was revealed that these three models gave approximate results to each other [76].

Each vehicle type in the simulation has its emission behavior. However, when the road network is examined in general, vehicle emissions differ according to emission models. In the literature, vehicle emissions are divided into two different classes, inventory and instantaneous. Many of the vehicle emission models in emission models are based on the combination of the total number of vehicles from the inventory emission model and the total distance traveled. There are many different pollutant parameters in such models [76]. In the instantaneous emission model, on the other hand, by simulating the emission of a single vehicle and using regression and load-based models, the emissions are calculated by considering a very small number of vehicles most of the time [77]. Both inventory and instantaneous emission models are included in this program through the SUMO program. There are 5 different emission models in SUMO: HBEFA v2.1, HBEFA v3.1, PHEMlight, Electric Vehicle Model, and MMP Electric Vehicle Model [78]. In this thesis study, HBEFA v3.1, which is the inventory emission model for non-autonomous vehicles, was used to calculate the emission emissions of vehicles, and the Electric Vehicle Model was used because autonomous vehicles only cause electricity consumption (indirect or direct emission emissions are neglected). In Table 3.5., the models used in this study from the emission models in SUMO are given.

Table 3.5. SUMO Emission Models [73].

Model	CO2	CO	HC	NOx	PMx	Fuel Consumption	Electricity Consumption
HBEFA v3.1	+	+	+	+	+	+	-
Electricity Vehicle Model	-	-	-	-	-	-	+

HBEFA provides emission parameters for all vehicle types in a wide variety of traffic networks [79]. With the HBEFA v3.1 emission model, parameters such as CO2, CO, HC, NOx, PMx, and Fuel Consumption can be accessed [80]. In this study, diesel-driven passenger car Euro norm (PC-D-EU4) was used for non-autonomous vehicles.

3.4. K-Nearest Neighbors (KNN) Regressor

KNN is a non-parametric machine learning method used for classification and regression. It is based on estimating the class of the vector formed by the independent variables of the value to be estimated in the KNN, based on the information in which class the nearest neighbors are intense. The KNN algorithm makes predictions on two basic values [81]. These:

- Distance: It is the distance of the point to be estimated with the Minkowski distance calculation formula from other points.
- K (Number of Neighbors): It is the calculation of how many nearest neighbors will be made. K value is a value that directly affects the result.

F1-Score value is used to measure the performance of the KNN Regressor algorithm. This value takes a value between 0 and 1. The closer it is to 1, the higher the success of the established model.

3.5. Decision Tree Regressor

After separating the independent variables into the group with the help of splits, it is one of the stages of the decision tree regressor algorithm, which finds which group this value belongs to by looking at the value to be estimated when it comes to the estimation stage and taking the standard deviation of the group to which this value belongs. This algorithm can be used in both classification and regression. The split process used in the algorithm is done with the help of a formula called information entropy in machine learning. Each segment separated at the end of the work is called a terminal leaf. After the splitting process, the model is created and after the score of each section is calculated in the created model, a value between 1 and 0 is calculated as the overall result. The closer this value is to 1, the higher the correlation of the independent variable with the dependent variable [82].

4. METHODOLOGY

In this section, SUMO, network design and sensors locations, vehicle types, traffic demand, simulation studies and scenarios, data, the performance of SND and California using detection rate, false alarm rate and mean time to detect, simulation integration between incident detection algorithms and real-time traffic management methods which are LCS and VSL, results on environmental effects and KNN Decision tree regressor model results will be discussed.

4.1. Simulation of the Study using Simulation Urban Mobility (SUMO)

Simulation Urban Mobility (Eclipse SUMO or simply SUMO) is an open-source, portable, microscopic, and continuous multimodal traffic simulation package designed to handle large networks. SUMO was developed by the German Aerospace Center and community users. It has been available free as open source since 2001 and has been an Eclipse Enterprise project since 2017. SUMO started to be implemented in 2001 with the first open-source version in 2002. There are two reasons for presenting the work as open source. The first is the desire to support the traffic simulation community with a free tool where their algorithms can be implemented. The second reason for making the simulation open source is the desire to get support from other institutions. SUMO is not just a traffic simulation, it is more of a suite of applications that help to prepare and perform traffic simulation [83].

Since the traffic simulation SUMO requires the representation of road networks and the simulation of traffic demand in its format, both need to be imported or created using different sources. SUMO is a purely microscopic traffic simulation. Each vehicle is given at least one identifier (name), time of departure, and identified by the route of the vehicle over the network. If desired, each vehicle can be explained in more detail. Departure and arrival features such as the lane to be used, speed or location can be defined. Each vehicle can be assigned a type that defines the physical characteristics of the vehicle and the variables of the motion model used. Each vehicle can also be assigned to one of the available pollutant or noise emission classes. Additional variables allow defining the appearance of the tool in the graphical user interface of the simulation. Vehicle definitions can be created using different sources. For large-scale scenarios, what are often called "origin/destination matrices" (O/D matrices) are used. They define movement between traffic assignment zones as the number of vehicles per time. Often, a single matrix is given for a single day, which is insufficient for microscopic traffic simulations as changes in direction over time are not represented. Sometimes 1 hour scale matrices are available. It is the best source for large-scale traffic simulations. The SUMO package includes "od2trips", an application for converting O/D matrices into single vehicle trips. Besides parsing the matrix, the application also discards an edge from the road network as the origin/destination location. The map from the traffic assignment zones to the edges is given to the application as a single input. The resulting trips consist of a start and end route with a departure time, but no explicit route information. Routes are usually calculated by performing a traffic assignment using a routing procedure such as shortest path calculations under different cost functions [83].

Another route calculation application, “jtrrouter”, uses definitions of turn percentages at the intersection to calculate routes over the network. Such an approach can be used to adjust demand on a section of a city’s road network consisting of up to ten nodes. Another application, dfrouter, calculates routes using information from loop detectors. This approach is highly successful when applied to highway scenarios where the road network does not contain rings and the highway entrances and exits are completely covered by detectors. It will fail in ringed city networks and if coverage with an induction loop is low. SUMO uses an extension of the car-follower model developed by Stefan Krauß. Lane changing is done using a model developed during the SUMO implementation [84, 85]. There are two versions of the traffic simulation. First, it is a pure command line application for efficient batch simulation. The second version is a graphics application that performs the simulation using OpenGL.

SUMO allows generating a variety of outputs for each simulation run. These range from simulated induction loops to single vehicle locations written at each time step for all vehicles, and complex values as information about each vehicle's journey or as aggregated measurements along a street or lane. SUMO has been extended with the model of noise emission, pollutant emission, and fuel consumption alongside traditional traffic measures. In 2006 the simulation was expanded with the possibility to interact with an external application via a socket connection. The SUMO Traffic Modeler allows us to define a population for a given area and calculate the mobility requests of this population, which can be used as an input for traffic simulation [86].

SUMO has applications in which it provides advantages in many areas. For example, vehicle communication, route selection, dynamic navigation, traffic light algorithms, and evaluation of surveillance systems are some of these applications. Probably the most popular application for the SUMO package is V2X - modeling traffic in vehicle-to-vehicle and vehicle-to-infrastructure communications research. To obtain a functioning environment for the emulation of vehicle communications, an application sample modeling the V2X application for simulation is required [87]. Additionally, a synchronization and message exchange mechanism should be included. The assignment of routes suitable for a complete request or a subset of vehicles has been studied both theoretically and as new applications. At the theoretical level, the interest lies in appropriate modeling of how traffic participants choose a route to their desired destination. Since the time to cross one edge of the road graph is highly dependent on the number of participants using that edge, calculating loaded routes over the network is a crucial step in the preparation of large-scale traffic simulations. Due to its fast execution speed, SUMO allows for searching algorithms for traffic assignment or user assignment on a microscopic basis. Usually, such algorithms are explored using macroscopic traffic flow models or using coarser road capacity models that do not resemble road congestion. Evaluation of traffic light programs or algorithms developed to make traffic lights adaptable to existing traffic is one of the main applications for microscopic traffic flow simulations. SUMO's fast execution time and open TraCI API for interaction with external applications make it a good candidate for both controlling a single intersection and evaluating new traffic control algorithms for network-wide investigations [88]. By distinguishing between different vehicle types, SUMO also allows for public transport simulation or emergency vehicle prioritization at intersections [89].

The ability of SUMO to simulate large-scale scenarios allows the evaluation of new traffic surveillance systems [83].

With the innovations added recently, SUMO can simulate emission and noise modeling and person-based intermodal traffic. As part of the iTETRIS project, SUMO has been made more efficient with a model for noise emission and a model for pollutant emission and fuel consumption. The implementation of the pollutant emission model within SUMO enables the emissions and fuel consumption of a vehicle to be collected throughout its entire drive and written to a file. It is also possible to write down the collected emissions for lanes or edges for defined, variable collection time intervals. The only noise output available collects noise emitted from the lanes or edges at predefined time intervals. No noise collection output per vehicle is available. In addition, it is possible to capture a vehicle's noise, emitted pollutants, and fuel consumption at any time step by TraCI. In addition, the emissions, consumption, and noise level collected for a lane or road can be taken. Besides, the conceptual center of intermodal traffic is the person. This person needs to make a series of trips, each of which can be taken by a different means of transport such as a personal car, public bus, or walking [83].

Figure 4.1 represents the vehicles circulating on the road network during the simulation. In SUMO, each vehicle is defined by a vehicle type that defines the vehicle's physical characteristics, the route the vehicle will follow, and the vehicle itself. A single route can be assigned to a single vehicle or multiple vehicles. At this point, routes can be defined in three different ways, (i) manually specifying all components of the route (i.e. set of edges), (ii) randomly generating routes, or (iii) with SUMO generation tools [90].

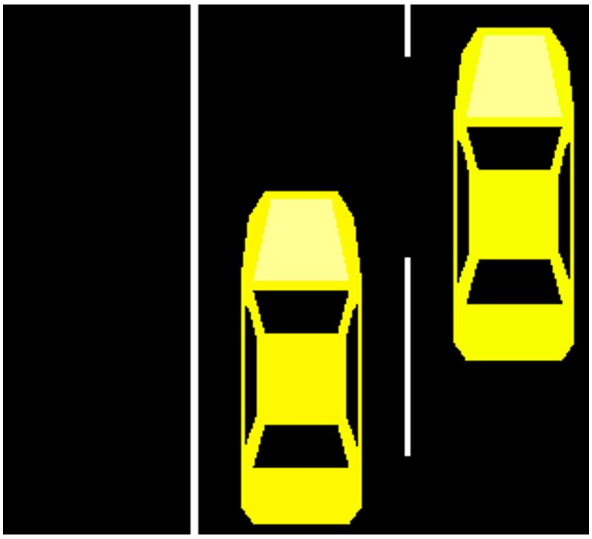


Figure 4.1. Representative Vehicles on SUMO.

The SUMO application performs a time-dependent simulation. The default step length is 1 second; however, can be selected as low as 1ms. A scenario can have a maximum duration of 49 days. The simulation model is space-continuous and internally defined by the position of each vehicle, the lane the vehicle is in, and the distance from the beginning of that lane. As it moves through the network, the speed of each vehicle is calculated using a model. Vehicle tracking models usually calculate the speed of a researched vehicle by looking at that vehicle's speed, the speed of the vehicle in front of it, and its distance from the vehicle in front. SUMO uses an extension of the stochastic vehicle tracking model developed by Stefan Krauß [84]. Krauß's model has also been compared with several vehicle tracking models to prove its function [91–93]. Some of the models added to SUMO are Kerner's three-phase model (Kerner et al., 2008), the intelligent driver model (IDM) [94], and the Wiedemann model [95]. Also in SUMO, the calculation of lane change is done using a model [85]. Figure 4.2 represents a single intersection simulated in SUMO.

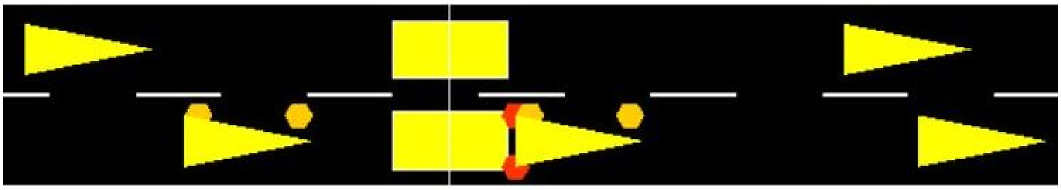


Figure 4.2. Road Network Design with Representative Simulation.

The SUMO traffic simulation program was expanded in 2006 through a link. The online feature of TraCI SUMO, called the Traffic Control Interface, was included by Wegener et al. [96]. With TraCI, the simulation program can be coded with the Python software language.

The parameters used in the SUMO traffic simulation application may vary. Values such as acceleration, deceleration, sigma, minimum clearance, and time interval differ according to vehicle types. For example, Table 4.1 shows how these values were obtained in the case of normal and fully autonomous vehicles from a study [97].

Table 4.1. Parameters Used in SUMO Simulations [97].

	Minimum Gap (m)	Acceleration (m/s2)	Deceleration (m/s2)	Emergency Deceleration(m/s2)	Sigma	Time Headway (s)
Human-Driven Vehicle	1.5	3.5	4.5	8	0.5	0.9
Fully Autonomous	0.5	3.8	4.5	8	0	0.6

In other studies, acceleration and deceleration values were taken as shown in

Table 4.2 and Table 4.3 [98–101].

Table 4.2. Parameters Used in SUMO Simulations.

	Acceleration(m/s2)	Deceleration(m/s2)	Reference
Human-Driven Vehicle	3	9	[98]
Autonomous	3.3	3.3	[99]

Table 4.3. Parameters Used in SUMO Simulations.

	Acceleration (m/s2)	Deceleration (m/s2)	Reference
Human-Driven Vehicle	3	5	[100]
Autonomous	2	3	[101]

4.1.1. Network Design

The road network is created in the simulation environment and this road network is uninterrupted. The length of the uninterrupted road network is 10.4 kilometers. The first 200 meters of this road network are defined as the entrance and the last 200 meters as the exit. When the input and output parts are not taken into account, the remaining 10 kilometers of main lines are the data collection area. Sensors have been added to the road network to collect data. The sensors used in this study are “E1 Induction Loop” detectors and there is a distance of 500 meters between each sensor. In Figure 4.3, the main road length of the uninterrupted road network is 10 km and there are 200-meter entrance and exit zones at the entrance and exit. When all parts are taken into account, the total length of the uninterrupted road network is 10.4 kilometers. There are 21 e1 induction loop detector-type sensors in total along the way. Data collection is done with these sensors. There is a distance of 500 meters between each sensor. The road network continues with 3 lanes along the entire road length. The lane width is fixed at 3.2 meters.

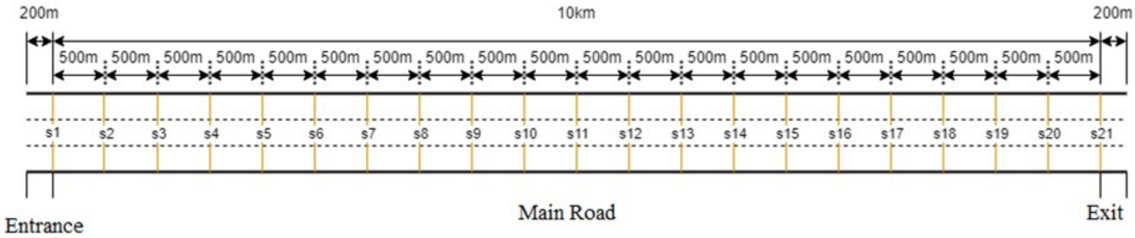


Figure 4.3. Illustration of Uninterrupted Road Network.

4.1.2. Vehicle Type Characteristic Features

In the simulation studies carried out on the SUMO Traffic Simulation program, two different vehicle types were defined as driven and autonomous vehicles. The factor that makes these vehicle types different from each other is the characteristic features assigned to the vehicles. Characteristics of driven and autonomous vehicles are given in Table 4.4.

Table 4.4. Autonomous and Human-Driven Vehicle Characteristics Features.

	Autonomous	Human-Driven
Acceleration (m/s2)	2.6	2.7
Deceleration (m/s2)	4.5	4.5
Length (m)	4.5	4.5
Maximum Speed (m/s)	30	30
Sigma (Driver Imperfection)	0.05	0.4
Speed Factor	0.9	0.9
Speed Deviation	0.1	0.35
Minimum Gap	1.5	1.5

The definition of vehicle type characteristics given in Table 4.4 is available in Table 4.5.

Table 4.5. Definition of Vehicle Type Characteristics.

Vehicle Parameters	Definition
Acceleration(m2/s)	The maximum speed increase that a given vehicle type can achieve in one second during the simulation
Deceleration(m2/s)	The maximum speed reduction value that a given vehicle type can achieve in one second during the simulation
Length (m)	Vehicle length
Maximum Speed (m/s)	Maximum achievable speed value assigned to the vehicle type
Sigma	It is also called driver imperfection. It regulates the acceleration and deceleration movements of the vehicles and its value is between 0 and 1. A sigma value equal to 0 indicates that the drive is faultless. If the sigma value is equal to 1, it indicates that the driver defect is at the highest level.
Speed Deviation	The speed deviation is the standard deviation of the standardized speed distributions. The autonomous vehicles used in this study show a more homogeneous speed distribution and therefore, speed deviations are lower.
Speed Factor	The speed factor assigns the vehicle types the value to be multiplied by the speed limits of the lanes. In both road networks created, 120 km/h was taken as the lane speed limit.
Minimum Gap	It determines the minimum distance between the vehicle in front and the vehicle following.

4.1.3. Traffic Demand

The traffic demands to be created on the road networks during the simulation were determined by analyzing the basic graphics resulting from the high demands placed on the road networks. The basic graphs examined are flow vs. density graphs.

In the analysis made for the uninterrupted road network, it has been observed that the traffic demands of 1200-1500 vehicles/hour/lane are appropriate.

Since there is no entrance/exit or change in the number of lanes in the uninterrupted road network, graphs were created using average values to determine the traffic demand, and the demands were determined. Traffic demands on the uninterrupted road are 1200, 1350, 1500 veh/hour/lane.

Considering the traffic demands it is seen that 3 different traffic demand combinations are given to the uninterrupted road network. The given traffic demands are gradually increased from a low level to a high level. It is aimed to observe different densities in the road network by applying different demand levels to the road networks. While low flow and low density are expected at low demand levels, it is expected that the density will increase with increasing demand levels and the flow will increase up to the critical density value and reach the maximum flow value and then decrease with increasing density. With the application of different demand levels and the realization of incident scenarios, different shockwave lengths will be observed. It is expected that the bottleneck caused by the incident at low demand levels will not affect the traffic significantly and shockwaves will not occur in general in these scenarios; however, in cases where they do occur, it will allow the examination of short shockwaves.

4.1.4. Simulation Studies

Simulation studies take 90 minutes. During the analysis of the collected data, the data corresponding to the first 15 and the last 15 minutes of the 90-minute data will be removed from the data set. The reason for this is that the first 15 minutes and the last 15 minutes are considered warm-up and cool-down intervals, excluded from the data set.

During the simulation studies, after the traffic demands to be given to the road networks were created, different incident scenarios were created. In this process, the variables to be used in simulation studies were determined. The variables are incident location, incident time, recovery time, percentage of autonomous vehicles, and traffic demands. The variables and their values are given in Table 4.6.

Table 4.6. Variables Used in the Simulation Study.

Variable	Value
Autonomous Vehicle Percentage	[0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100]
Traffic Demands	[1200, 1350, 1500]
Incident Location (m)	rand(4500, 8000)
Incident Time (s)	rand(900, 2700)
Recovery Time (s)	rand(600, 1500)
Incident Lane	Right, Middle, Left

Considering the variables given in Table 4.6, there are 33 different scenarios in the simulations made over the uninterrupted road network with 11 percent of autonomous vehicles and 3 different traffic demands. With the same autonomous vehicle percentage and traffic demand variables, scenarios where there is no incident are also simulated. Therefore, the final scenario number is 66. The reason for simulating scenarios where there is no incident is to create a basis for the simulation study and there is a need for non-incident cases in the incident detection algorithm.

The simulation studies carried out on the variables specified in Table 4.6 were carried out using the SUMO Traffic Simulation Program. During the simulation of scenarios, a statistically sufficient number of seeds should be used to eliminate randomness. 100 different seeds were used in each scenario simulation made during the project. By using 100 different seeds, a more suitable data set to be analyzed statistically will be obtained. The reason for this is that each scenario is run 100 times to give different results, and these results are averaged. Thus, randomness has largely disappeared and the results of statistical analyses have become more logical and accurate. There are 66 simulated scenarios in total. Since each scenario was re-simulated with 100 different seeds, a total of 6600 simulations were carried out.

4.1.5. Data

Data was collected every second during the simulation period. The collected data were obtained with sensors placed in the simulation network at intervals of 500 meters. Data was collected from the sensors every second. The second data collected were kept for 15 seconds and were processed into the data set at the end of 15 seconds. The data processed in the data set has been deleted and the second data of the new 15-second interval has been started to be kept. This data collection algorithm continues in the same way from the beginning to the end of the simulations.

The data obtained from the sensors placed at intervals of 500 meters are divided into three the number of vehicles, vehicle speed, and occupation rate. The area detected by the sensors defined as the "e1 detector", which is included in the SUMO traffic simulation application, is 4 meters. These sensors, which use induction circuits as their working principle, increase the induction of the iron parts of the vehicle when the vehicle passes over them [102]. Thus, it is determined whether there is a vehicle in the 4-meter sensor area . The data given by the sensors as output is given in Figure 4.4.

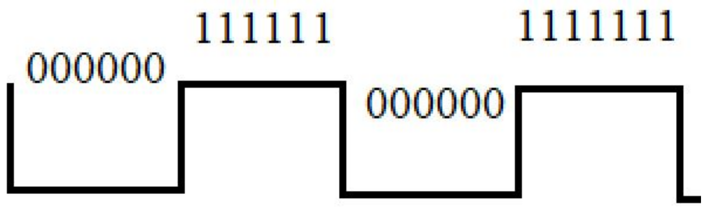


Figure 4.4. Representative Output Format of Induction Flow Sensors.

The collected vehicle count, vehicle speed, and occupancy rate data are calculated with the outputs obtained from these sensors. The algorithms and formulas used by the sensors to calculate this data are explained in detail.

Vehicle count: Induction flow is low when there is no vehicle on the sensors. When the vehicle is found, the induction flow increases and the sensors detect the presence of the vehicle. Thus, the number of vehicles passing over the sensors can be easily detected. In this study, the data of how many vehicles passed through the sensors at one-second intervals were kept and this data was collected at 15-second intervals. Therefore, the number of vehicles passing through the sensors at 15-second intervals throughout the simulation was obtained.

Vehicle speed: Using the output data of the sensors, it is calculated how many seconds the vehicles occupy the 4-meter sensor area. Vehicle speeds can be calculated using the occupation time, vehicle length, and sensor area length.

Occupancy rate: The occupancy rate is found by dividing the time that the 4-meter sensor areas are occupied by the vehicles by the total time. In this study, the occupancy rate data are kept every second during the simulation, and the average occupancy area is calculated at the end of 15-second time intervals and processed into the data set. Thus, the occupancy rate of each sensor was obtained at each data collection frequency.

After the collected data, the obtained data were converted into the desired data type, flow, density, and average speed, by using the transformation formulas. The application of these transformations and the formulas used are explained in detail.

Conversion of occupancy rate data to density data: While obtaining the density data, which is one of the performance criteria of this study, occupancy data, one of the sensor outputs, was used.

Conversion of vehicle number data to flow data: The number of vehicles passing through the sensors is used while obtaining the flow data. In the scenario simulations made throughout the study, the number of vehicles passing through each sensor at 15-second intervals was collected and stored. The unit of flow data, which is one of the performance criteria, is the number of vehicles passing per hour. To reach this unit, the 15-second flow data was multiplied by 240 and converted into hourly flow data.

Conversion of vehicle speed data to average vehicle speed data: In this study, the speed of the vehicles passing over the sensors every second is kept. Therefore, speeds that are collected by sensors were averaged, and the average vehicle speeds occurring in each 15-second interval in each sensor region were calculated and entered into the data set.

After the parameters used in the study were obtained, the traffic basic graphics were drawn. By using these graphics, the traffic demands to be given to the road networks were decided in the simulation study. The graphs to be used in determining the traffic demands were selected and used at certain points of the road networks. Since there is no geometrical change along the road in the uninterrupted road network, graphs are obtained with the data obtained from a single sensor. Graphs were created using the sensors in the regions shown in Figure 4.5. Since the graphs were created separately for each demand combination, the flow-density graph was obtained and the demands given to the road networks were decided in line with the examination of these graphs.

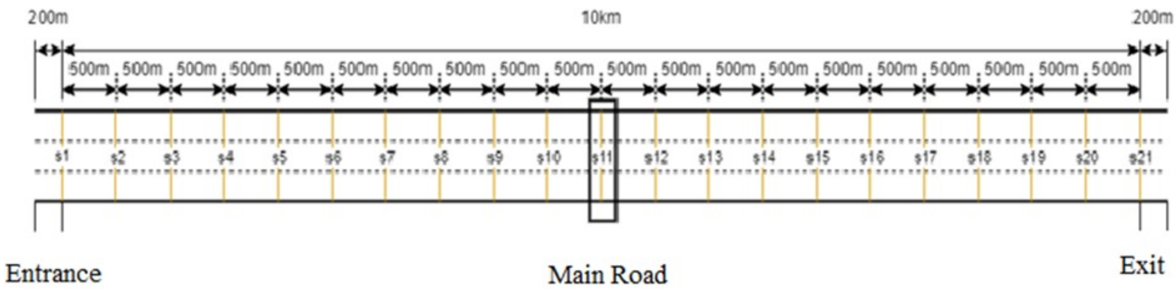
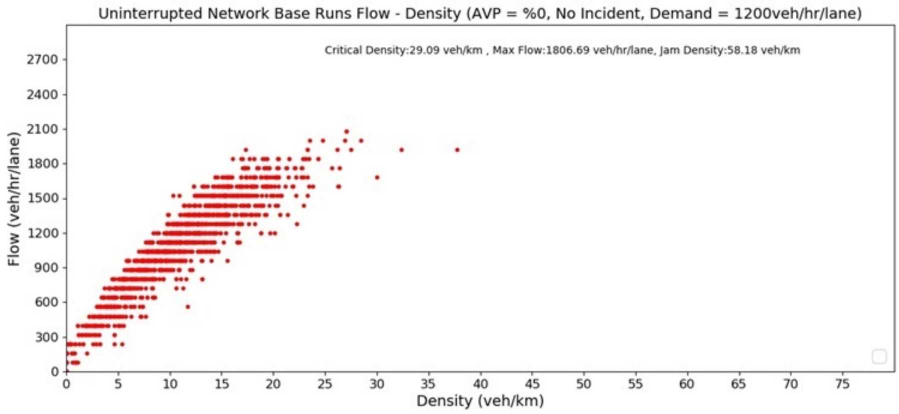


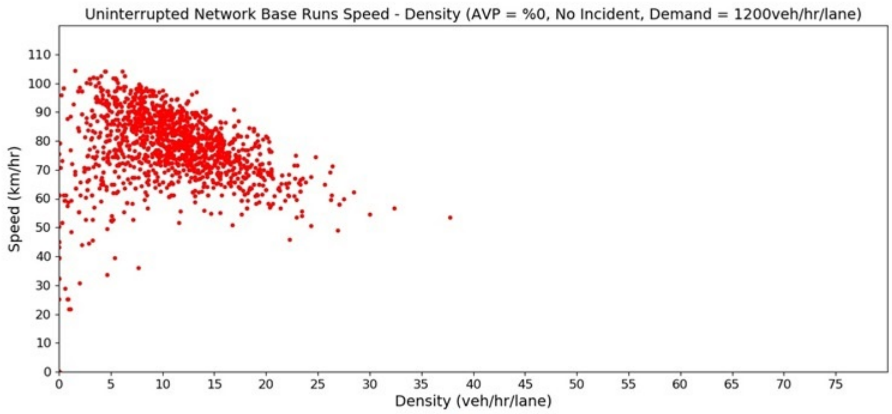
Figure 4.5. The sensor from which the data used in creating the flow-density graphs are obtained.

4.2. Simulation Results

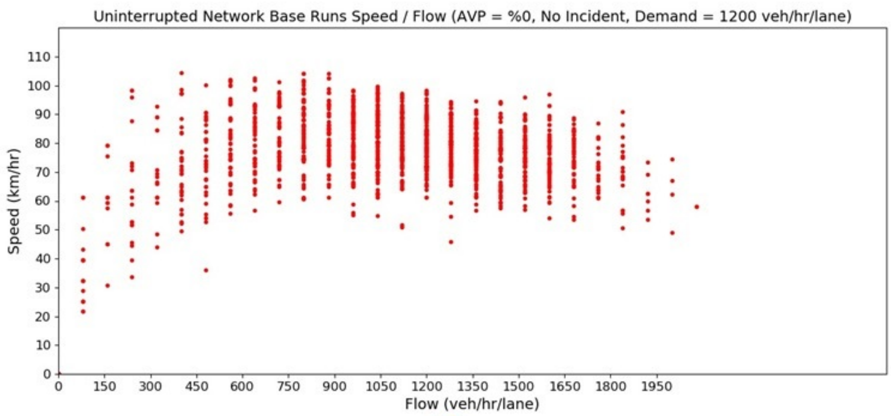
The graphs in Figure 4.6 are created by using the density, speed, and flow data obtained via simulating the basic scenario where the percentage of no-incident and autonomous vehicles is 0% in the uninterrupted road network with 1200 vehicles/hour/lane traffic demand.The data used in the drawing of the graphs is the data obtained from the 11th sensor located at the midpoint of the uninterrupted road network. These graphs are used to reveal the characteristic features of the uninterrupted road network. When the density-flow graph given in Figure 4.6a is examined, it is observed that the data are clustered in the region where the density and flow values are low. This is due to the low demand for traffic to the road network. As stated in the same graph, the critical density value is 29.09 vehicles/km, the capacity of the road, that is, the maximum flow value is 1806 vehicles/hour/lane, and the jam density is 58.18 vehicles/km. When Figure 4.6b is examined, it is seen that the data are clustered in the low-density and high-speed regions.



(a)



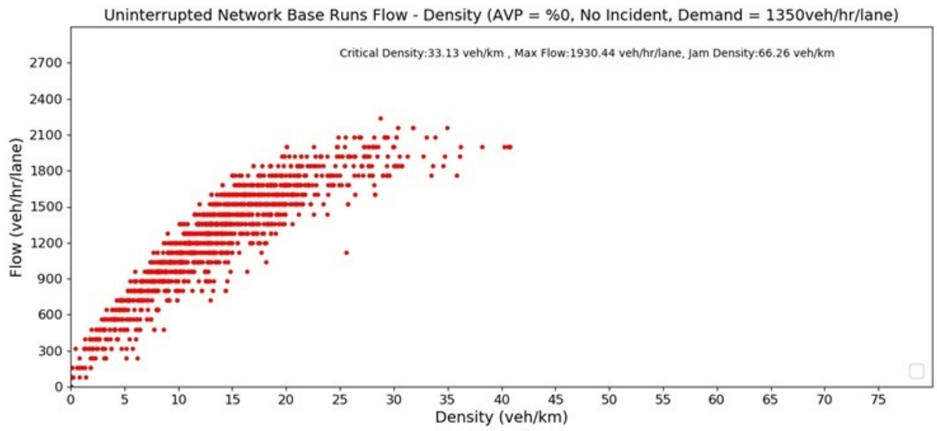
(b)



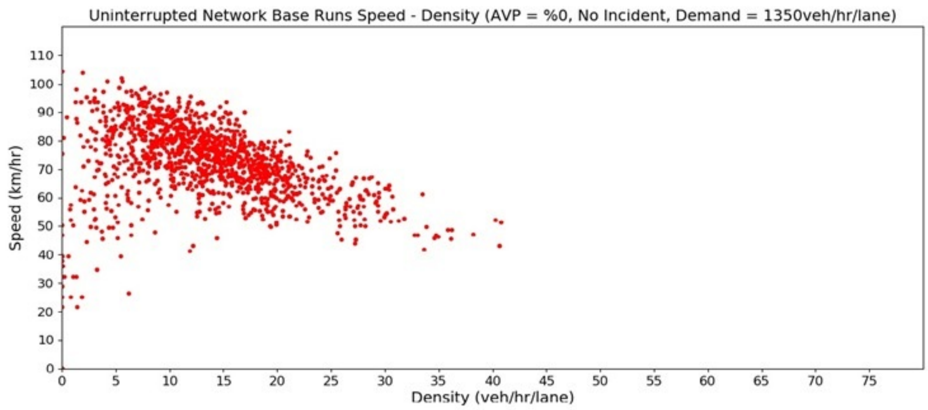
(c)

Figure 4.6. (a) density-flow, (b) density-speed, (c) flow-speed graphs created with the data obtained from the 11th sensor of the basic scenario simulated with 1200 vehicles/hour/lane traffic road in the uninterrupted road network.

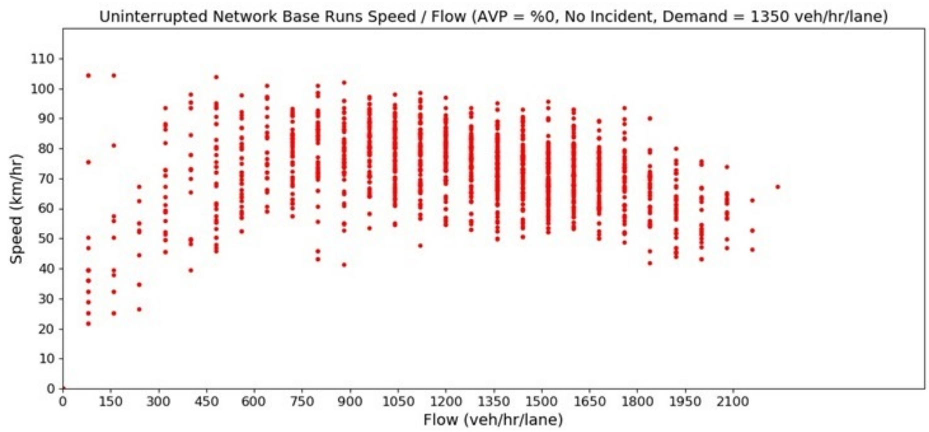
Figure 4.7 is created by using the density, speed, and flow data obtained where the percentage of no-incident and autonomous vehicles is 0% in the uninterrupted road network with 1350 vehicles/hour/lane traffic demand. When the density-flow graph given in Figure 4.7a is examined, it is seen that the critical density value is 33.13 vehicles/km, the capacity of the road, that is, the maximum flow value is 1930.44 vehicles/hour/lane, and the jam density is 66.26 vehicles/km. When Figure 4.7b is examined, it is observed that the data are clustered in a slightly higher density and low-speed region compared to the density-speed graph created with 1200 vehicles/hour/lane traffic demand. The reason for this is that the graphs given in Figure 4.7 are created with a traffic demand of 1350 vehicles/hour/lane.



(a)



(b)



(c)

Figure 4.7. (a) density-flow, (b) density-speed, (c) flow-speed graphs created with the data obtained from the 11th sensor of the basic scenario simulated with 1350 vehicles/hour/lane traffic road in the uninterrupted road network.

Figure 4.8 was created by using the density, speed, and flow data obtained where the percentage of no-incident and autonomous vehicles is 0% in the uninterrupted road network with 1500 vehicles/hour/lane traffic demand. When the density-flow graph given in Figure 4.8a is examined, it is seen that the critical density value is 34.75 vehicles/km, the capacity of the road, that is, the maximum flow value is 1957 vehicles/hour/lane, and the jam density is 69.5 vehicles/km. When Figure 4.8b is examined, it is observed that the data are clustered in the higher density and low-speed region compared to the density-speed graph created with 1200 vehicles/hour/lane traffic demand. The reason for this is that the graphs given in Figure 4.8 are created with a traffic demand of 1500 vehicles/hour/lane.

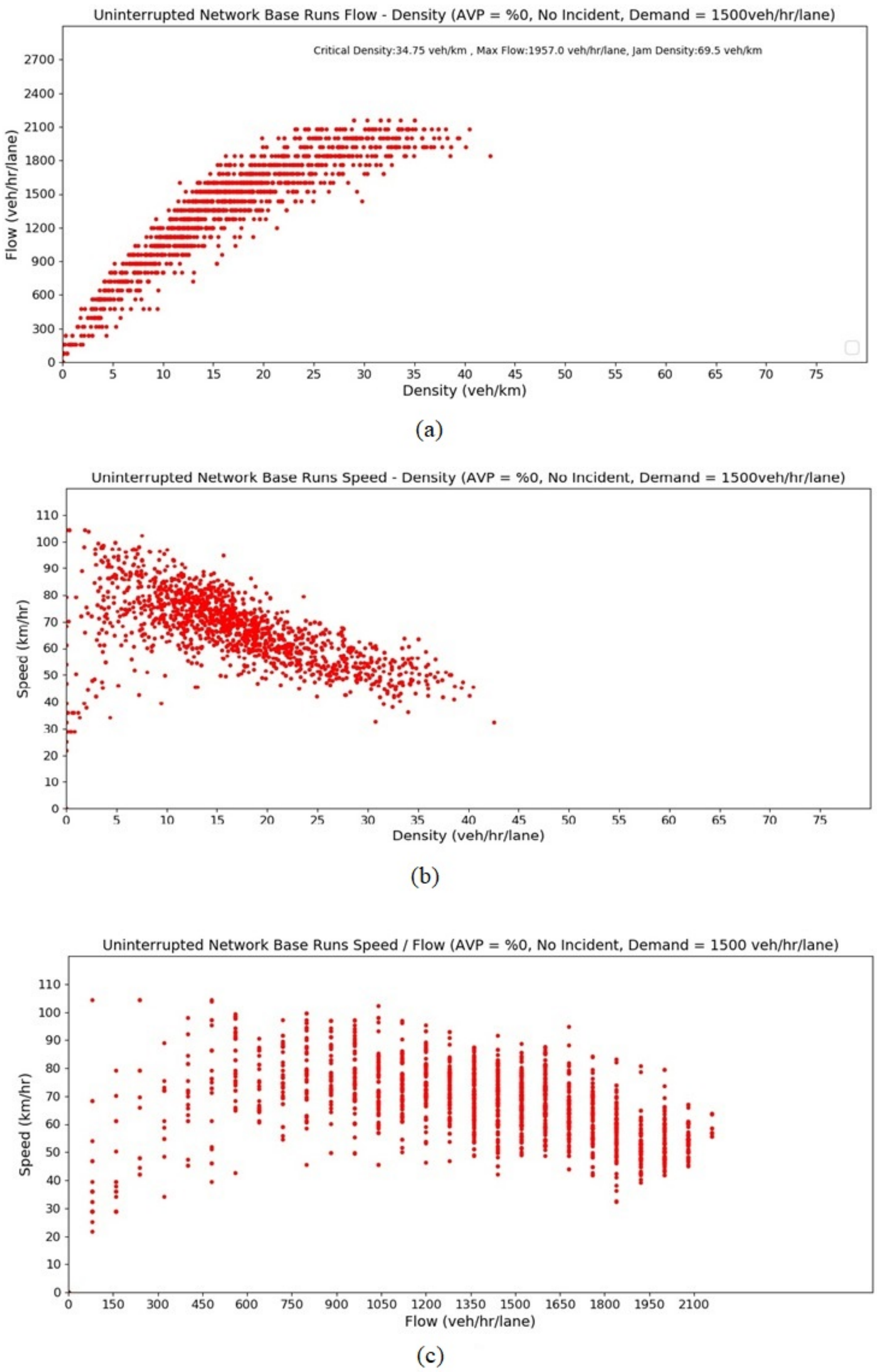


Figure 4.8. (a) density-flow, (b) density-speed, (c) flow-speed graphs created with the data obtained from the 11th sensor of the basic scenario simulated with 1500 vehicles/hour/lane traffic road in the uninterrupted road network.

In Table 4.7, the columns of the dataset consist of data processing frequency, location, flow, density, and average speed data. The detailed description of these data columns is as follows.

Table 4.7. Cross section of the dataset created from the uninterrupted road network.

Data Processing Frequency	Location	Flow (vehicle/hour)	Density (vehicle/km)	Avg. Speed (km/hour)
26	1	1040	7.50	52.00
26	2	1280	7.57	79.53
26	3	1440	14.08	62.10
26	4	1280	8.96	73.64
26	5	1360	10.43	74.62
26	6	560	2.61	80.40
26	7	880	6.04	70.20
26	8	880	3.86	96.40
26	9	1280	6.99	84.11
26	10	320	0.83	78.00
26	11	880	3.99	91.60
26	12	1120	6.43	93.60
26	13	1280	6.80	83.70
26	14	320	0.81	84.00
26	15	1040	4.73	99.36
26	16	720	2.74	99.90
26	17	640	2.26	97.71
26	18	880	3.35	101.31
26	19	880	3.11	101.25
26	20	240	0.21	102.00
26	21	480	1.19	101.40

- Data processing frequency: Data processing frequency data gives information about the simulation time. During the simulation, data are collected every second and the collected data are processed every 15 seconds. After every 15 seconds, the data processing frequency increases by 1. For example, in the dataset section given in Table 4.7, the data of the 26th data processing frequency, that is, the 26th 15-second slice is given.
- The location data provides information about the sensor location. The consecutive numbers in the location column are the sensors in the road network. For

example, position 1 represents the sensor at 500 meters, position 2 represents the sensor at 1000 meters, and position 3 represents the sensor at 1500 meters.

- Flow data are calculated at 15-second intervals, that is, for each sensor at each step, and converted to hourly data with a conversion formula.
- Density: Density data are obtained by converting the 15-second occupancy rates of the sensors into density data with the help of the conversion formula.
- Average speed: Average speed data are obtained by storing the speed of the vehicles passing the sensors for 15 seconds and taking the average speed after every 15 seconds.

In Figure 4.9, there is a density-time graph for each percentage of autonomous vehicles in the short-duration (672 seconds) middle lane incident scenario in the uninterrupted road network. The traffic demand given to the road network is 1200 vehicles/hour/lane. The x-axis of the figure represents time, while the y-axis gives the density value. When Figure 4.9 is examined, it is seen that the density value increases rapidly after the incident occurs when 50% of the traffic consists of autonomous vehicles. In the presence of an incident, the highest density value is observed in the case of a 0% autonomous vehicle percentage. After the incident is over, it is seen that 0% and 10% autonomous vehicle percentages differ from other autonomous vehicle percentage cases and the density values decrease later in these autonomous vehicle percentage cases.

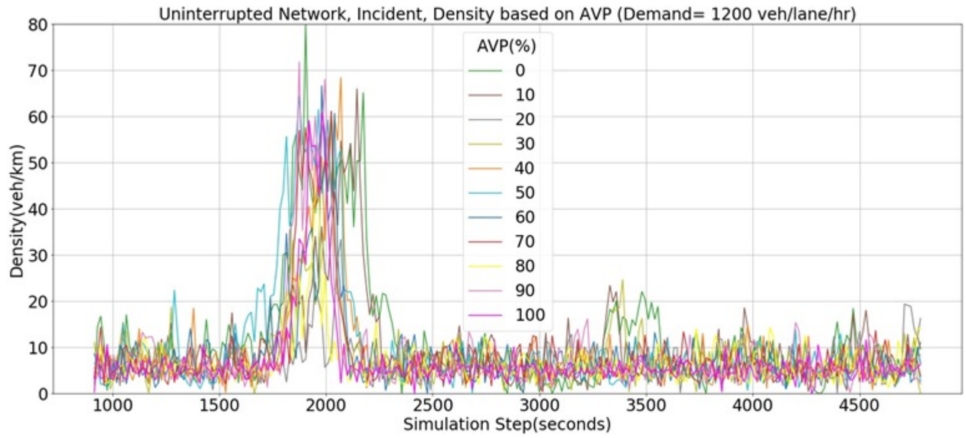


Figure 4.9. Density-time graph for each autonomous percentage of the short duration (672 seconds) middle lane incident scenario in the uninterrupted road network (Traffic Demand = 1200 vehicles/hr/lane).

The density-time graph given in Figure 4.10 was created within the same incident scenario as Figure 4.9. The only difference is that the traffic demand has increased from 1200 vehicles/hour/lane to 1350 vehicles/hour/lane. When Figure 4.10 is examined, it is seen that the density values start to increase earlier in cases where the percentage of autonomous vehicles is high. After the incident is over, it is seen that the density values decrease more rapidly in cases where the percentage of autonomous vehicles is high. It has been observed that after the incident, in cases where the percentage of autonomous vehicles is low, the density values hover around 20 vehicles/km for a while before becoming pre-incident, and then decrease a little more to reach the pre-incident status.

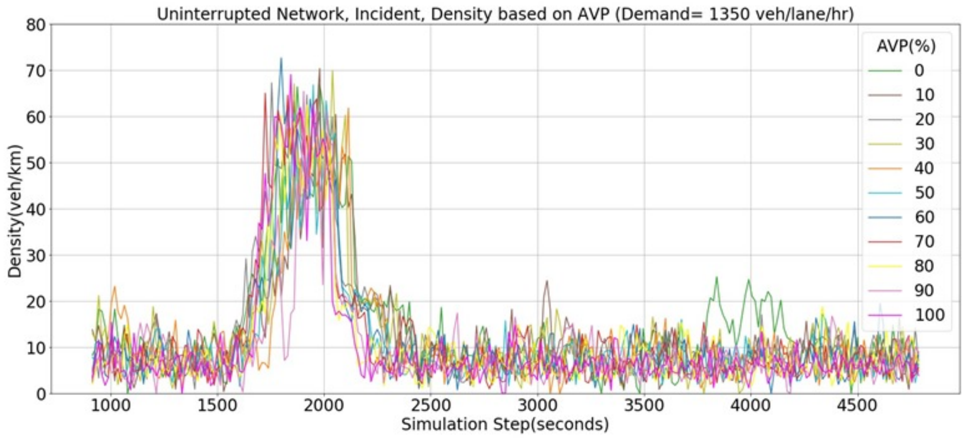


Figure 4.10. Density-time graph for each autonomous percentage of the short duration (672 seconds) middle lane incident scenario in the uninterrupted road network (Traffic Demand = 1350 vehicles/hr/lane).

Figure 4.11 was created and the difference between them is that the traffic demand has increased from 1350 vehicles/lane/hour to 1500 vehicles/lane/hour. It is seen that in cases where the percentage of autonomous vehicles is 90% and 100%, the density values increase faster than the other percentage of autonomous vehicles, and after the incident, they fall faster and regain their original form. In the case where the percentage of autonomous vehicles was 0%, it took longer for the traffic to recover after the incident compared to the others.

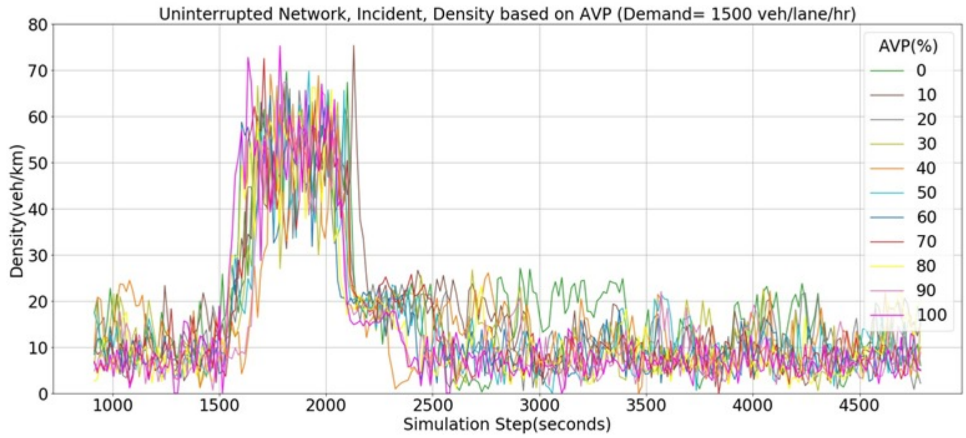
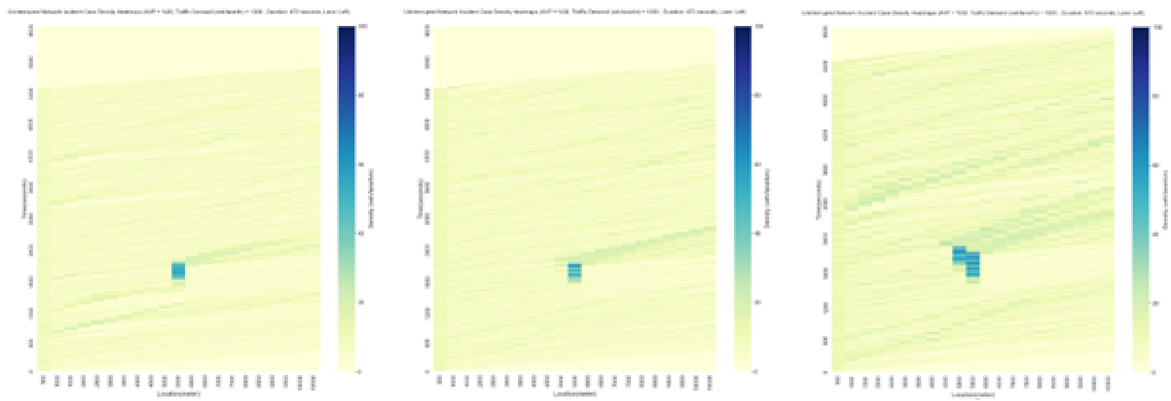


Figure 4.11. Density-time graph for each autonomous percentage of the short duration (672 seconds) middle lane incident scenario in the uninterrupted road network (Traffic Demand = 1500 vehicles/hr/lane).

The x-axis of the density heat maps given in Figure 4.12 represents the location where the data was collected, while the y-axis represents the time. Within the density heatmap, areas with yellow colors indicate low-density values, while blue areas indicate high-density areas. All three density heat maps given in Figure 4.12 were created using the simulation results of the same incident scenario. The only variable is the traffic demand to the road network. Figure 4.12 heat map was created with traffic demand of Figure 4.12a 1200 vehicles/hour/lane, Figure 4.12b 1350 vehicles/hour/lane, Figure 4.12c 1500 vehicles/hour/lane. When these heat maps are compared, it is observed that when the traffic demand is 1500 vehicles/hour/lane, the shock wave length increases, and the blue zone, that is, the area with high-density values, grows.



(a) (b) (c)

Figure 4.12. (a) Traffic demand = 1200 veh/hour/lane, (b) Traffic demand = 1350 veh/hour/lane, (c) Traffic demand = 1500 veh/hour/lane density heatmap of middle lane incident scenarios of short duration (672 seconds) based on 50% AVP in the uninterrupted road network.

In the uninterrupted road network in Figure 4.13, the density-time graph shows the density values that occurred at the time of the incident that lasted for 1440 seconds in the middle lane, according to the percentage of autonomous vehicles. The x-axis shows the time, while the y-axis shows the density value. In this scenario, the traffic demand on the road is 1500 vehicles/lane/hour. When the graph is examined, it is determined that while the percentage of autonomous vehicles is 100% immediately after the incident, the density increases rapidly, while the density decreases earlier than the other autonomous vehicle percentages after the incident is over. It has been determined that the density value shows a fluctuating change when the percentage of autonomous vehicles is 50%, and the density value remains at the value after the incident and does not decrease when the percentage of autonomous vehicles is 80%.

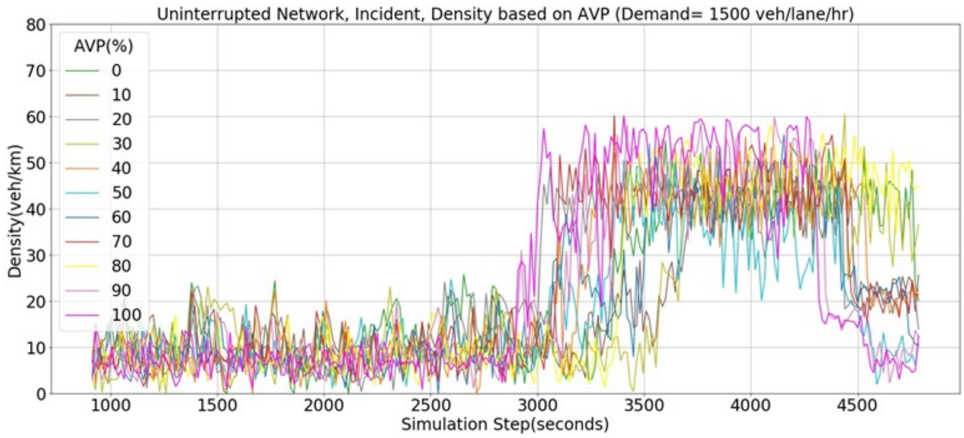


Figure 4.13. Density-time graph for each autonomous percentage of the long duration (1440 seconds) middle lane incident scenario in the uninterrupted road network (Traffic Demand = 1500 vehicles/hr/lane).

In the density-time graph in Figure 4.14, the variation of the densities obtained considering the incident scenario that took place for 1396 seconds in the right lane of the uninterrupted road network according to time is obtained. The y-axis represents the density value, while the x-axis represents the time. The traffic demand is determined as 1500 vehicles/lane/hour in the scenario. In cases where the percentage of autonomous vehicles is 50% or more, it is seen that the density increase occurs faster than when the AVP is less than 50%, and it is seen that the density value decreases more rapidly as the autonomous vehicles percentage increases after the incident.

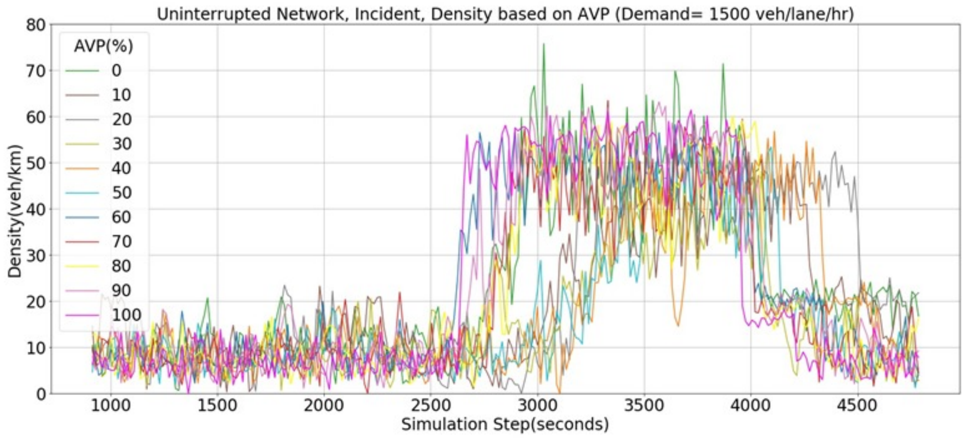


Figure 4.14. Density-time graph for each autonomous percentage of the long duration (1396 seconds) right lane incident scenario in the uninterrupted road network (Traffic Demand = 1500 vehicles/hr/lane).

In the density-time graph in Figure 4.15 of the uninterrupted road network, the incident scenario with 1435 seconds occurred in the left lane. The X-axis indicates the time, and the Y-axis indicates the density values. At the time of the incident, the density increase was primarily achieved when the AVP was 100%, while the density value was obtained during the incident when the AVP was at least 100%. While the density increased slowly when the AVP was 0%, higher densities occurred during the incident period than the density values obtained with the percentages of other autonomous vehicles, and the slowest decrease in density at the end of the incident occurred when the AVP was 0%

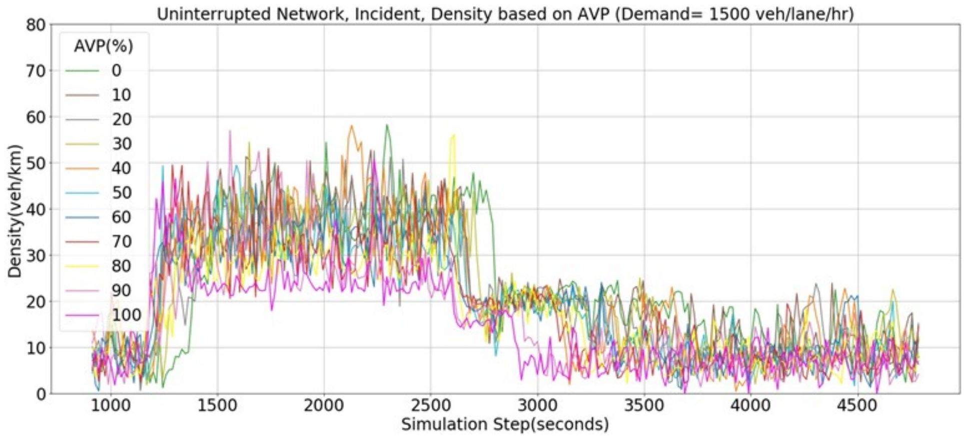


Figure 4.15. Density-time graph for each autonomous percentage of the long duration (1435 seconds) left lane incident scenario in the uninterrupted road network (Traffic Demand = 1500 vehicles/hr/lane).

. The heatmap given in Figure 4.16 shows the density changes obtained from the sensors resulting from the 1440-second incident in the middle lane of the uninterrupted road network. The X and Y axis represents the location and time respectively. When graph (a) with 0% autonomous vehicle percentage is examined, the increase in density after the incident can be understood from the color of the density turning blue. The duration and size of the resulting density are higher than the scenarios where the AVP increases. This can be seen in graphs Figure 4.16b, c and d from the smaller and smaller density field in blue. The length of the resulting shock wave can be understood from the number of columns covered by the blue area, and it has been observed that the resulting shock wave becomes shorter and shorter as the AVP is increased.

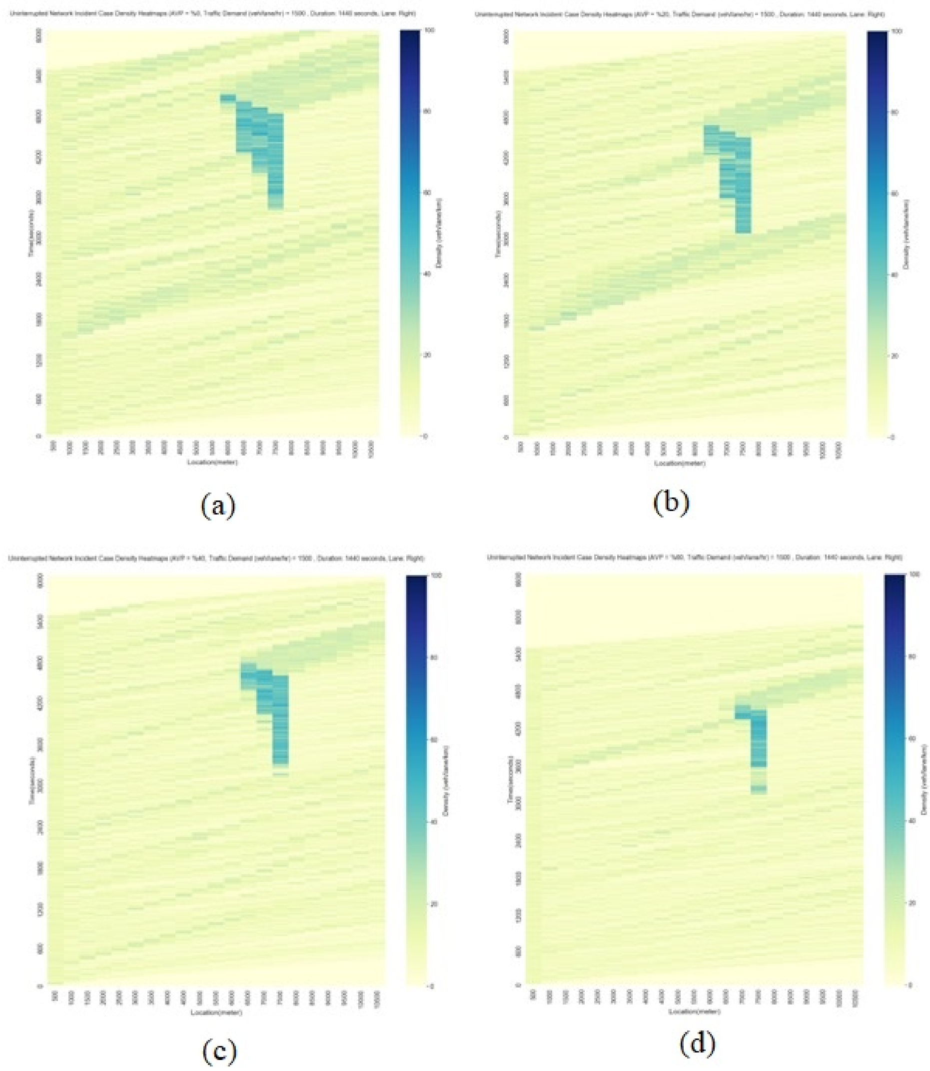


Figure 4.16. (a) 0% AVP, (b) 20% AVP, (c) 40% AVP, (d) 60% AVP density heatmap of middle lane incident scenarios of long duration (1440 seconds) in the uninterrupted road network.

Figure 4.17 is the heat map that expresses the location and time-dependent status of the density change after the 1396-second incident that occurred in the right lane of the uninterrupted road network. When the heat maps are examined, it is observed that as the percentage of autonomous vehicles increases, the shock wave lengths due to the change in density after the incident shorten, the increase in density, and the duration of this increase. When the density values read from the sensors are examined, the situation with the least duration of density formation and the shortest shock wavelength is the scenario with a 40% autonomous vehicle percentage, which is indicated in the graph Figure 4.17c.

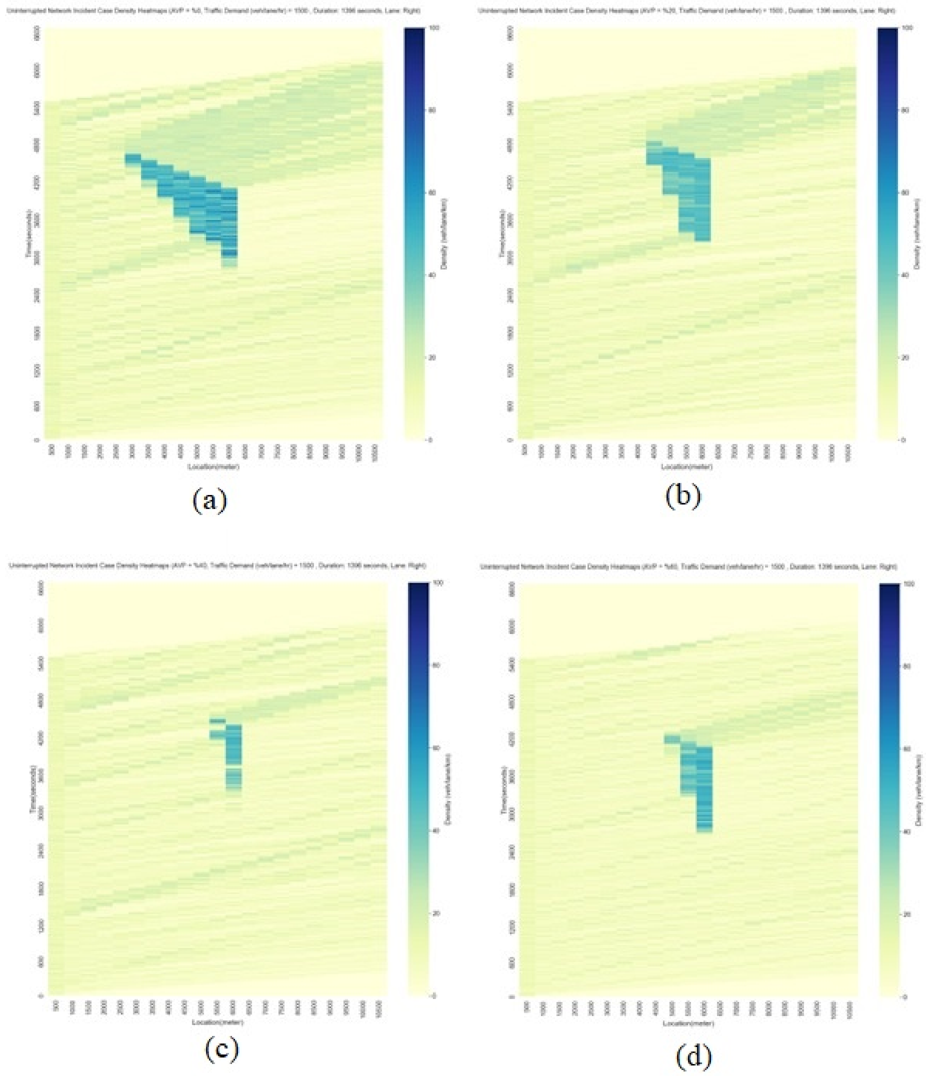


Figure 4.17. (a) 0% AVP, (b) 20% AVP, (c) 40% AVP, (d) 60% AVP density heatmap of right lane incident scenarios of long duration (1396 seconds) in the uninterrupted road network.

In Figure 4.18. the density changes in the heat maps obtained with the 1435 second-duration incident scenario occurring in the left lane of the uninterrupted road network are expressed with the blue area. When the resulting changes were examined, it was determined that the most significant density change occurred when the percentage of autonomous vehicles was 0% and the shock wave formed was longer than the shock waves formed with other autonomous vehicle percentages. It is seen that the least increase in density after the incident occurs in scenario Figure 4.18d where there is a 60% autonomous vehicle percentage, and it is shown that the density increases and the shock wavelengths become shorter as the AVP increases.

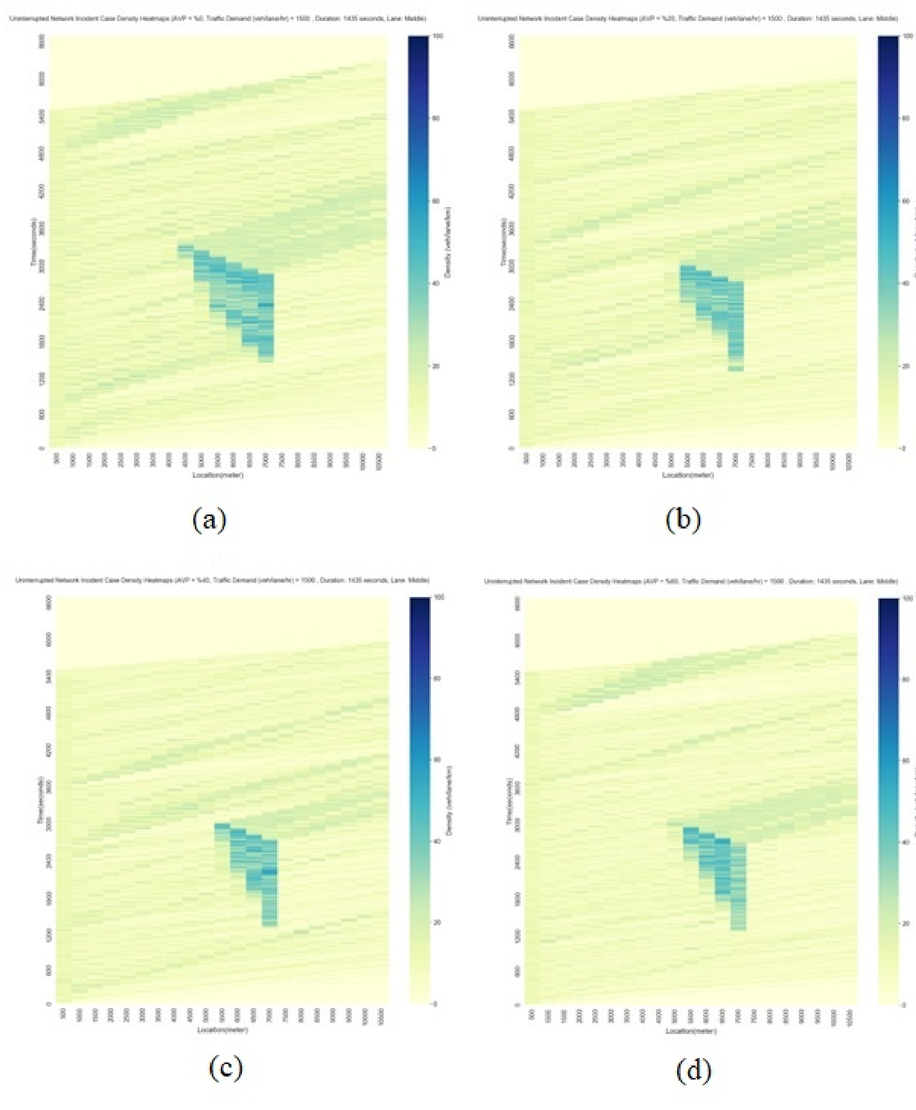


Figure 4.18. (a) 0% AVP, (b) 20% AVP, (c) 40% AVP, (d) 60% AVP density heatmap of left lane incident scenarios of long duration (1435 seconds) in the uninterrupted road network.

In Figure 4.19. the density-time graph obtained in the middle lane with a duration of 672 seconds in the uninterrupted road network is given. When the graph showing the variation of density change over time for each autonomous vehicle percentage is examined, it is observed that the fastest increase in density at the time of incident occurs when 100% autonomous vehicle percentage is present. The scenario with a 100% autonomous vehicle percentage, which returns to the pre-incident density value during the incident period, is also faster than the other AVP scenarios in terms of a decrease in the post-incident density value. As the percentage of autonomous vehicles increases, densities decrease faster.

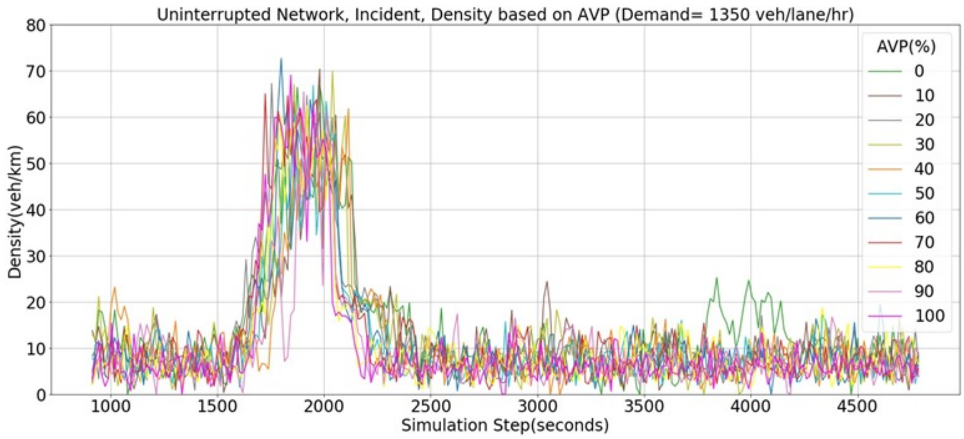


Figure 4.19. Density-time graph for each autonomous percentage of the short duration (672 seconds) middle lane incident scenario in the uninterrupted road network (Traffic Demand = 1350 vehicles/hr/lane).

In Figure 4.20 the incident scenario with a duration of 1039 seconds occurred in the middle lane, and the traffic demand on the road in the scenario is 1350 vehicles/lane/hour. Density changes are shown depending on time. It is observed that the pre-incident density value is formed when the highest 50% AVP is present, and as in the 672-second incident scenario, the density increase occurred the fastest in the case of 100% OAY. While the post-incident density values cannot catch the pre-incident situation between 2500-3000 seconds in all scenarios, the rate of catching the pre-incident density values increases as the percentage of autonomous vehicles increases.

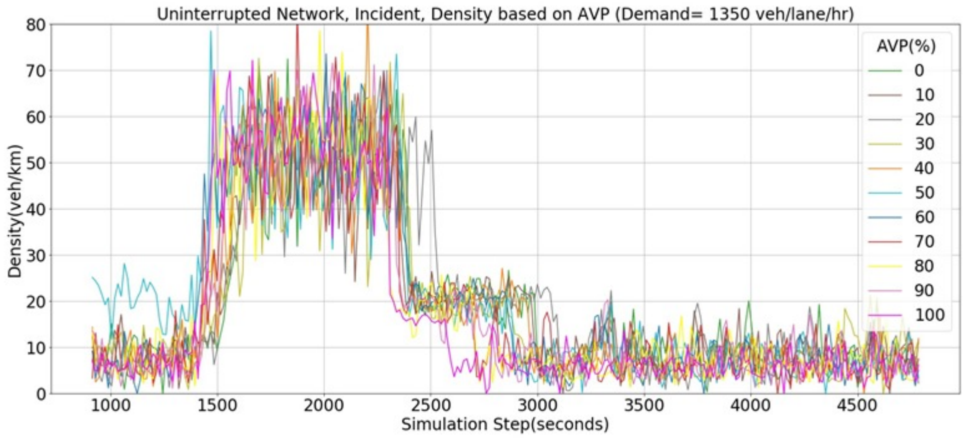


Figure 4.20. Density-time graph for each autonomous percentage of the medium duration (1039 seconds) middle lane incident scenario in the uninterrupted road network (Traffic Demand = 1350 vehicles/hr/lane).

The density-time graph, which was formed based on the incident that occurred for 1485 seconds in the middle lane of the road with a traffic demand of 1350 vehicles/lane/hour, is given In Figure 4.21 The X-axis shows the time and the Y-axis shows the density values. When the density increases due to the incident are examined, it is observed that the highest density value is reached in the scenario with a 0% autonomous vehicle percentage. As the percentage of autonomous vehicles increases, the post-incident density values decrease and the speed of reaching the pre-incident situation increases. The slowest density decrease was obtained in cases with 10% and 0% autonomous vehicle percentage, and in the case of 100% autonomous vehicle percentage, the density decrease occurred the fastest compared to other scenarios.

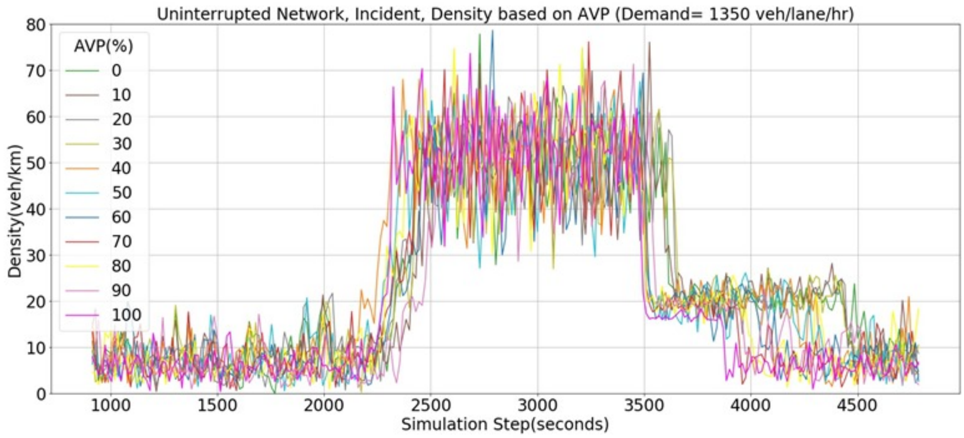


Figure 4.21. Density-time graph for each autonomous percentage of the long duration (1485 seconds) middle lane incident scenario in the uninterrupted road network (Traffic Demand = 1350 vehicles/hr/lane).

In Figure 4.22, the density change obtained with the short duration (672 seconds) incident scenario in the middle lane of the uninterrupted road network is shown by color changes. The heatmap for 4 different percentages of autonomous vehicles was created for each scenario. The shock wave formed via the short-term incident occurred in the scenario with the longest 0% autonomous vehicle percentage, and it is observed that as the percentage of autonomous vehicles increases, the resulting shock wavelengths decrease.

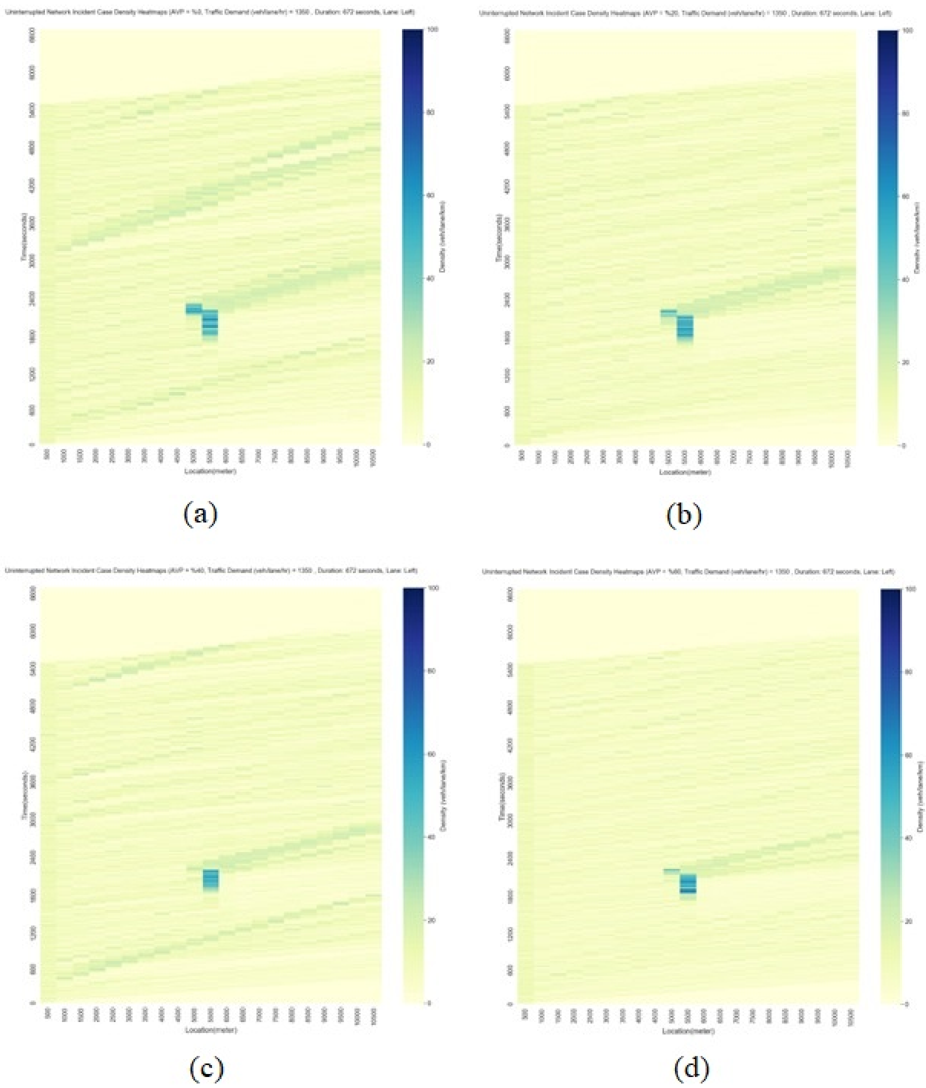


Figure 4.22. (a) 0% AVP, (b) 20% AVP, (c) 40% AVP, (d) 60% AVP density heatmap of middle lane incident scenarios of short duration (672 seconds) in the uninterrupted road network.

Figure 4.23 is the heat maps obtained with the incident scenario in the middle lane of medium duration (1039 seconds) on the uninterrupted road. Heatmaps show density changes depending on location and time. It is observed that as the duration of the incident increases, the shock wavelength is longer than the short-term incident scenario. It is observed that as the percentage of autonomous vehicles increases, the shock wavelength decreases, and the density increases for a shorter time.

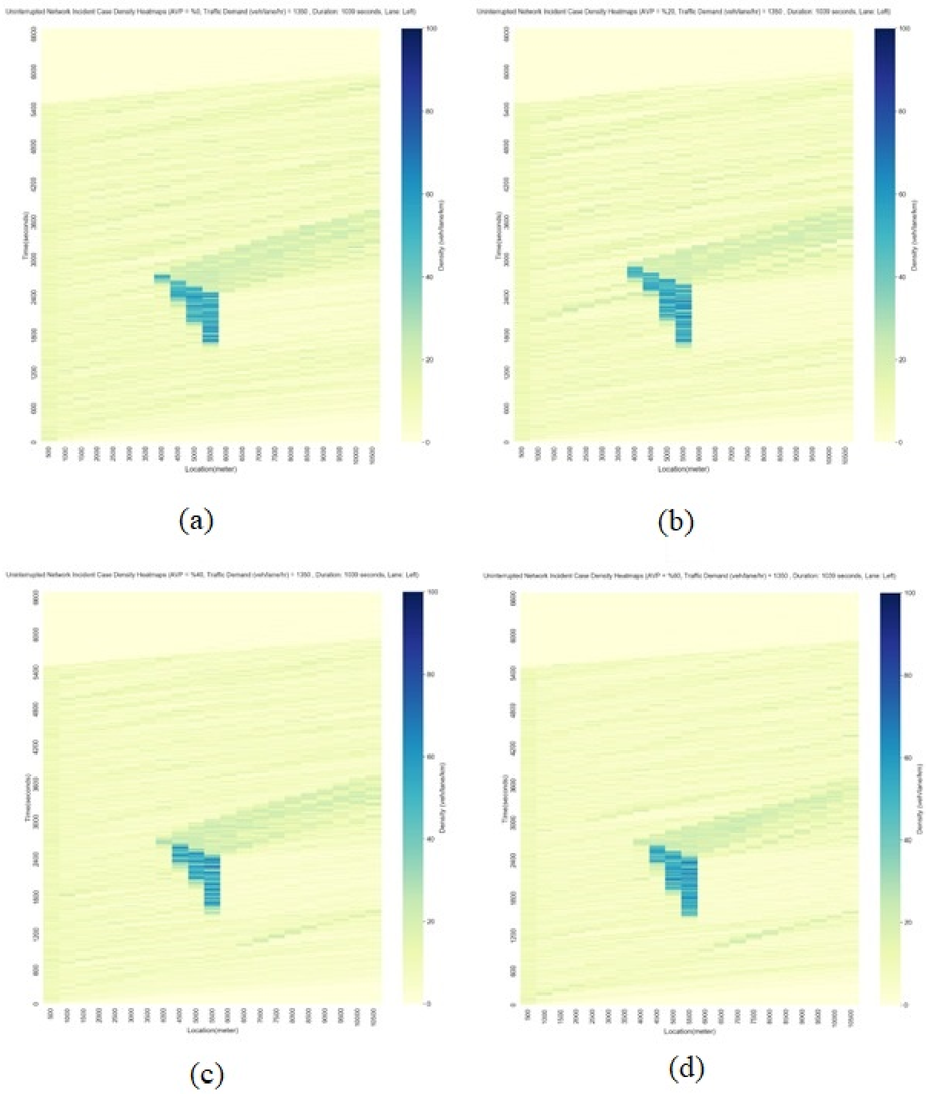


Figure 4.23. (a) 0% AVP, (b) 20% AVP, (c) 40% AVP, (d) 60% AVP density heatmap of middle lane incident scenarios of medium duration (1039 seconds) in the uninterrupted road network.

The heat maps showing the location and time-dependent density changes obtained with a long duration (1485 seconds) incident are given in Figure 4.24 for 4 different autonomous vehicle percentage value scenarios. It is observed that the density and shock wavelength due to the length of the incident duration are longer than the short and medium-duration incident scenarios. In case long incident, the increase in the density change depending on the percentage of autonomous vehicles becomes clearer, and the shortest shock wavelength occurred in the scenario with a 60% AVP.

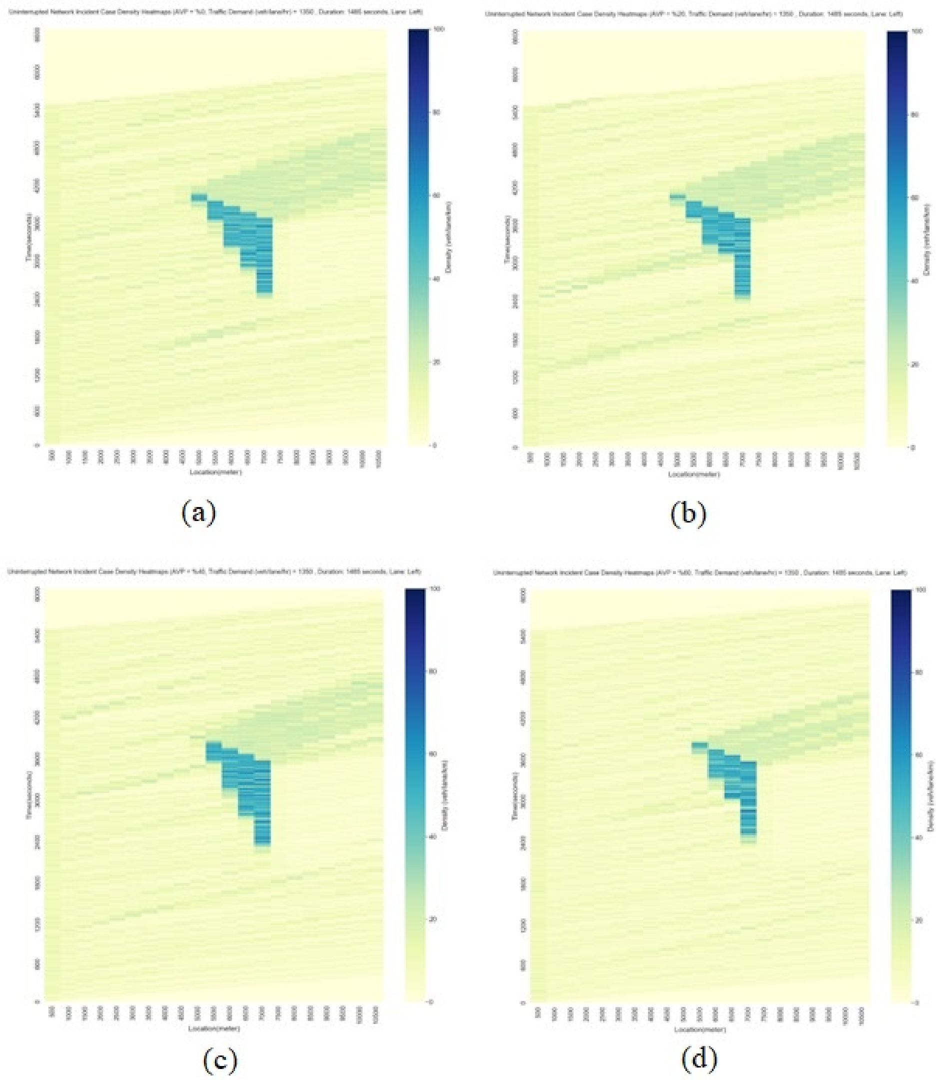


Figure 4.24. (a) 0% AVP, (b) 20% AVP, (c) 40% AVP, (d) 60% AVP density heatmap of middle lane incident scenarios of long duration (1485 seconds) in the uninterrupted road network.

The average density, average speed, and average flow changes with the long-term (1485 seconds) middle lane incident in the uninterrupted road network are shown in Table 4.8. The obtained changes were taken from the sensor located in position 1 before the location where the incident occurred. When the data obtained are examined, it is observed that the lowest density situation occurs when the percentage of autonomous vehicles is 100%, and the density change in percentage is realized in the scenario with the highest percentage of autonomous vehicles of 50%. It was determined that the average speed value increased as the percentage of autonomous vehicles increased, and the highest average flow value occurred in the scenario with a 60% autonomous vehicle percentage.

Table 4.8. Traffic parameters of the long-term (1485 seconds) middle lane incident scenario in the uninterrupted road network, collected from sensor 1 before the incident location and classified according to the percentage of autonomous vehicles.

Autonomous Percentage (%)	Avg. Density(Vehicle / km)	Change in Density (%)	Avg. Speed (km/hr)	Change in Speed (%)	Avg. Flow (Vehicle/Hour)	Change in Flow (%)
0	35.21		24.79		1725.47	
10	34.91	-0.84	26.23	5.81	1783.58	3.37
20	34.45	-2.16	26.63	7.41	1774.32	2.83
30	34.06	-3.26	27.08	9.26	1744.84	1.12
40	32.24	-8.43	32.09	29.46	1727.16	0.1
50	29.37	-16.6	36.76	48.3	1694.32	-1.81
60	33.7	-4.3	31.51	27.1	1821.47	5.56
70	32.13	-8.75	34.57	39.47	1759.16	1.95
80	33.14	-5.88	36.53	47.36	1787.79	3.61
90	31.92	-9.35	37.21	50.1	1803.61	4.53
100	30.27	-14.03	39.67	60.03	1795.26	4.04

The density, speed, and flow changes that occurred with the incident in the middle lane with a duration of 1425 seconds are given for each autonomous vehicle percentage in Table 4.9, with the data obtained from the sensor located 1 before the location where the incident occurred. When the results are examined, it can be observed that the density value tends to decrease in general as the percentage of autonomous vehicles increases. Depending on the density change, it has been determined that the average speed value is obtained in the scenario where the percentage of autonomous vehicles is at most 90%. As the percentage of autonomous vehicles decreases, the average speed values generally decrease due to the increase in density. When the average flow values were examined, it was determined that the highest flow value was obtained in the case of 100% autonomous vehicle percentage.

Table 4.9. Traffic parameters of the long-term (1425 seconds) middle lane incident scenario in the uninterrupted road network, collected from sensor 1 before the incident location and classified according to the percentage of autonomous vehicles.

Autonomous Percentage (%)	Avg. Density(Vehicle / km)	Change in Density (%)	Avg. Speed (km/hr)	Change in Speed (%)	Avg. Flow (Vehicle/Hour)	Change in Flow (%)
0	33.41		18.30		1679	
10	37.69	12.82	15.50	-15.28	1762	4.94
20	32.09	-3.93	23.66	29.27	1711	1.91
30	35.00	4.78	19.46	6.33	1739	3.57
40	33.74	1.01	20.10	9.84	1717	2.26
50	28.46	-14.80	30.21	65.06	1669	-0.60
60	33.24	-0.51	24.51	33.92	1769	5.36
70	25.37	-24.06	39.78	117.37	1657	-1.31
80	24.36	-27.09	45.55	148.89	1681	0.12
90	25.07	-24.95	47.90	161.75	1710	1.85
100	29.08	-12.96	41.52	126.90	1850	10.18

4.2.1. Performance Comparison of SND and California Algorithm based on Incident Duration, Incident Lane, and AVP

3 different performance criteria measurements are used in this thesis. These;

- Detection Rate (DR): The incident detection rate is calculated as a percentage by dividing the number of incidents detected by the applied model by the total number of incidents in the simulation environment. This performance measure gives information about the effectiveness of the applied model.
- False Alarm Rate (FAR): The false alarm rate is calculated as a percentage by dividing the number of false incident detections of the applied model by the total number of incident detections. This criterion also gives information about the

effectiveness of the applied model.

- Mean Time to Detect (MTTD): Mean time to detect gives the mean time, in seconds, from the moment of the incident to the moment of detection. Unlike the others, this performance measure gives information about the efficiency of the model applied [103].

The integration of SND and California incident detection algorithms into the simulation environment will be discussed in the following sections. The results given in this section are obtained by applying algorithms to the data obtained with simulation studies, rather than the data obtained with the integration of incident detection algorithms into the simulation environment. The benefit of drawing and analyzing these results is to have an idea about the performance of the applied algorithms.

The results obtained when the SND and California incident detection algorithms are applied to the results of the simulation studies on the uninterrupted road network are available in Table 4.10.

Table 4.10. The result of the incident detection algorithms applied to the results of the simulation studies on the uninterrupted road network.

	DR	FAR	MTTD
SND	136.69%	26.84%	193.95
California	53.59%	12.77%	241.95

The fact that the detection rate (DR) performance criterion is close to 100% indicates that the applied incident detection algorithm works with a high accuracy rate because as this rate approaches 100%, the number of incidents detected by the applied algorithm and the number of incidents get closer to each other. As seen in Table 4.10, the SND algorithm has the closest detection rate to 100%. The smaller the false alarm rate (FAR), the better the result, because as this rate decreases, it can be concluded that the number of false detections decreases. When Table 4.10 is examined, it is seen that the California algorithm has the lowest false alarm rate;

however, the detection rate of the California algorithm has the largest deviation from 100% compared to the other algorithm. The lower the mean time to detect (MTTD), the shorter the incident detection takes. The SND algorithm gave the best results in this performance measure.

The results given in Table 4.10 are the results of applying the incident detection algorithms to the whole data set and do not show to what extent different variables have an impact on the performance of the incident detection algorithms. Table 4.11 shows the change in the performance of the incident detection algorithms according to the percentage of autonomous vehicles, the duration of the incident, and the incident lane. When Table 4.11 is examined, it is seen that the detection rate (DR) performance criterion in short-term incidents in the uninterrupted road network in the SND algorithm shows the greatest deviation from 100%. In the California algorithm, long-term incidents show the largest deviation. In both algorithms, false alarm rate (FAR) and mean time to detect (MTTD) reached the highest level in long-term incidents. While the California algorithm gave better results in false alarm rates, in short, medium, and long-term incidents, the SND algorithm gave better results in the mean time to detect. The detection rate, on the other hand, gave better results with the California algorithm in short and medium-duration incidents, while it gave better results with the SND algorithm in long-duration incidents.

Table 4.11. The performances of incident detection algorithms in different incident duration and uninterrupted road network.

		DR	FAR	Change in FAR (%)	MTTD	Change in MTTD (%)
SND	Short Duration Incident	152.79%	20.58%		149.99	
	Medium Duration Incident	142.79%	25.22%	22.52%	183.73	22.49%
	Long Duration Incident	124.34%	35.50%	72.48%	240.81	60.55%
California	Short Duration Incident	64.72%	20.00%		188.09	
	Medium Duration Incident	66.84%	17.81%	-10.96%	201.94	32.97%
	Long Duration Incident	59.14%	26.65%	33.22%	268.52	32.97%

Table 4.12 shows how the SND and California incident detection algorithms perform according to different incident lanes in the uninterrupted road network. It has been observed that middle lane incidents have a deviation greater than 100% in the detection rate (DR) performance criterion in both algorithms. Likewise, when the false alarm rate (FAR) is analyzed, the highest rates are again found in the middle lane incidents. Mean time to detect (MTTD) is highest in mid-lane crashes compared to other incident lanes. While the SND algorithm gave better results in all lanes at the MTTD value, the California algorithm gave good results in all lanes at a false alarm rate. In the detection rate, the California algorithm gave better results in the middle and left lanes, while the SND algorithm gave better results in the right lane.

Table 4.12. The performances of incident detection algorithms in different incident lanes and uninterrupted road network.

		DR	FAR	Change in FAR (%)	MTTD	Change in MTTD (%)
SND	Right Lane Incident	120.78%	13.18%		117.20	
	Middle Lane Incident	204.76%	42.81%	224.84%	204.18	74.22%
	Left Lane Incident	139.71%	31.69%	140.44%	154.08	31.47%
California	Right Lane Incident	64.75%	9.20%		214.26	
	Middle Lane Incident	47.79%	25.47%	176.90%	248.87	16.15%
	Left Lane Incident	67.10%	15.52%	68.75%	235.34	9.84%

In Table 4.13, the performance of the incident detection algorithms according to the changing percentage of autonomous vehicles in the uninterrupted road network is given. When Table 13 is examined, it is observed that the detection rate (DR), false alarm rate (FAR) and mean time to detect (MTTD) performance criteria deteriorate up to 30% autonomous vehicle percentage. However, while the percentage of autonomous vehicles increases from 30% to 100%, there are improvements in DR, FAR, and MTTD performance criteria. When a general examination is made, it is seen that all performance measures give better results when the percentage of autonomous vehicles is 50% or more. While the SND algorithm gives better results for all autonomous percentages in the detection rate and mean time to detect, the California algorithm shows the best performance in the FAR performance measure.

Table 4.13. The performances of incident detection algorithms according to autonomous vehicle percentages in the uninterrupted road network.

		DR	FAR	Change in FAR (%)	MTTD	Change in MTTD (%)
SND	%0 AVP	133.62%	24.88%		200.10	
	%10 AVP	134.85%	24.19%	-2.77%	210.14	5.02%
	%20 AVP	135.61%	23.75%	-4.54%	205.28	2.59%
	%30 AVP	134.96%	24.13%	-3.02%	204.55	2.22%
	%40 AVP	132.14%	25.71%	3.32%	198.76	-0.67%
	%50 AVP	135.12%	24.10%	-3.13%	196.39	-1.85%
	%60 AVP	135.48%	23.83%	-4.21%	193.57	-3.26%
	%70 AVP	131.42%	26.11%	4.94%	193.90	-3.10%
	%80 AVP	132.48%	25.50%	2.48%	194.38	-2.86%
	%90 AVP	133.02%	25.19%	1.23%	195.41	-2.34%
	%100 AVP	130.84%	26.44%	6.25%	191.78	-4.16%
California	%0 AVP	48.95%	14.22%		247.07	
	%10 AVP	45.18%	16.90%	18.84%	248.93	0.76%
	%20 AVP	46.60%	15.85%	11.45%	248.32	0.51%
	%30 AVP	45.86%	16.38%	15.23%	247.28	0.09%
	%40 AVP	46.43%	15.98%	12.40%	246.11	-0.39%
	%50 AVP	48.61%	14.42%	1.41%	245.28	-0.72%
	%60 AVP	49.66%	13.59%	-4.41%	244.86	-0.89%
	%70 AVP	50.43%	13.15%	-7.53%	245.77	-0.53%
	%80 AVP	53.94%	10.78%	-24.20%	245.86	-0.49%
	%90 AVP	54.27%	10.57%	-25.67%	247.67	0.25%
	%100 AVP	53.29%	11.16%	-21.53%	246.54	-0.21%

Figure 4.25 are obtained by plotting the density data obtained with simulation studies on the uninterrupted road network against time. To observe the performance of the incident detection algorithms, the data obtained within the simulation studies were given as input to the incident detection models and how they reacted to the data in hand was examined. Therefore, the results obtained in the given Figures that show how they respond to the data at hand and their performance is observed, rather than the results obtained during the real-time simulation. Integration of incident detection algorithms into the simulation environment were done in the subsection 4.2.2.

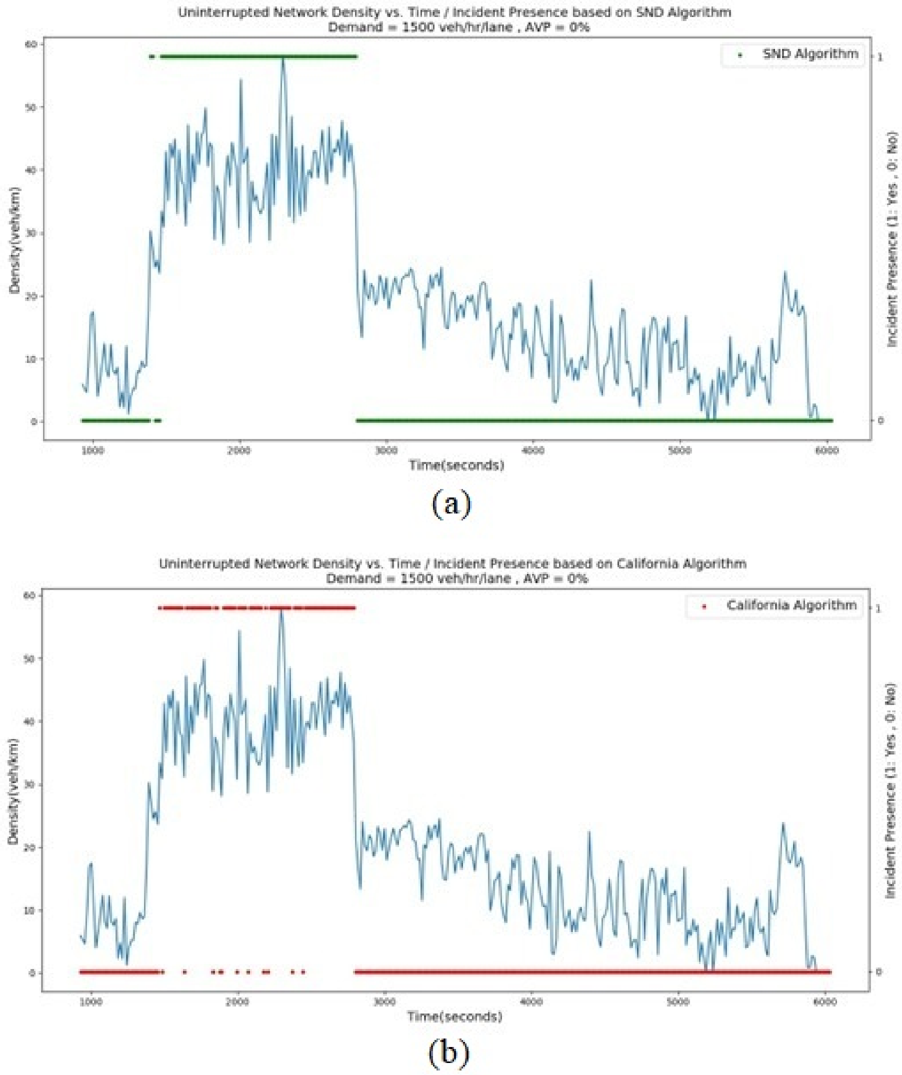


Figure 4.25. (a) SND, (b) California incident detection algorithms performance according to left lane incident scenario based on long duration (1425 seconds) in uninterrupted road network.

Density, speed, and flow data obtained with simulation studies are kept for each data processing frequency (15 seconds). Figure 4.25 was obtained by inputting the data kept at each data processing frequency into the incident detection algorithms. That is, the presence of an incident is checked every 15 seconds. In this way, the performance of the algorithms was measured. In Figure 4.25, the traffic demand given to the road network is 1500 vehicles/hour/lane and it can be seen how the incident detection algorithms perform in this traffic demand in the long-term (1425 seconds) left lane incident scenario in the uninterrupted road network. In the scenario used for Figure 4.25, there is no autonomous vehicle in the road network. When Figure 4.25 is examined, it is seen that the California algorithm gives the output of no incident even though there is an incident during the incident period. In the other algorithm, this only happened for a short time at the start of the incident.

In Figure 4.26, the traffic demand given to the road network is 1500 vehicles/hour/lane, and it can be seen how the incident detection algorithms perform in the long-term (1440 seconds) middle lane incident scenario in the uninterrupted road network in this traffic demand. In the scenario used for Figure 4.26, there is no autonomous vehicle in the road network. When Figure 4.26 is examined, it is observed that the California algorithm gives the signal of no incident even though there is an incident for a short time at the beginning of the incident. On the other hand, it was observed that the SND algorithm gave the signal that there was an incident even though there was no incident at a point after the incident period.

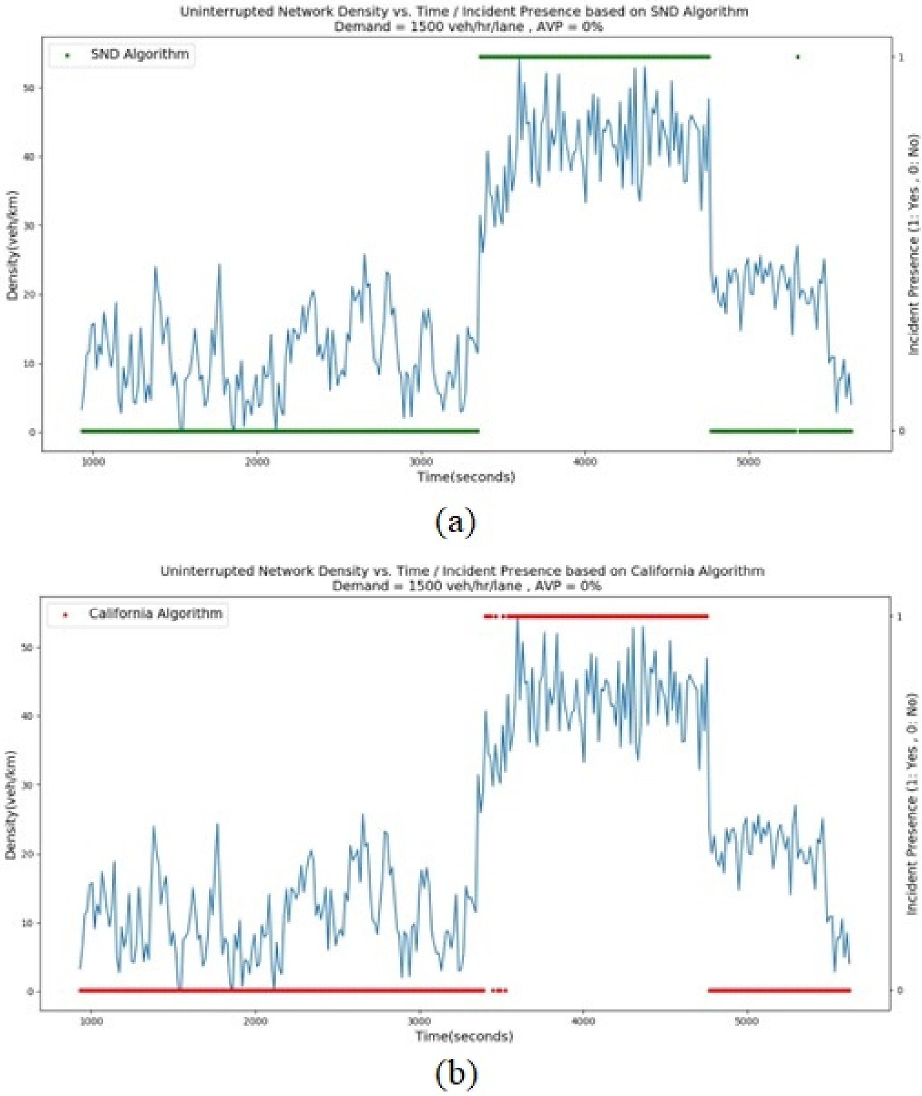


Figure 4.26. (a) SND, (b) California incident detection algorithms performance according to middle lane incident scenario based on long duration (1440 seconds) in uninterrupted road network.

The traffic demand given to the road network as given in Figure 4.27 is 1500 vehicles/hour/lane, and it can be seen how the incident detection algorithms perform in this traffic demand in the long-term (1395 seconds) right lane incident scenario in the uninterrupted road network. In the scenario used for Figure 4.27, there is no autonomous vehicle in the road network. When Figure 4.27 is examined, it is seen that the California algorithm gave the signal of no incident even though there was an incident for a short time at the beginning of the incident, while the SND algorithm made the same error at only one point. In addition, it has been observed that the California algorithm gives the signal of no incident when there is an incident at the midpoint of the incident process.

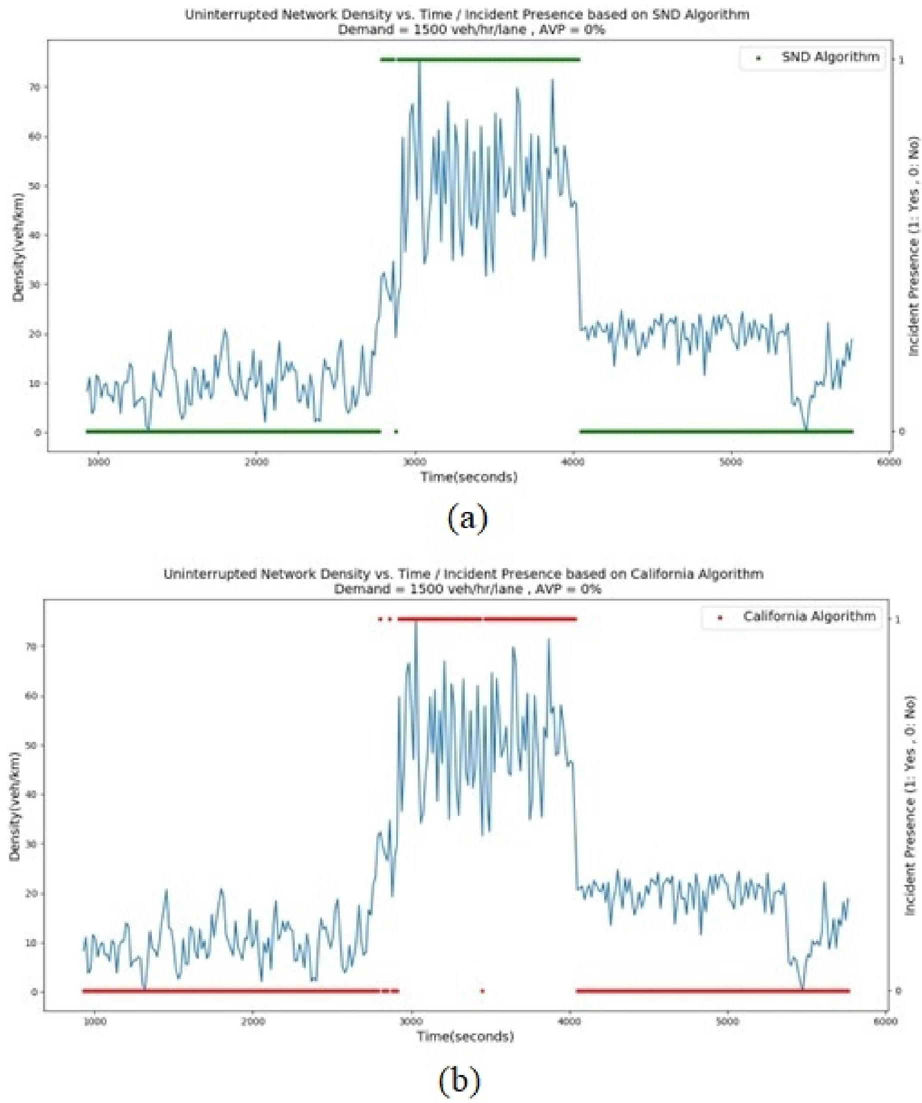
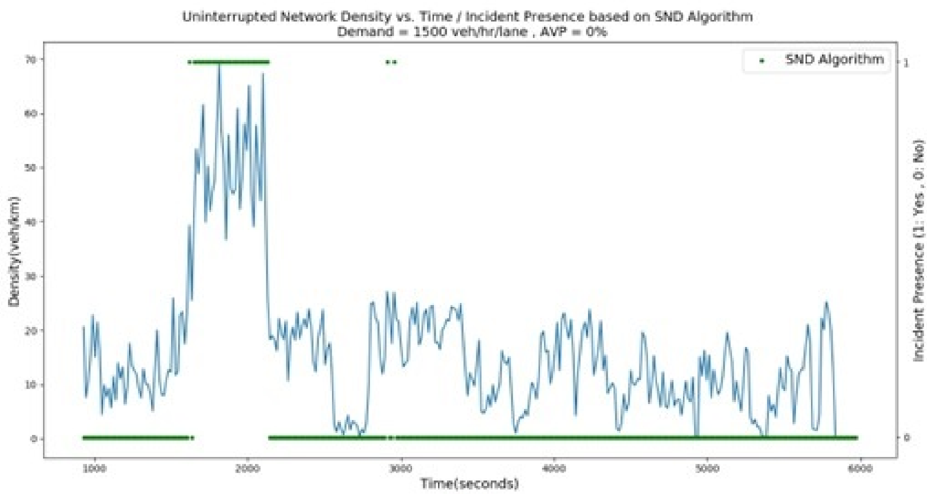
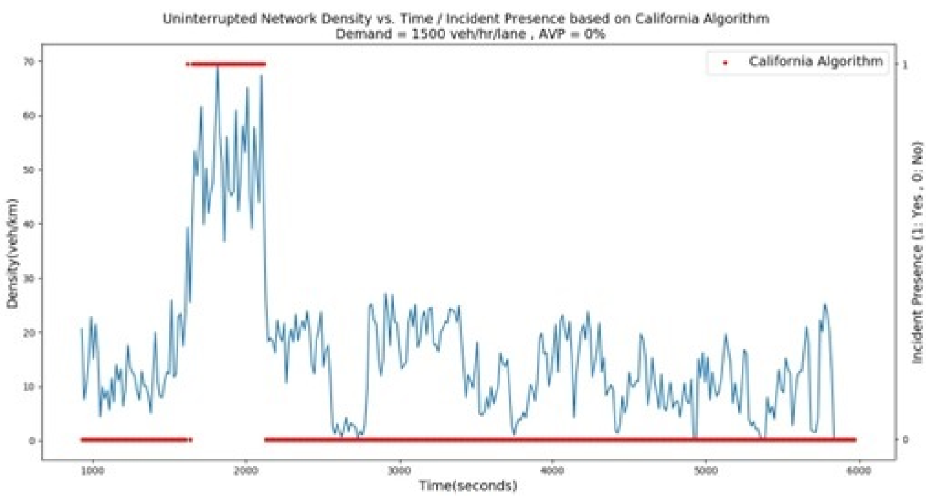


Figure 4.27. (a) SND, (b) California incident detection algorithms performance according to right lane incident scenario based on long duration (1395 seconds) in uninterrupted road network.

In Figure 4.28, the traffic demand given to the road network is 1500 vehicles/hour/lane and it can be seen how the incident detection algorithms perform in this traffic demand in the short-term (660 seconds) middle lane incident scenario in the uninterrupted road network. In the scenario used for Figure 4.28, there is no autonomous vehicle in the road network. When Figure 4.28 is examined, it is observed that the SND algorithm gives an incident signal 2 times in the absence of an incident.



(a)



(b)

Figure 4.28. (a) SND, (b) California incident detection algorithms performance according to middle lane incident scenario based on short duration (660 seconds) in uninterrupted road network.

In Figure 4.29, the traffic demand given to the road network is 1500 vehicles/hour/lane and it can be seen how the incident detection algorithms perform in this traffic demand in the middle lane incident scenario of medium duration (1025 seconds) in the uninterrupted road network. In the scenario used for Figure 4.29, there is no autonomous vehicle in the road network. When Figure 4.29 is examined, it has been observed that the SND algorithm gives an incident signal once in the period when there is no incident.

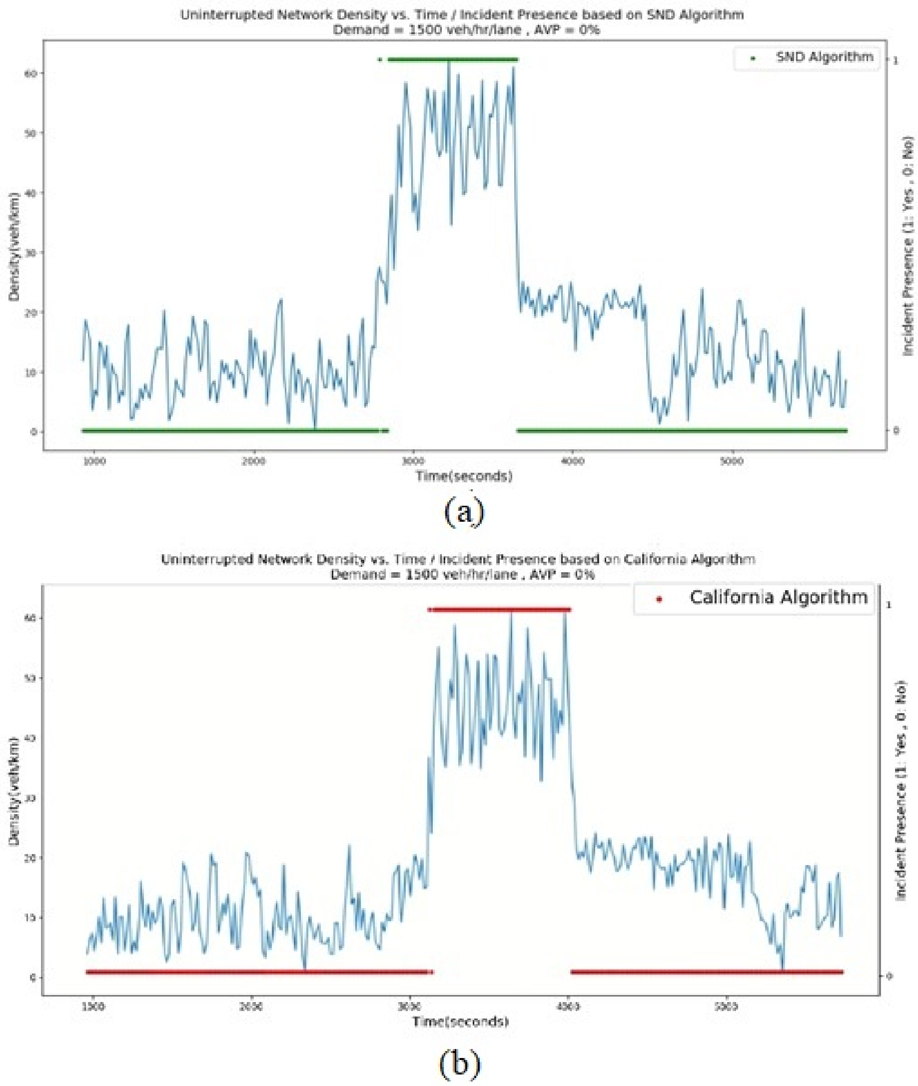
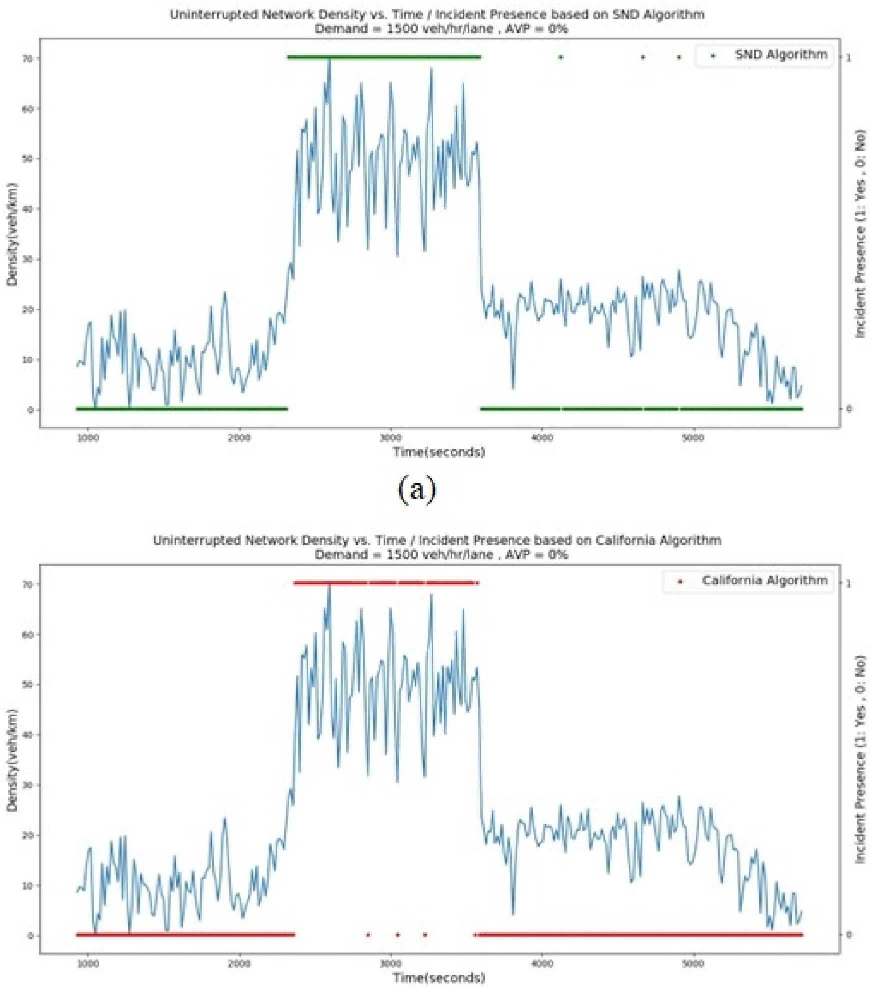


Figure 4.29. (a) SND, (b) California incident detection algorithms performance according to middle lane incident scenario based on medium duration (1025 seconds) in uninterrupted road network.

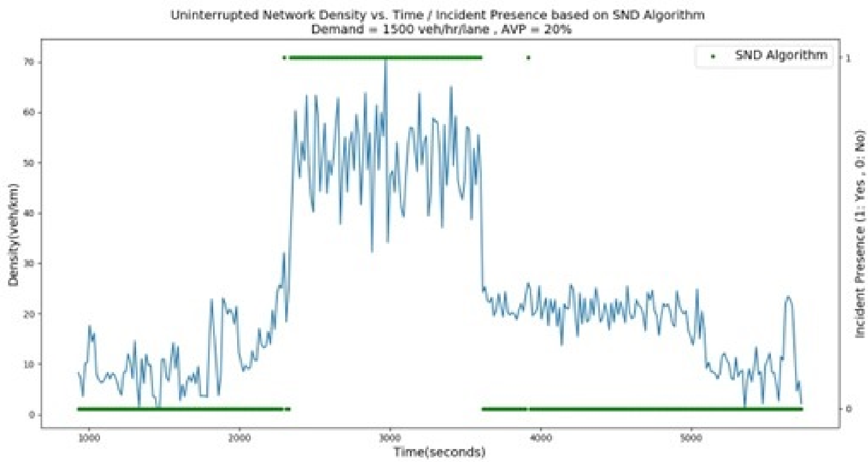
In Figure 4.30, the traffic demand given to the road network is 1500 vehicles/hour/lane, and it can be seen how the incident detection algorithms perform in the long-term (1485 seconds) middle lane incident scenario in the uninterrupted road network in this traffic demand. In the scenario used for Figure 4.30, there is no autonomous vehicle in the road network. When Figure 4.30 is examined, it is observed that the SND algorithm gives an incident signal 3 times in the absence of an incident. It has been observed that the California algorithm gives the signal of no incident 3 times during the time of the incident.



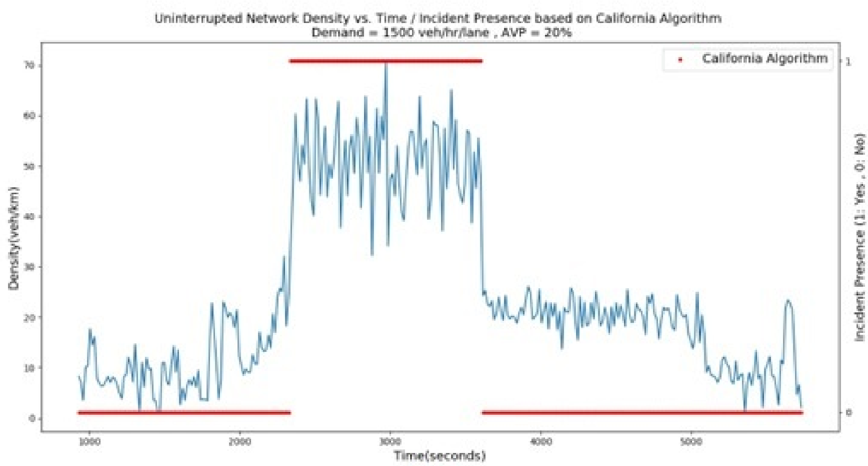
(b)

Figure 4.30. (a) SND, (b) California incident detection algorithms performance according to middle lane incident scenario based on long duration (1485 seconds) in uninterrupted road network.

In Figure 4.31, the traffic demand given to the road network is 1500 vehicles/hour/lane, and it can be seen how the incident detection algorithms perform in the long-term (1485 seconds) middle lane incident scenario in the uninterrupted road network in this traffic demand. In the scenario used for Figure 4.31, the percentage of autonomous vehicles is 20%. When Figure 4.31 is examined, it is seen that the SND algorithm gives a no incident signal for a short time at the beginning of the incident. In addition, it has been observed that the SND algorithm gives an incident signal once in the process where there is no incident.



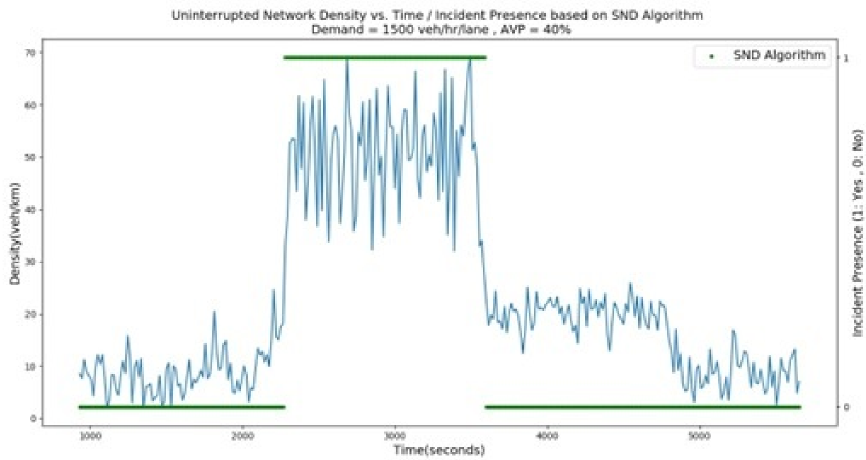
(a)



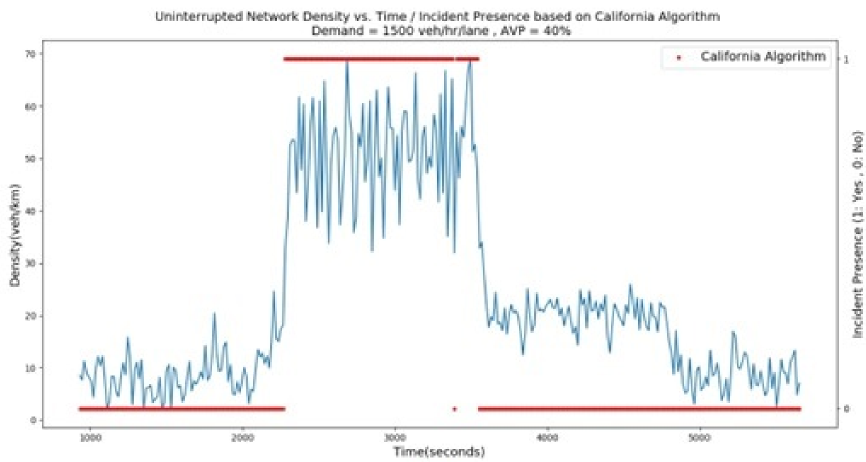
(b)

Figure 4.31. (a) SND, (b) California incident detection algorithms performance according to middle lane incident scenario based on long duration (1485 seconds) and 20% AVP in uninterrupted road network.

In Figure 4.32, the traffic demand given to the road network is 1500 vehicles/hour/lane, and it can be seen how the incident detection algorithms perform in the long-term (1485 seconds) middle lane incident scenario in the uninterrupted road network in this traffic demand. In the scenario used for Figure 4.32, the percentage of autonomous vehicles is 40%. When Figure 4.32 is examined, it is seen that the incident detection algorithms perform closely. It has been observed that only the California algorithm gives a no-incident signal once in the process of the incident.



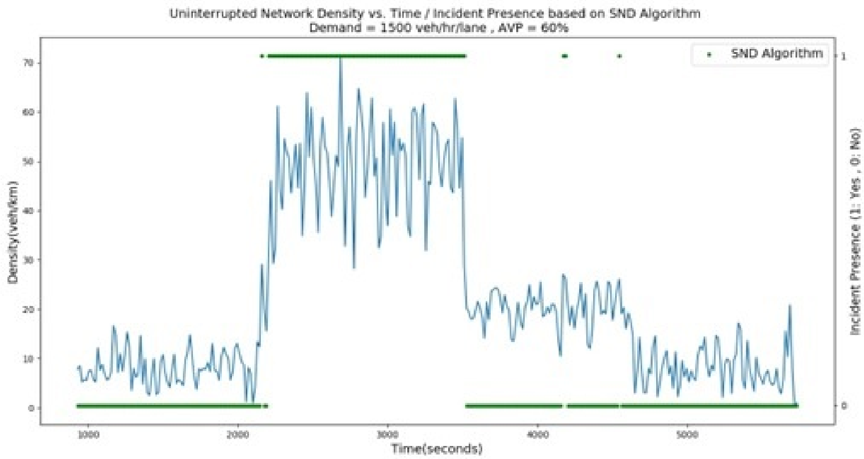
(a)



(b)

Figure 4.32. (a) SND, (b) California incident detection algorithms performance according to middle lane incident scenario based on long duration (1485 seconds) and 40% AVP in uninterrupted road network.

In Figure 4.33, the traffic demand given to the road network is 1500 vehicles/hour/lane, and it can be seen how the incident detection algorithms perform in the long-term (1485 seconds) middle lane incident scenario in the uninterrupted road network in this traffic demand. In the scenario used for Figure 4.33, the percentage of autonomous vehicles is 60%. When Figure 4.33 is examined, it has been observed that the California algorithm gives the signal of no incident twice in the process of the incident. It has been observed that the SND algorithm gives the signal that there is an incident 3 times in the time when there is no incident.



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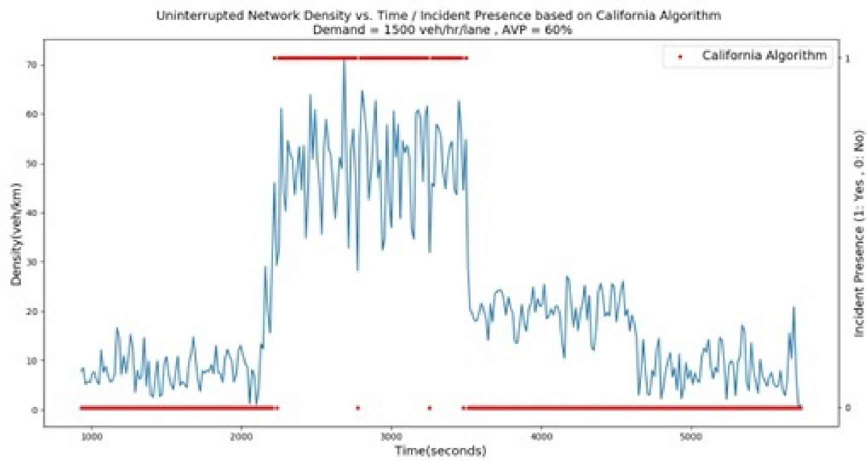


(b)

Figure 4.33. (a) SND, (b) California incident detection algorithms performance according to middle lane incident scenario based on long duration (1485 seconds) and 60% AVP in uninterrupted road network.

4.2.2. Simulation Integration

Combinations of incident detection algorithms and traffic management methods described in the previous sections have been integrated into the SUMO Traffic Simulation Program environment. During the integration studies, a separate model was created for each combination of incident detection and traffic management algorithms.

Combinations of incident detection algorithms and traffic management systems integrated into the simulation environment are available.

- SND and LCS
- SND and VSL
- California Algorithm and LCS
- California Algorithm and VSL

For the integration studies carried out, first of all, systems that will provide input to incident detection and traffic management algorithms should be established. The systems installed in this direction are explained in detail.

VSL traffic management method works by using the electronic traffic sign, which is as far as the control distance from the incident location. LCS traffic management method works with the use of two electronic traffic signs. The first of these signs is located at the sensor location before the incident location. The second is located as far back as the control distance from the first electronic sign. For this reason, one of the inputs to be given to VSL and LCS traffic management algorithms is the incident location, and an incident location detection system has been established to accurately detect this location.

The incident location detection system is a system integrated with incident detection algorithms. incident detection algorithms work by inputting traffic parameter data collected separately for each sensor in the last 15 seconds of every minute to the system. All incident detection algorithms used in this study perform an incident presence check for each sensor. If an incident presence signal is received from any sensor, this sensor is determined as the incident location. If the incident detection algorithm detects an incident in 2 or more consecutive sensors, the sensor position that is farthest in the direction of traffic flow is taken as the incident location.

In Figure 4.34, the incident detection algorithm gives an incident signal in 2 sensors. The incident occurring on the road network is represented by the blue block. The sensor that gives the signal that there is an incident in the farthest direction in the traffic flow direction is detected and determined as the incident location.

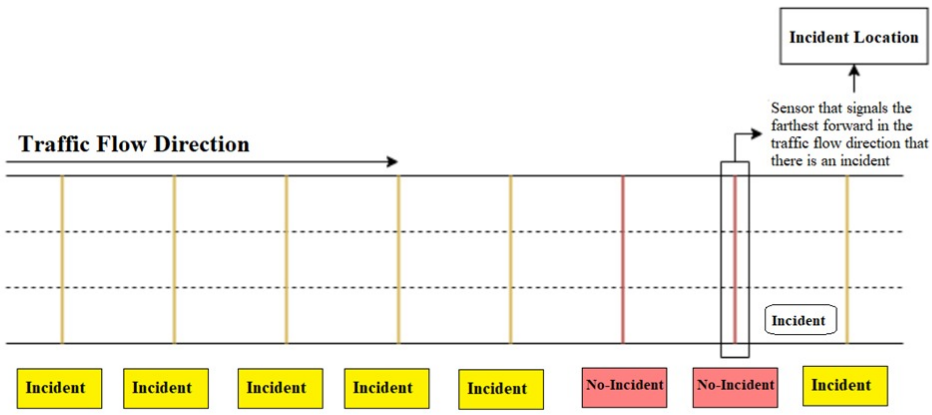


Figure 4.34. Incident Location Detection System.

While incident detection and traffic management methods are integrated into the simulation environment, an environmental data storage system is established to detect the environmental effects of the systems created. The environmental data collected are CO2, CO, PMX, NOX, and HC emissions. To collect these data, first of all, empty lists are defined. The lists defined by square brackets below are the lists where the release data are collected. The square brackets are empty, indicating that the lists are empty.

- CO2-Emission = [ ]
- CO-Emission = [ ]

- HC-Emission = [ ]
- NOX-Emission = [ ]
- PMX-Emission = [ ]

The data processing frequency in the simulations made within the study is 15 seconds. A list of vehicles on the road network is created every 15 seconds. Emission data for each vehicle is collected separately. The emission data collected gives the emissions per second. At the end of every 15 seconds, the sum of the second oscillation data collected for 15 seconds is added to the lists. Thus, until the last step of the simulation study, 15 seconds of oscillation data are collected in lists. When the simulation study is completed, these data are collected in a single dataset and obtained as output. Briefly, CO2, CO, HC, PMX, and NOX data are obtained for each 15-second interval of the simulation run.

The overall simulation and data flow that occurs when simulating each combination of incident detection and traffic management methods are the same. Although the systems used and the inputs to the algorithms are different, the simulation flow is the same. There is a general simulation flow in the image given in Figure 4.35.

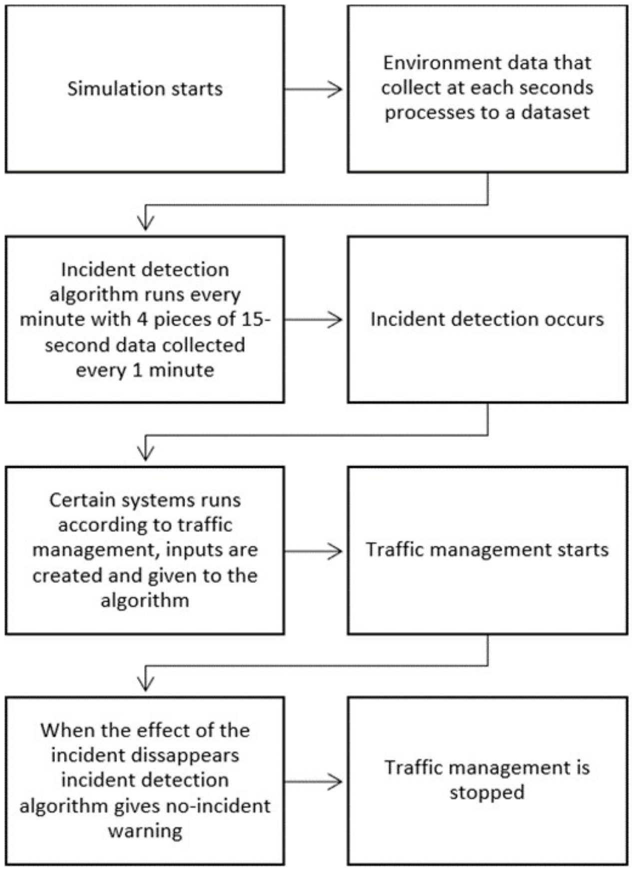


Figure 4.35. General Simulation Flowchart.

During the integration of the created models into the simulation environment, the part that distinguishes these models from each other is that the incident detection and traffic management algorithms are different from each other. Therefore, the inputs needed by the systems and algorithms used to start working vary for the integration of each combination into the simulation environment. In the next chapter, the modeling of all incident detection and traffic management methods in the simulation environment is explained. In this way, the elements that make up the differences apart from the general simulation flow will be seen.

- When the SND algorithm is modeled together with VSL and LCS traffic management methods and integrated into the simulation environment, it uses real-time density data collected from the sensors as input. If the simulation is done on an uninterrupted road network, 21 average density values collected in the last

15 seconds of every 1 minute from 21 sensors in the road network are given as input to the SND Equation given in Equation 3.1. If the simulation is done on a participatory road network, 41 average intensity values collected from 41 sensors in the last 15 seconds of every 1 minute.

- When the SND algorithm is modeled with VSL and LCS traffic management methods, it gives an incident location as output. To give this output, an incident location detection system is established.
- The California algorithm uses real-time density data collected from sensors as input when it is integrated into the simulation environment by modeling it together with VSL and LCS traffic management methods. If the simulation is done on an uninterrupted road network, 21 average intensity values collected in the last 15 seconds of every 1 minute from 21 sensors in the road network are given as input to the California algorithm. If the simulation is done on a participatory road network, 41 average intensity values collected from 41 sensors in the last 15 seconds of every 1 minute.
- When the California algorithm is modeled with VSL and LCS traffic management methods, it gives an incident location as output. To give this output, an incident location detection system is established.
- The VSL traffic management method is activated 300 seconds after the incident detection and takes the incident status as input. The target speed is 50 km/h on the electronic traffic sign placed 1000 meters back from the detected incident location. Autonomous vehicles adapt to the target speed reflected on the sign at a rate of 100%, while vehicles with a driver adapt at a rate of 50%. The VSL traffic management method stops working 300 seconds after the incident detection algorithm gives the no incident signal.
- The LCS traffic management method is activated 300 seconds after the incident detection and takes the incident status as input. Traffic management is carried out with 2 electronic traffic signs within the scope of the LCS method. The electronic traffic sign near the incident area is located at the sensor location before the incident area. The remote electronic traffic sign is placed as far back as the control distance from the nearby sign. The control distance used in simulation

studies is 1500 meters. Autonomous vehicles comply with both LCS at the rate of 100%, while vehicles with drivers comply with the LCS close to the incident area at a rate of 80%, and to the distant LCS at a rate of 70%. 300 seconds after the incident detection algorithm gives the no-incident signal, the LCS traffic management method stops working.

- In this thesis, the outputs obtained from the simulation studies on the uninterrupted road network are given. CO2 (Carbon Dioxide) results by comparing the algorithm, demand, and autonomous percentage, and CO (Carbon monoxide), HC (Hydrocarbon), NOx (Nitrogen oxides), and PMx (Particulate substances) algorithm comparisons are also given. The randomness principle was taken as a basis under each title and the results of each title were simulated on different seeds. In the SUMO simulation program, since autonomous vehicles do not directly cause carbon dioxide emissions, CO2 emissions caused by the amount of electricity they consume are converted according to European standards, and CO2 emissions are obtained [104].

In Table 4.14, the conversion coefficients of CO2 emissions in electricity production in European countries are given in mg CO2/Wh. In addition, the total number of vehicles in each country is given in the 'Total Vehicles' column. These countries are clustered among themselves based on their conversion coefficients. The determination of the boundaries of the clusters was decided based on the breaks in the transformation coefficients. In total, 4 clusters were determined, of which Cluster IV consists only of Turkey. The reason for this is that the analyzes in the research are requested to be carried out only through Turkey. Weighted conversion coefficients were determined based on the total tool for the conversion factor of each cluster. The weighted average of 79.5 mg CO2/Wh in Cluster I is 271, 549, and 621 in Cluster II, Cluster III, and Cluster IV, respectively. Since autonomous vehicles work with electricity, the amount of electricity consumed by each vehicle during the simulation is kept as Watt. hour/second. To evaluate the environmental consequences, the electricity consumption of each autonomous vehicle must be converted to CO2. Using the electricity-CO2 conversion coefficients of the clusters in Table 4.14, results were obtained for all 4 clusters.

Table 4.14. CO_2 Emissions in Electricity Production of European Countries [105,106].

CLUSTERS	Country	mg CO2 per Wh	Total vehicles	Weighted Avg.
CLUSTER-I	Sweden	13	4887116	79.5
	Lithuania	18	1498688	
	France	59	32416180	
	Austria	85	4978852	
	Latvia	105	727164	
	Finland	113	4368796	
	Slovakia	132	2393577	
	Denmark	166	2651726	
	Belgium	170	5889210	
CLUSTER-II	Croatia	210	1724900	271
	Luxembourg	219	426346	
	Slovenia	254	1165371	
	Italy	256	39545232	
	Hungary	260	3812013	
	Spain	265	24558126	
	United Kingdom	281	31517597	
	Romania	306	8897377	
	Portugal	325	5452119	
CLUSTER-III	Ireland	425	2253210	549
	Germany	441	47715977	
	Bulgaria	470	2829946	
	Netherlands	505	8677911	
	Czechia	513	5924995	
	Greece	623	5406451	
	Malta	648	307130	
	Cyprus	677	572501	
	Poland	773	24360166	
	Estonia	819	978022	
CLUSTER-IV	Turkey	621	25594663	621

Table 4.15 shows how many million metric tons of CO_2 emissions are caused by generating 1 million kWh of electricity from non-renewable energy sources. Table 4.16

shows the role of energy resources in electricity generation in Turkey.

Table 4.15. CO_2 Emissions from Non-Renewable Energy Sources in Electricity Generation [107].

	Electricity Generation (million kWh)	CO_2 Emissions (million metric tons)	CO_2 Emission at 1 million kWh (million metric tons)
Coal	757763	767	0.00101219
Natural Gas	1402438	576	0.000410713
Petroleum	13665	13	0.000951336

Table 4.16. Distribution of Energy Sources of Electricity Produced per Terawatt Hour in Turkey [108].

	Electricity Generated in Terawatt Hours in Turkey (TWh)	Energy Distribution Percentage (%)
Coal	70	23.03%
Natural Gas	106.1	34.90%
Petroleum	78.1	25.69%
Renewables	49.8	16.38%

Algorithm comparisons are given in Figure 4.36. The research was conducted with a 50% autonomous vehicle percentage and 1350 vehicles/hour/lane. The y-axis of the graph represents CO_2 emissions (milligrams/second), while the x-axis represents time (seconds). The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. There are only incidents in the algorithms, they represent LCS-SND, VSL-SND, LCS-CAL, and LCS-SND scenarios. Among them, SND and CAL are incident detection algorithms, and LCS and VSL are real-time traffic management methods. For these algorithms to work in harmony with each other, the analysis was carried out on 4 different combinations, and these 4 combinations were compared with the incident exist algorithm, which does not have any real-time traffic management methods and incident detection algorithms. Each analysis was also performed for the CO2-Electric coefficients of 79.5, 271, 549, and 621 mg/Wh. It is seen that the scenario with only an incident in low CO2-Electric coefficients causes high CO2 emissions, while scenarios with high CO2-Electricity coefficients lose their superiority over the only incident scenario. The reason for this is that low CO2-Electricity coefficients lead to less direct and indirect CO2 emissions since energy sources are provided by renewable energy sources. When an incident occurred in all CO2-Electricity coefficients, the LCS-CAL scenario led to less CO2 emissions compared to other scenarios. However, after the incident effect passed, the LCS-CAL scenario generally caused more CO2 emissions than other scenarios. In addition, while the LCS-CAL scenario was not as beneficial as the other scenarios with low CO2-Electricity coefficient, the LCS-CAL scenario showed similar performance to other scenarios with high CO2-Electricity coefficient. The other scenarios performed similarly to each other after the incident occurred and after the incident effect had passed.

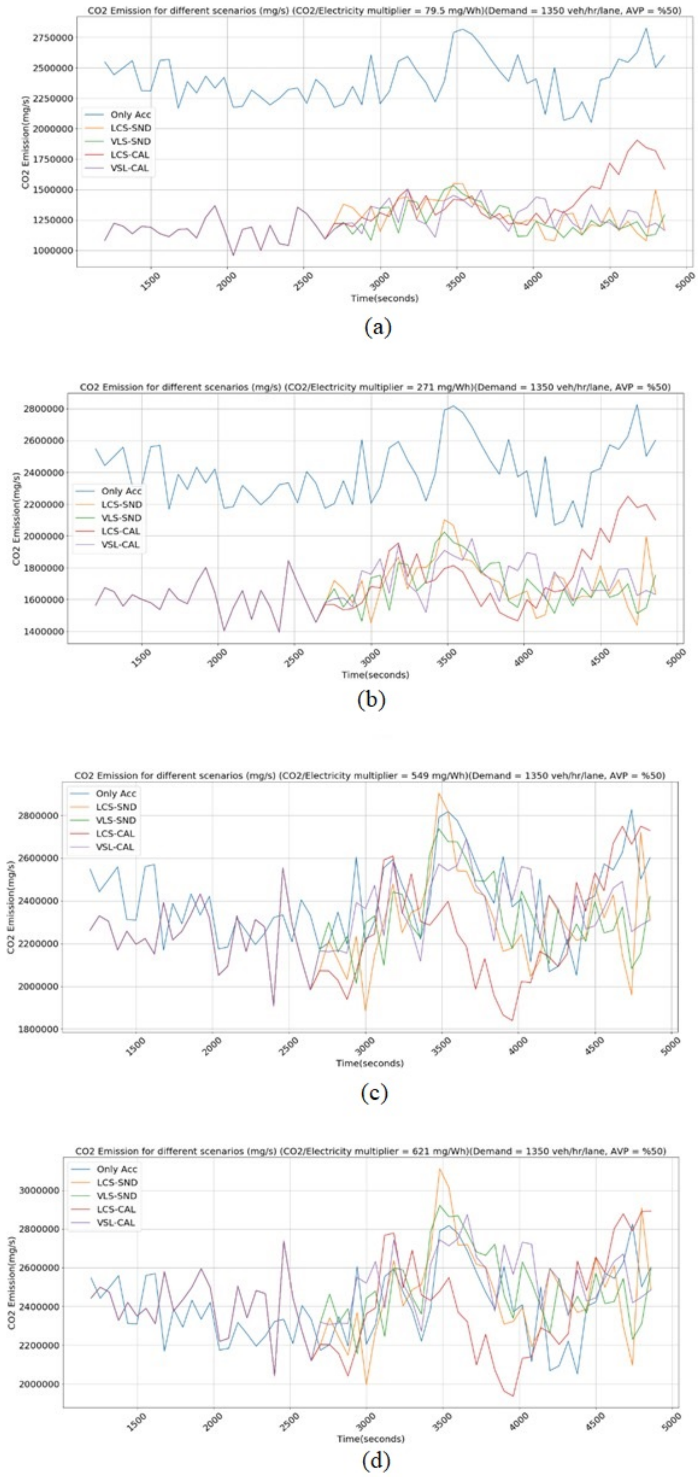
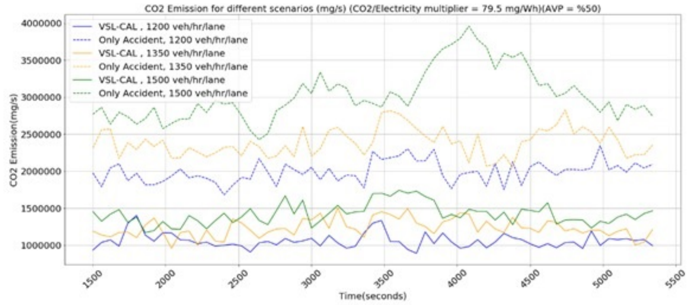


Figure 4.36. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Algorithm Comparison of CO2 Emissions in Different Scenarios and Different CO2 Electricity Coefficients in Uninterrupted Road Network (Demand = 1350 veh/hour/lane,AVP = %50).

Demand comparisons of CO_2 emissions in the VSL-CAL scenario and different CO_2-Electricity coefficients in the uninterrupted road network are given in Figure 4.37. The research was conducted with a 50% autonomous vehicle percentage and CO_2-Electricity coefficients of 79.5, 271, 549, and 621 mg/Wh. The y-axis of the graph represents CO_2 emissions (milligrams/second), while the x-axis represents time (seconds). The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. The scenario of only incidents with high demand and all CO_2-Electricity coefficients generally resulted in more CO_2 emissions than the VSL-CAL scenario. In addition, while the VSL-CAL scenario with a low CO_2-Electricity coefficient and high demand generally leads to lower CO_2 emissions compared to the incident-only scenario, while the demand decreases and the CO_2-Electricity coefficient increases, it is seen that the VSL-CAL scenario does not perform well compared to the incident-only scenario. This means that the VSL-CAL scenario can lead to productive results in places where electricity is mostly produced with renewable energy sources and where traffic density is high.



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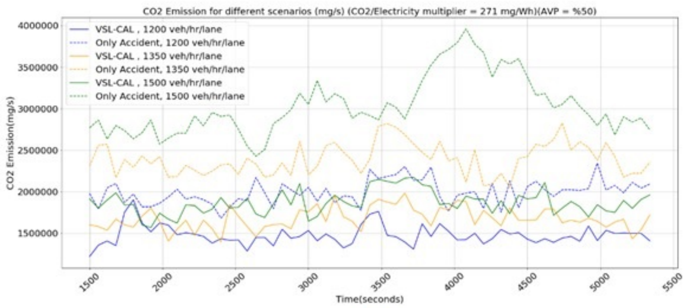

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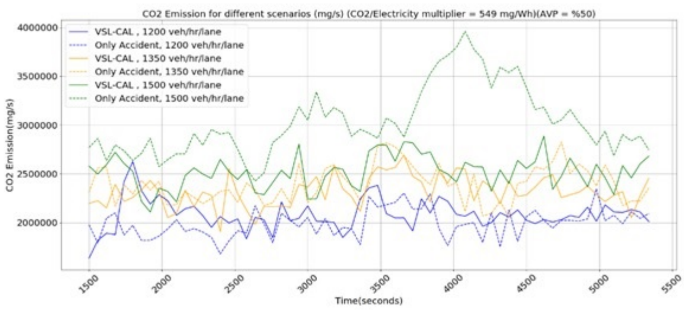

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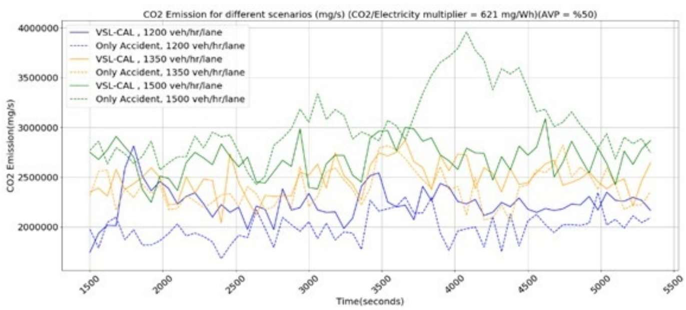
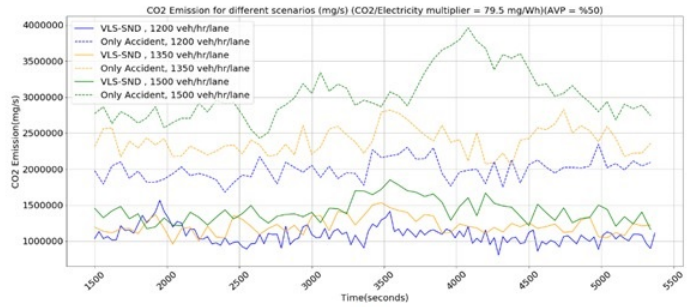


(d)

Figure 4.37. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Demand Comparison of CO2 Emissions at Different CO2 Electricity Coefficients of VSL-CAL Scenarios in Uninterrupted Road Network (AVP = %50).

Demand comparisons of CO2 emissions in the VSL-SND scenario and different CO2-Electricity coefficients in the uninterrupted road network are given in Figure 4.38. The research was conducted with a 50% autonomous vehicle percentage and CO2-Electric coefficients of 79.5, 271, 549, and 621 mg/WH. The y-axis of the graph represents CO2 emissions (milligrams/second), while the x-axis represents time (seconds). The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. The scenario of an incident with high demand and all CO2-Electricity coefficients generally caused more CO2 emissions than the VSL-SND scenario. However, with a low CO2-Electricity coefficient and high demand, the VSL-SND scenario generally leads to lower CO2 emissions compared to the incident-only scenario, while the demand decreases and the CO2-Electricity coefficient increases, it is seen that the VSL-SND scenario does not perform well compared to the incident-only scenario. It can be concluded that the VSL-SND scenario can lead to efficient results in places where electricity is produced mostly with renewable energy sources and where traffic density is high. In cases where the CO2-Electricity coefficient is high, at low demands, at the time of the incident, and after the incident effect has passed, the VSL-SND scenario caused more emissions than the only incident scenario.



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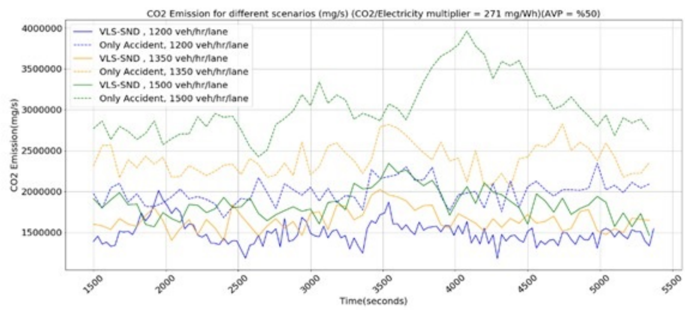

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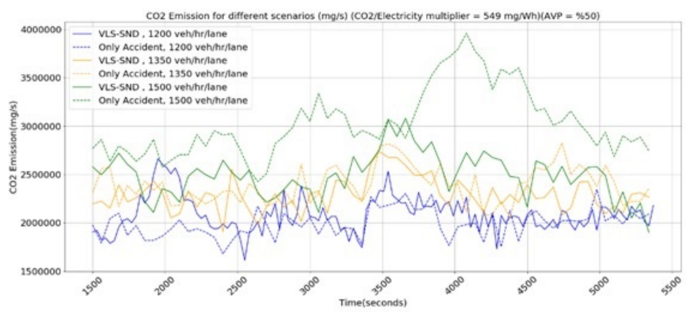

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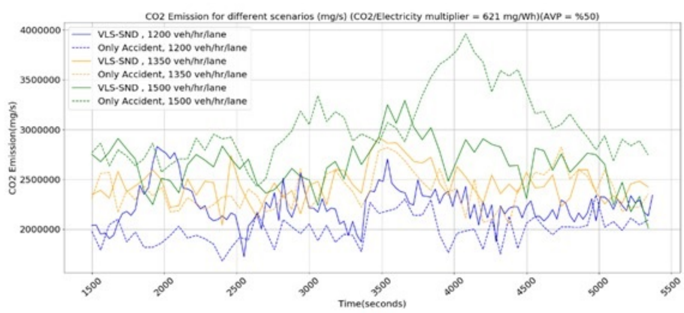
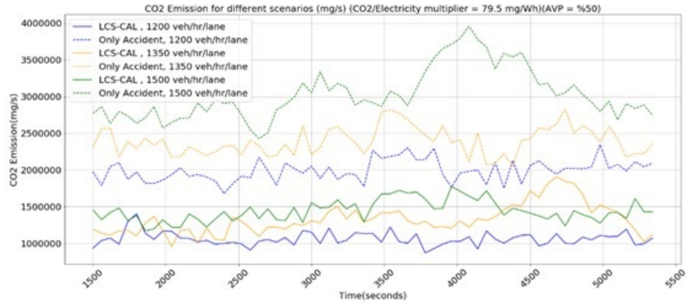


(d)

Figure 4.38. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Demand Comparison of CO2 Emissions at Different CO2 Electricity Coefficients of VSL-SND Scenarios in Uninterrupted Road Network (AVP = %50).

Demand comparisons of CO2 emissions in the LCS-CAL scenario and different CO2-Electricity coefficients in the uninterrupted road network are given in Figure 4.39. The research was conducted with a 50% autonomous vehicle percentage and CO2-Electric coefficients of 79.5, 271, 549, and 621 mg/WH. The y-axis of the graph represents CO2 emissions (milligrams/second), while the x-axis represents time (seconds). The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. The scenario with only an incident with high demand and all CO2-Electricity coefficients generally caused more CO2 emissions than the LCS-CAL scenario. In addition, with a low CO2-Electricity coefficient and high demand, the LCS-CAL scenario generally leads to lower CO2 emissions compared to the incident-only scenario, while the demand decreases and the CO2-Electricity coefficient increases, while the LCS-CAL scenario does not perform well compared to the incident only scenario. With a high CO2-Electricity coefficient and low demand, the LCS-CAL scenario generally caused more CO2 emissions than the only incident scenario both at the time of the incident and after the incident effect had passed. It can be said that in countries that do not produce electricity mostly with fossil resources, the algorithms perform better in all demands and cause less CO2 emissions compared to the only incident scenario. However, it can be said that in countries that generally meet their energy needs from non-renewable energy sources, algorithms give bad results in low demands and occasionally lead to good results in high demands.



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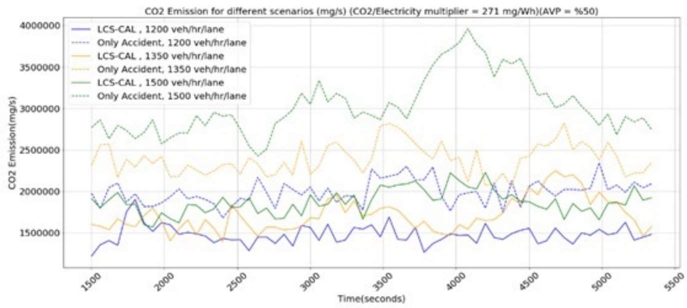

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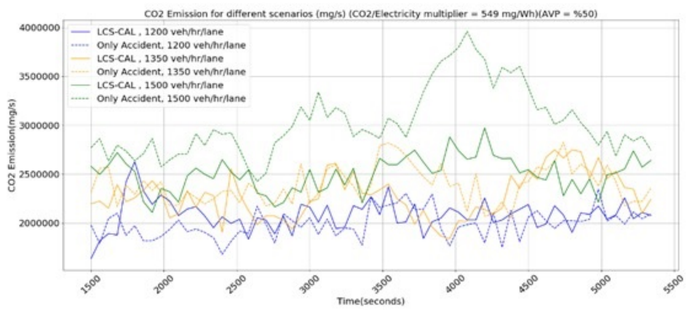

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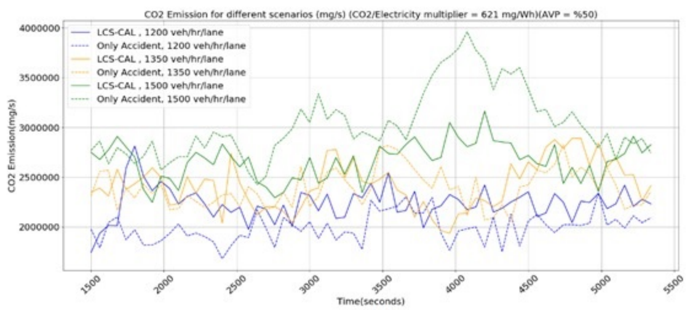

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Figure 4.39. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Demand Comparison of CO2 Emissions at Different CO2 Electricity Coefficients of LCS-CAL Scenarios in Uninterrupted Road Network (AVP = %50).

Demand comparisons of CO_2 emissions in the uninterrupted road network in the LCS-SND scenario and different CO2-Electricity coefficients are given in Figure 4.40. The research was conducted with a 50% autonomous vehicle percentage and CO2-Electric coefficients of 79.5, 271, 549, and 621 mg/WH. The y-axis of the graph represents CO2 emissions (milligrams/second), while the x-axis represents time (seconds). The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. Only the incident scenario with high demand and all CO2-Electricity coefficients generally caused more CO2 emissions than the LCS-SND scenario. In addition, with a low CO2-Electricity coefficient and high demand, the LCS-SND scenario generally leads to lower CO2 emissions compared to the incident-only scenario, while the demand decreases and the CO2-Electricity coefficient increases, it is seen that the LCS-SND scenario does not perform well compared to the incident only scenario. It is seen that in high CO2-Electricity coefficient and low demands, the LCS-SND scenario causes higher CO2 emissions both at the time of the incident and after the impact of the incident has passed, compared to the only incident scenario.

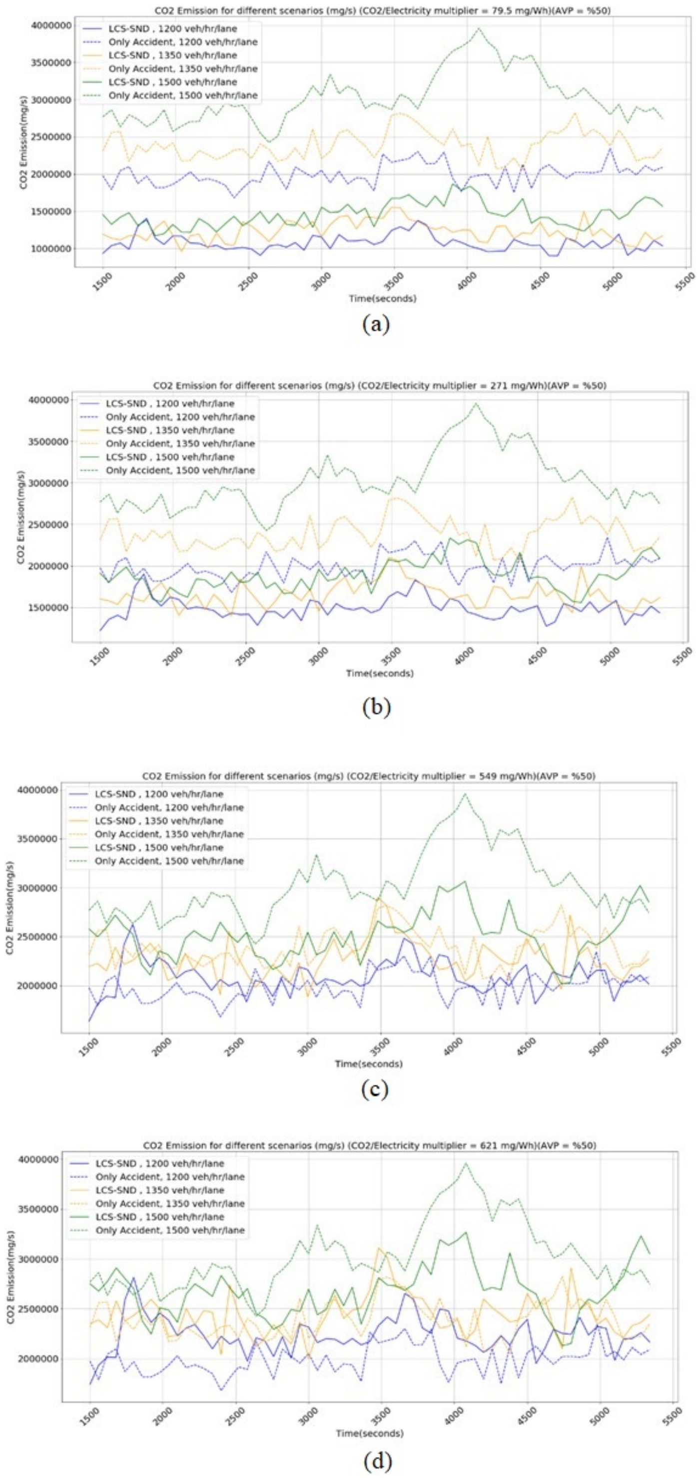
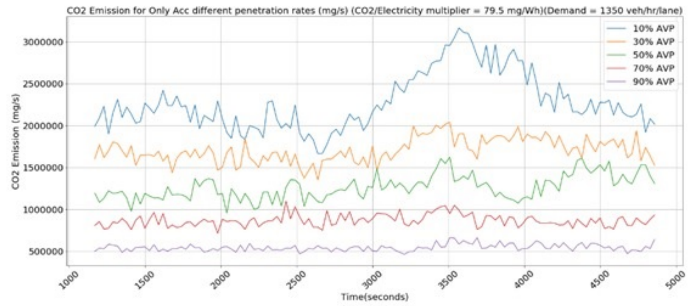


Figure 4.40. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Demand Comparison of CO2 Emissions at Different CO2 Electricity Coefficients of LCS-SND Scenarios in Uninterrupted Road Network (AVP = %50).

In the graphs that give the results of the simulation study on the CO2 emission (milligrams/second), which varies depending on the autonomous vehicle percentage in the scenario where there is only an incident on the uninterrupted road, the x-axis shows the time in seconds, while the y-axis shows the CO2 emission in mg/second and is given in the Figure 4.41. The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. The low emission coefficient obtained in countries using mostly renewable energy is 79.5 mg/Wh and the differences are examined by increasing the emission coefficient to 621 mg/Wh since non-renewable energy is used in undeveloped and developing countries. According to the simulation results for countries using renewable energy, a decrease in CO2 emissions was observed as the rate of autonomous vehicles increased. In the incident lasting 1393 seconds in the traffic flow with a 10% autonomous vehicle percentage, the maximum emission is between 2000000-250000 mg/sec before the incident occurs, while the emission after the incident rises to over 3000000 mg/sec. On the other hand, in the current 30%, 50%, 70%, and 90% autonomous vehicles, the emissions before and after the incident do not exceed 2000000 mg/second. In the case where the emission coefficient is 271 mg/Wh, although it is observed that the emission decreases as the autonomous vehicle ratio increases, it is not observed that there is a decrease in the emission as the autonomous vehicle ratio increases in the cases with the emission coefficient of 549 and 621 mg/Wh. the relationship has been determined. For this reason, while the transition to the use of autonomous vehicles in countries using renewable energy will cause a decrease in emissions, there may be an increase in the damage to the environment with the increase in the rate of autonomous vehicles in countries using non-renewable energy sources. In cases where there is an emission coefficient of 71.5 mg/Wh, the amount of emissions per second at all autonomous vehicle percentages is lower before and after the incident in cases with an emission coefficient of 549 and 621 mg/Wh.



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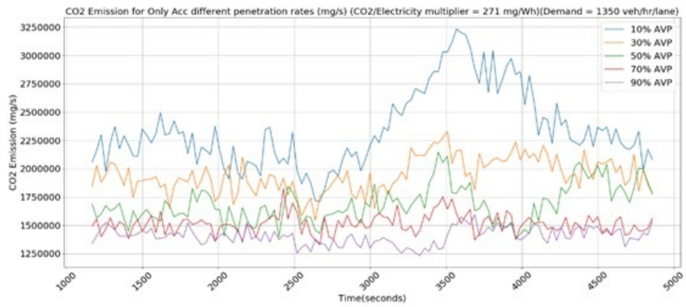

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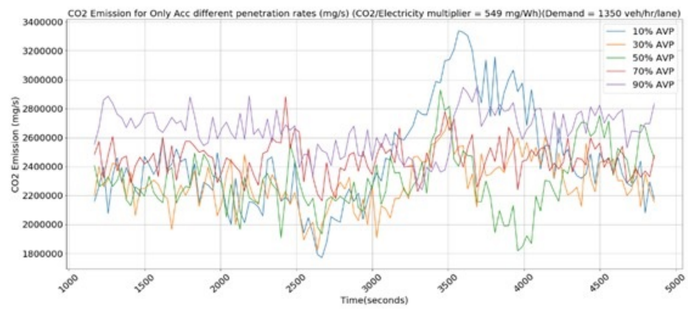

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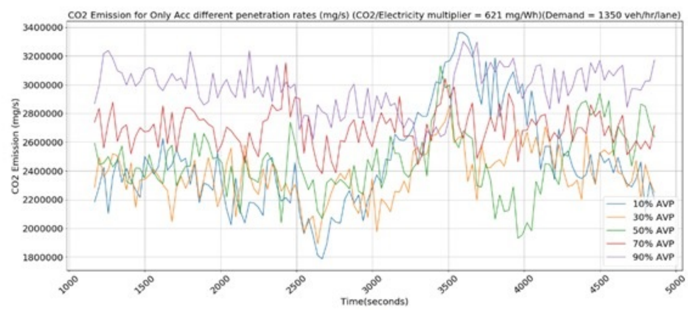


(d)

Figure 4.41. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Comparison of Incident Scenarios to Different AVP at Different CO2 Electricity Coefficients of CO2 Emission in Uninterrupted Road Network (Demand = 1350 veh/hour/lane).

In the simulation made on the comparison of the effects of autonomous vehicle percentages using VSL-CAL incident detection algorithms on CO2 emission differences by using different CO2 electric coefficients in the uninterrupted road network, the traffic demand was determined as 1350 vehicles/hour/lane. In Figure 4.42, the x-axis shows the time in seconds, while the y-axis shows the CO2 emission in mg/second. The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. While 4 different electricity coefficients used in emission calculations were determined as 71.5 mg/Wh in developed countries using renewable energy, it was determined as 621 mg/Wh for countries using non-renewable energy. As the rate of autonomous vehicles increases, there is a decrease in CO2 emissions in cases where the emission coefficient of 71.5 mg/Wh is used before and after the incident, while in the case with a coefficient of 271 mg/Wh, approximately 3 times less CO2 emission occurs compared to the scenario where there is a 90% autonomous vehicle. In the incident that lasted for 1393 seconds, before the incident, in cases with emission coefficients of 549 and 621 mg/Wh, the highest CO2 emission was observed in case of 90% of autonomous vehicles, while the highest emission occurred in the case of 10% autonomous vehicles after the incident. Among the minimum emission emissions, countries that use renewable energy have decreased by approximately 4 times compared to underdeveloped countries, thanks to autonomous vehicles.

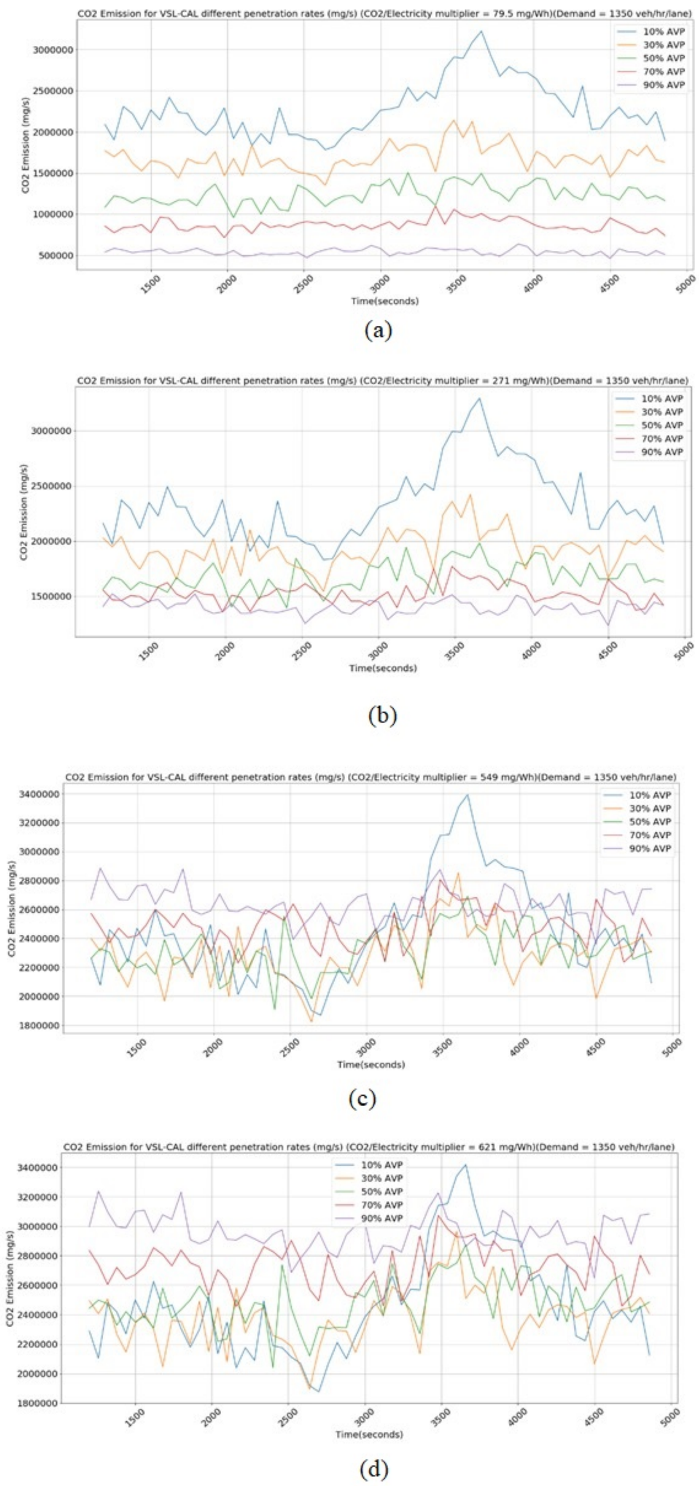
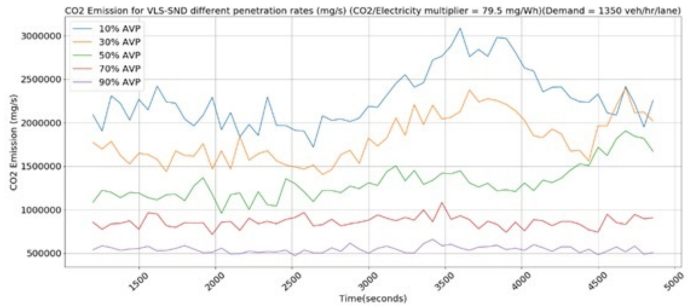


Figure 4.42. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Comparison of VSL-CAL Scenarios to Different AVP at Different CO2 Electricity Coefficients of CO2 Emissions in Uninterrupted Road Network (Demand = 1350 veh/hour/lane).

1350 vehicles/hour/lane is used as traffic demand in the simulation made on the change in CO_2 emissions due to the use of VSL-SND in the uninterrupted road network, depending on different CO_2 electric coefficients and autonomous vehicle percentages. In the graphs obtained, while the x-axis shows the time in seconds, the y-axis shows the CO_2 emission in mg/second which is given in Figure 4.43. The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. When the emission amounts are examined, in cases where the emission coefficients of 549 mg/Wh and 621 mg/Wh, which are undeveloped and developing using non-renewable energy, are used, the lowest emission amount occurs in the case of 10% autonomous vehicles, while 79.5 mg/Wh and 271 mg/Wh used for renewable energy countries. In countries with a Wh emission coefficient, the lowest CO_2 emissions occurred in the case of 90% of autonomous vehicles. In countries where renewable energies are used, there is no change in the emission emissions due to the autonomous vehicle percentages before and after the incident, which lasts for 1393 seconds. has been shown not to exist.



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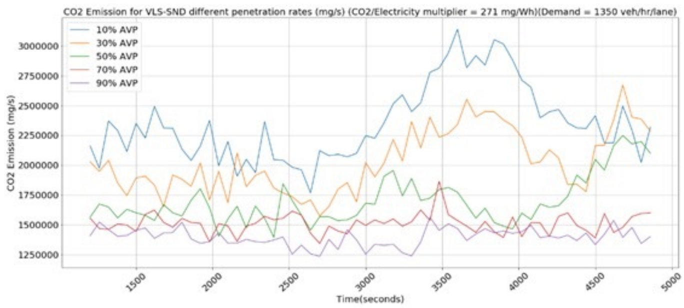

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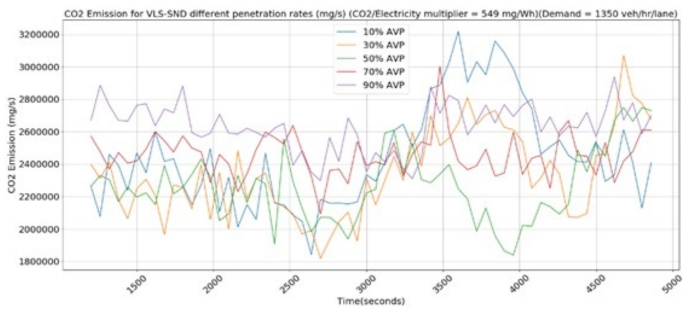

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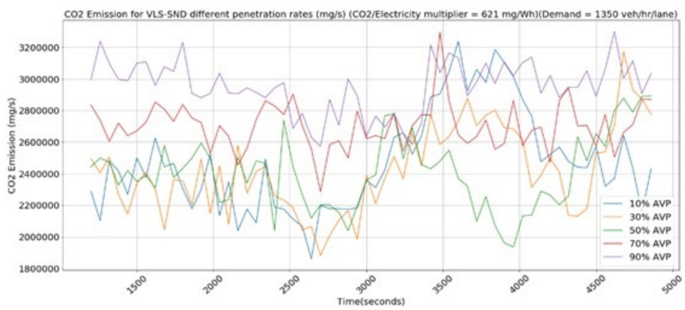

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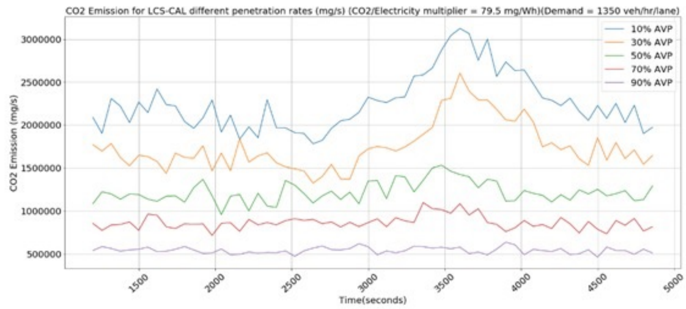
Figure 4.43. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Comparison of VSL-SND Scenarios to Different AVP at Different CO2 Electricity Coefficients of CO2 Emissions in Uninterrupted Road Network (Demand = 1350 veh/hour/lane).

In the uninterrupted road network, the change of CO_2 emissions occurring at different CO_2 electric coefficients depending on the percentage of autonomous vehicles, by using LCS-CAL incident detection and real-time traffic management methods on the road with 1350 vehicle/hour/lane traffic demand, is shown in the Figure 4.44. The reason for using different electricity coefficients is the differences in CO_2 emissions per unit in countries using renewable and non-renewable energy. In the given graphs, the x-axis shows the time in seconds, while the y-axis shows the CO_2 emission in mg/second. The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. When the scenario in which the emission coefficient of 71.5 mg/WH is used is examined, it is observed that when the percentage of autonomous vehicles is 10% in the traffic flow, approximately 6 times more CO_2 emissions occur per second compared to the situation where the percentage of autonomous vehicles is 90%. occurs in the scenario. In the scenario with a coefficient of 271 mg/Wh, while the emission amounts change less than the percentage of autonomous vehicles before the incident, the emission amounts increase approximately 1.5 times in cases where there are 10% and 30% autonomous vehicles after the incident. In the scenarios with 549 and 621 mg/Wh coefficients, although it is observed that there is an increase in the amount of emissions with the increase in the percentage of autonomous vehicles before the incident, it has been determined that the emission amount increases as the percentage of autonomous vehicles decrease after the incident and the highest CO_2 emission value is encountered in the flow with 10% autonomous vehicles. For this reason, with the increase in the number of autonomous vehicles, CO_2 emissions in underdeveloped and developing countries may not be reduced to the desired level.



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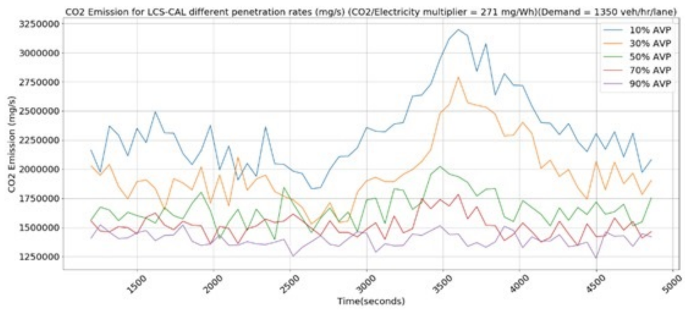

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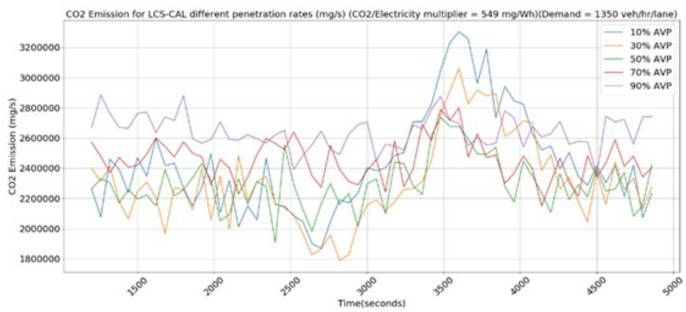

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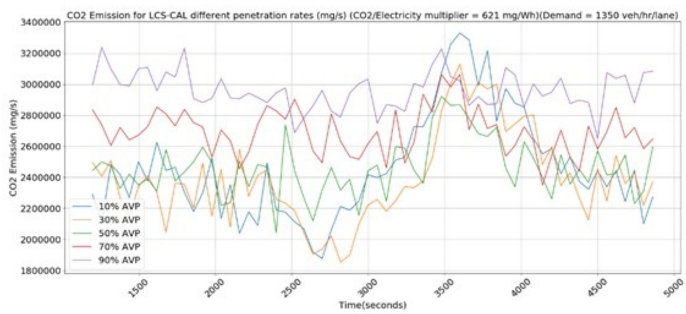
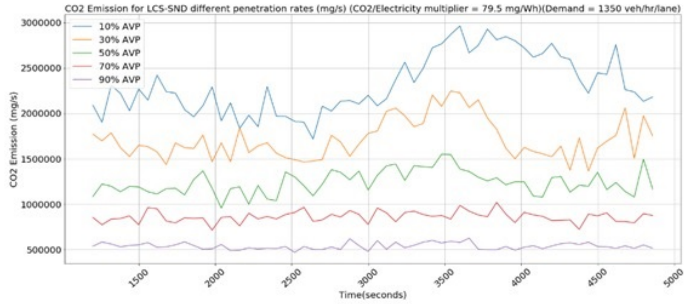


(d)

Figure 4.44. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Comparison of LCS-CAL Scenarios to Different AVP at Different CO2 Electricity Coefficients of CO2 Emissions in Uninterrupted Road Network (Demand = 1350 veh/hour/lane).

In the uninterrupted road network, the traffic demand was determined as 1350 vehicles/hour/lane in the graphs obtained with the scenarios prepared by comparing the LCS-SND scenarios with different CO2 electricity coefficients according to the different percentages of autonomous vehicles in the CO2 emission of the uninterrupted road network. In 4 different scenarios prepared, the CO2 emission indirectly caused by electrical energy has been obtained by converting it with different coefficients for countries that obtain their energy from renewable or non-renewable sources. In Figure 4.45, the x-axis shows the time in seconds, while the y-axis shows the CO2 emissions in mg/second. The duration of the incident was 1393 seconds and the incident occurred at the 5736th meter of the main road in the left lane. When CO2 emissions are examined, the least emission before and after the incident occurs in the scenario with the lowest electricity coefficient, while in this scenario, a direct decrease in the amount of emissions is achieved by increasing the percentage of autonomous vehicles, and in the scenario where the fluctuations in the amount of emissions after the incident is minimal, it is the LCS-SNY scenario. When the electric coefficient is 271 mg/Wh, in cases where the percentages of autonomous vehicles are 10% and 30%, although there is no significant change in the emission amounts compared to the first scenario, it has been observed that there is an approximately 1.5-fold increase in emission emissions when the percentage of autonomous vehicles is more than 50%. In cases where the electric coefficient is 549 and 621 mg/Wh, it is observed that the change in the amount of emission due to the percentage of autonomous vehicles before and after the incident is the least, while before the incident, especially as the percentage of autonomous vehicles decreases, there is a decrease in the emission, but with a rapid increase after the incident, the autonomous vehicle reaches the highest emission amount. It has been observed that it is reached in scenarios with low vehicle percentages. While the maximum emission amounts are close to each other, there is a difference of approximately 4 times between the minimum emission amounts obtained. For this reason, environmental benefits arise as the electrical energy used in autonomous vehicles is met from renewable energy sources in developing countries, while emissions reduction due to the number of autonomous vehicles cannot be achieved in countries that provide energy with non-renewable energy and the damage to the environment indirectly increases.



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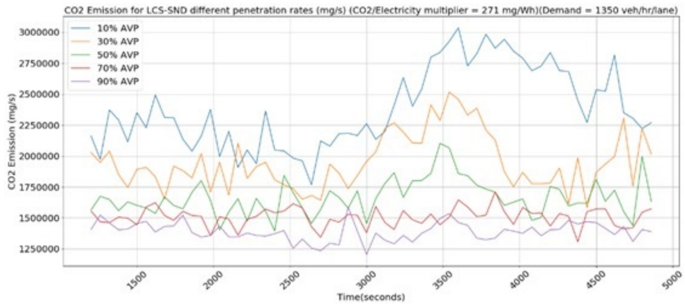

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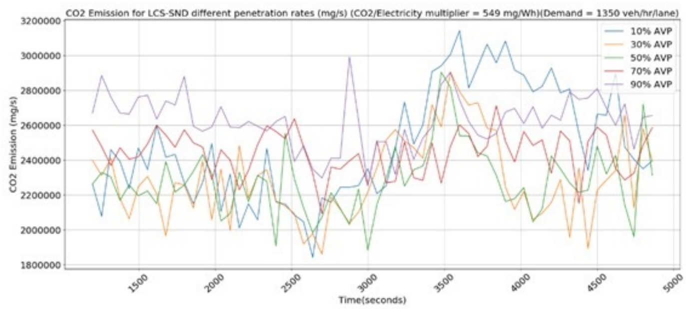

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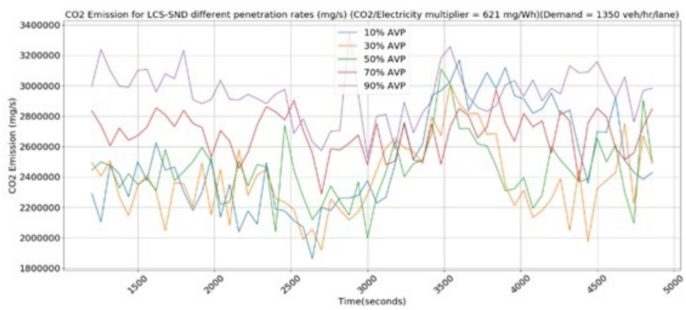

(d)

Figure 4.45. (a) 79.5 mg/Wh, (b) 271 mg/Wh, (c) 549 mg/Wh, (d) 621 mg/Wh - Comparison of LCS-SND Scenarios to Different AVP at Different CO2 Electricity Coefficients of CO2 Emissions in Uninterrupted Road Network (Demand = 1350 veh/hour/lane).

The results in Table 4.17 were obtained by managing the 1393-second left lane incident scenario with a combination of LCS-CAL, LCS-SND, VSL-CAL, and VSL-SND in the presence of 50% autonomous vehicles in 1500 vehicles/hour/lane traffic demand. In addition, there are the consequences of the scenario where only the incident exists, autonomous vehicles do not exist and the incident is not managed. Comparisons of incident detection and real-time traffic management methods combinations were made based on the incident scenario only. These comparisons are made over CO2 emissions, CO2 emissions (including CO2 released in electricity production), CO emissions, Electricity consumption, HC emissions, NOX emissions, and PMX emissions. “CO2 emissions (including CO2 released in electricity production)” data was obtained with the coefficient calculated over the conditions in Turkey in Cluster-IV. When the molecules released during electricity generation are not taken into account, a decrease of 55-60% is observed in all oscillation data. However, when the CO2 released during electricity production is included, that is, when the data in the ”CO2 emission (including the CO2 released in electricity production)” column is examined, an improvement in the range of 10-15% is observed. It was observed that the combination that caused the least CO2 emission was LCS-CAL. The LCS-CAL scenario resulted in 14.68% less CO2 emissions compared to the incident-only scenario. Although the VSL-SND scenario is the scenario with the worst result, it is seen that it causes 11.55% less CO2 emissions compared to the only incident scenario. Therefore, it can be concluded that all incident detection and real-time traffic management methods combinations are efficient applications in the presence of 50% autonomous vehicles and 1500 vehicles/hour/lane in Turkey conditions.

Table 4.17. Comparison of Algorithms on Uninterrupted Road Network in Turkish Conditions and Different Scenarios (Demand = 1500 veh/hour/lane, AVP = 50%, Incident time = 1393 seconds, Incident location = 5736 meters, Incident Lane = Left lane).

Variables	CO2 Emission (mg)	CO2 Emission (Including CO2 Released in Electricity Production) (mg)	CO Emission (mg)	Electric Consumption(Wh)	HC Emission (mg)	NOX Emission (mg)	PMX Emission (mg)
Only Incident	57,079,593.75	57,079,593.75	949,084.92	-	24,536.03	23,480.55	1,110.81
LCS_CAL	25,276,916.81	48,701,047.59	379,775.23	37,720.02	10,865.41	10,265.62	505.97
Change % (Compared to Only Incident Scenario)	-55.72%	-14.68%	-59.99%	-	-55.72%	-56.28%	-54.45%
LCS_SND	25,565,392.33	49,231,271.89	388,160.70	38,109.31	10,989.42	10,386.32	513.02
% (Compared to Only Incident Scenario)	-55.21%	-13.75%	-59.10%	-	-55.21%	-55.77%	-53.82%
VSL_CAL	25,021,982.67	50,394,622.40	371,948.59	40,857.71	10,755.83	10,129.88	501.45
Change % (Compared to Only Incident Scenario)	-56.16%	-11.71%	-60.81%	-	-56.16%	-56.86%	-54.86%
VSL_SND	24,903,354.96	50,486,637.02	388,648.48	41,196.91	10,704.85	10,092.47	501.54
Change % (Compared to Only Incident Scenario)	-56.37%	-11.55%	-59.05%	-	-56.37%	-57.02%	-54.85%

The results in Tables 4.18, 4.19, 4.20, and 4.21 were obtained by applying the integration of different incident detection and traffic management methods to the left lane incident scenario lasting 1393 seconds with different percentages of autonomous vehicles in the simulation environment. The 0% autonomous vehicle data of Table 4.18, 4.19, 4.20, and 4.21 contains only the results of the scenario where there is an incident, there is no autonomous vehicle and the traffic is not managed. Other autonomous vehicle percentage data are the results of the scenario where the traffic is managed with the specified combination.

The results in Table 4.18 were obtained via the real-time traffic management methods by working together with the California incident detection algorithm and VSL traffic management methods. The traffic demand given to the road network is 1350 vehicles/hour/lane. Since the autonomous vehicles used in simulation studies are also electric vehicles, these vehicles do not emit CO2, CO, HC, NOX, and PMX. For this reason, in cases where the traffic vehicle composition consists of 100% autonomous vehicles, there is no CO2, CO, HC, NOX, and PMX emissions, and the emission of these molecules decreases as the percentage of autonomous vehicles increases. However, a significant amount of CO2 is released to the environment during the production of electricity, which is used as fuel by electric vehicles. This factor has been taken into account when calculating the data in the column "CO2 Emission (Including CO2 Released in Electricity Generation) (mg)". The obtained values were found by using the coefficient calculated over the amount of CO2 released while generating electricity in Turkey. When this data are examined, it is seen that 40% autonomous vehicle percentage gives the best results when CAL and VSL methods are used together with autonomous vehicles in Turkey conditions. However, no percentage of autonomous vehicles has decreased CO2 emissions, including the 40% autonomous vehicle percentage.

Table 4.18. AVP Comparison in Turkey Conditions and VSL-CAL Scenario in Uninterrupted Road Network (Demand = 1350 veh/hour/lane, AVP = 50%, Incident time = 1393 seconds, Incident location = 5736 meters, Incident Lane = Left lane).

Variables	CO2 Emission (mg)	CO2 Emission (Including CO2 Released in Electricity Production) (mg)	CO Emission (mg)	Electric Consumption(Wh)	HC Emission (mg)	NOX Emission (mg)	PMX Emission (mg)
0 %	49,798,921.61	49,798,921.61	660,154.91	-	21,406.25	20,128.61	1,005.44
10 %	48,084,666.68	52,276,090.16	709,747.86	6,749.47	20,669.43	19,630.75	952.41
Change w.r.t. 0% AVP	-3.44%	4.97%	7.51%	-	-3.44%	-2.47%	-5.27%
20 %	42,397,050.53	50,426,665.79	637,559.51	12,930.14	18,224.59	17,322.67	838.39
Change w.r.t. 0% AVP	-14.86%	1.26%	-3.42%	-	-14.86%	-13.94%	-16.61%
30 %	41,425,601.75	53,232,017.60	740,585.14	19,011.94	17,807.09	17,057.71	820.47
Change w.r.t. 0% AVP	-16.81%	6.89%	12.18%	-	-16.81%	-15.26%	-18.40%
40 %	30,239,998.63	49,946,780.58	454,302.74	31,733.95	12,998.82	12,273.10	604.58
Change w.r.t. 0% AVP	-39.28%	0.30%	-31.18%	-	-39.28%	-39.03%	-39.87%
50 %	25,021,982.67	50,394,622.40	371,948.59	40,857.71	10,755.83	10,129.88	501.45
Change w.r.t. 0% AVP	-49.75%	1.20%	-43.66%	-	-49.75%	-49.67%	-50.13%
60 %	19,208,158.69	51,749,802.75	286,749.98	52,402.00	8,256.73	7,734.54	387.34
Change w.r.t. 0% AVP	-61.43%	3.92%	-56.56%	-	-61.43%	-61.57%	-61.48%
70 %	12,723,513.49	53,661,584.09	178,608.03	65,922.82	5,469.27	5,044.02	254.67
Change w.r.t. 0% AVP	-74.45%	7.76%	-72.94%	-	-74.45%	-74.94%	-74.67%
80 %	8,714,449.03	55,407,848.70	133,068.88	75,190.66	3,745.96	3,466.97	174.44
Change w.r.t. 0% AVP	-82.50%	11.26%	-79.84%	-	-82.50%	-82.78%	-82.65%
90 %	3,957,916.59	58,497,863.19	60,640.55	87,826.00	1,701.34	1,562.46	78.31
Change w.r.t. 0% AVP	-92.05%	17.47%	-90.81%	-	-92.05%	-92.24%	-92.21%
100 %	-	65,389,959.19	-	105,297.84	-	-	-
Change w.r.t. 0% AVP	-100.00%	31.31%	-100.00%	-	-100.00%	-100.00%	-100.00%

The results in Table 4.19 were obtained via the real-time traffic management methods by working together with the SND incident detection algorithm and VSL traffic management methods. The traffic demand used is 1350 vehicles/hour/lane. In cases where the traffic vehicle composition consists of 100% autonomous vehicles, there is no CO2, CO, HC, NOX, and PMX emissions, and the emission of these molecules decreases as the percentage of autonomous vehicles increases. The values given in the column "CO2 Emission (Including CO2 Released in Electricity Generation) (mg)" are calculated using the coefficient obtained over the amount of CO2 released during electricity generation in Turkey. When this data are examined, it is seen that 50% autonomous vehicle percentage gives the best results when SND and VSL methods are used together with autonomous vehicles in Turkey conditions. However, no percentage of autonomous vehicles, including 50% percentage of autonomous vehicles, did not reduce CO2 emissions compared to the scenario where only the incident exists and the autonomous vehicles do not exist. For this reason, it has been determined that real-time traffic management methods with SND and VSL methods using autonomous vehicles are not efficient in terms of CO2 emissions in Turkish conditions.

The results in Table 4.20 were obtained via the real-time traffic management methods by working together with the California incident detection algorithm and the LCS traffic management methods. The traffic demand given to the road network is 1350 vehicles/hour/lane. The obtained "CO2 Emission (Including CO2 Released in Electricity Generation) (mg)" data are calculated using the coefficient obtained over the amount of CO2 released during electricity generation in Turkey. When this data are examined, it is seen that 40% autonomous vehicle percentage gives the best results when CAL and LCS methods are used together with autonomous vehicles in Turkey conditions. Except for the 40% and 50% autonomous vehicle percentages, it is seen that CO2 emissions cannot be reduced in any percentage of autonomous vehicles.

Table 4.19. AVP Comparison in Turkey Conditions and VSL-SND Scenario in Uninterrupted Road Network (Demand = 1350 veh/hour/lane, AVP = 50%, Incident time = 1393 seconds, Incident location = 5736 meters, Incident Lane = Left Lane).

Variables	CO2 Emission (mg)	CO2 Emission (Including CO2 Released in Electricity Production) (mg)	CO Emission (mg)	Electric Consumption(Wh)	HC Emission (mg)	NOX Emission (mg)	PMX Emission (mg)
0 %	49,798,921.61	49,798,921.61	660,154.91	-	21,406.25	20,128.61	1,005.44
10 %	48,084,666.68	52,276,090.16	709,747.86	6,749.47	20,669.43	19,630.75	952.41
Change w.r.t. 0% AVP	-3.44%	4.97%	7.51%	-	-3.44%	-2.47%	-5.27%
20 %	42,534,180.74	50,521,038.06	644,625.24	12,861.28	18,283.55	17,359.81	836.17
Change w.r.t. 0% AVP	-14.59%	1.45%	-2.35%	-	-14.59%	-13.76%	-16.84%
30 %	41,434,139.77	53,947,195.34	676,570.55	20,149.85	17,810.72	16,979.95	818.59
Change w.r.t. 0% AVP	-16.80%	8.33%	2.49%	-	-16.80%	-15.64%	-18.58%
40 %	31,341,027.19	50,688,131.74	453,158.13	31,154.76	13,472.09	12,741.68	623.64
Change w.r.t. 0% AVP	-37.06%	1.79%	-31.36%	-	-37.06%	-36.70%	-37.97%
50 %	24,903,354.96	50,486,637.02	388,648.48	41,196.91	10,704.85	10,092.47	501.54
Change w.r.t. 0% AVP	-49.99%	1.38%	-41.13%	-	-49.99%	-49.86%	-50.12%
60 %	18,130,811.34	51,330,422.46	269,702.42	53,461.53	7,793.63	7,265.43	365.78
Change w.r.t. 0% AVP	-63.59%	3.08%	-59.15%	-	-63.59%	-63.90%	-63.62%
70 %	12,723,513.49	53,661,584.09	178,608.03	65,922.82	5,469.27	5,044.02	254.67
Change w.r.t. 0% AVP	-74.45%	7.76%	-72.94%	-	-74.45%	-74.94%	-74.67%
80 %	8,863,327.24	55,049,211.34	134,356.32	74,373.40	3,809.96	3,525.96	177.29
Change w.r.t. 0% AVP	-82.20%	10.54%	-79.65%	-	-82.20%	-82.48%	-82.37%
90 %	3,916,061.79	58,359,814.66	59,884.51	87,671.10	1,683.35	1,548.58	77.13
Change w.r.t. 0% AVP	-92.14%	17.19%	-90.93%	-	-92.14%	-92.31%	-92.33%
100 %	-	66,326,844.04	-	106,806.51	-	-	-
Change w.r.t. 0% AVP	-100.00%	33.19%	-100.00%	-	-100.00%	-100.00%	-100.00%

Table 4.20. Comparison in Turkey Conditions and LCS-CAL Scenario in Uninterrupted Road Network (Demand = 1350 veh/hour/lane, AVP = 50%, Incident time = 1393 seconds, Incident location = 5736 meters, Incident lane = Left lane).

Variables	CO2 Emission (mg)	CO2 Emission (Including CO2 Released in Electricity Production) (mg)	CO Emission (mg)	Electric Consumption(Wh)	HC Emission (mg)	NOX Emission (mg)	PMX Emission (mg)
0 %	49,798,921.61	49,798,921.61	660,154.91	-	21,406.25	20,128.61	1,005.44
10 %	48,892,315.57	52,839,569.25	717,951.22	6,356.29	21,016.59	20,016.74	973.14
Change w.r.t. 0% AVP	-1.82%	6.11%	8.75%	-	-1.82%	-0.56%	-3.21%
20 %	42,540,349.56	50,836,692.08	634,761.64	13,359.65	18,286.19	17,396.55	835.09
Change w.r.t. 0% AVP	-14.58%	2.08%	-3.85%	-	-14.58%	-13.57%	-16.94%
30 %	40,537,656.67	52,264,322.13	696,274.77	18,883.52	17,425.38	16,682.49	798.54
Change w.r.t. 0% AVP	-18.60%	4.95%	5.47%	-	-18.60%	-17.12%	-20.58%
40 %	30,657,122.90	48,081,344.59	438,419.79	28,058.33	13,178.11	12,463.65	605.07
Change w.r.t. 0% AVP	-38.44%	-3.45%	-33.59%	-	-38.44%	-38.08%	-39.82%
50 %	25,565,392.33	49,231,271.89	388,160.70	38,109.31	10,989.42	10,386.32	513.02
Change w.r.t. 0% AVP	-48.66%	-1.14%	-41.20%	-	-48.66%	-48.40%	-48.98%
60 %	19,003,279.48	50,653,156.46	279,127.76	50,965.99	8,168.66	7,656.51	383.44
Change w.r.t. 0% AVP	-61.84%	1.72%	-57.72%	-	-61.84%	-61.96%	-61.86%
70 %	13,037,967.07	51,977,469.89	182,628.37	62,704.51	5,604.44	5,195.88	260.67
Change w.r.t. to 0% AVP	-73.82%	4.37%	-72.34%	-	-73.82%	-74.19%	-74.07%
80 %	8,342,547.74	54,807,640.62	117,417.09	74,823.02	3,586.09	3,316.09	167.63
Change w.r.t. 0% AVP	-83.25%	10.06%	-82.21%	-	-83.25%	-83.53%	-83.33%
90 %	4,552,956.72	56,112,880.24	70,661.85	83,027.25	1,957.12	1,819.13	92.20
Change w.r.t. 0% AVP	-90.86%	12.68%	-89.30%	-	-90.86%	-90.96%	-90.83%
100 %	-	62,366,615.60	-	100,429.33	-	-	-
Change w.r.t. 0% AVP	-100.00%	25.24%	-100.00%	-	-100.00%	-100.00%	-100.00%

The results in Table 4.21 were obtained via the real-time traffic management methods by working together with the SND incident detection algorithm and LCS traffic management methods. In cases where the traffic vehicle composition consists of 100% autonomous vehicles, there is no CO2, CO, HC, NOX, and PMX emissions, and the emission of these molecules decreases as the percentage of autonomous vehicles increases. The values given in the column "CO2 Emission (Including CO2 Released in Electricity Generation) (mg)" are calculated using the coefficient obtained over the amount of CO2 released during electricity generation in Turkey. When this data are examined, it has been observed that 40% and 50% autonomous vehicle percentages show a decrease in CO2 emissions when SND and LCS methods are used together with autonomous vehicles in Turkey conditions, compared to the scenario where there is only an incident and no autonomous vehicle. It has been determined that the percentage of autonomous vehicles that reduces CO2 emissions the most is 40%. For this reason, it has been observed that SND and LCS management can give efficient results in terms of CO2 emissions when used together with autonomous vehicles.

Table 4.21. AVP Comparison in Turkey Conditions and LCS-SND Scenario in Uninterrupted Road Network (Demand = 1350 veh/hour/lane, AVP = 50%, Incident time = 1393 seconds, Incident location = 5736 meters, Incident lane = Left lane).

Variables	CO2 Emission (mg)	CO2 Emission (Including CO2 Released in Electricity Production) (mg)	CO Emission (mg)	Electric Consumption(Wh)	HC Emission (mg)	NOX Emission (mg)	PMX Emission (mg)
0 %	49,798,921.61	49,798,921.61	660,154.91	-	21,406.25	20,128.61	1,005.44
10 %	48,042,985.50	52,130,262.05	708,712.93	6,581.77	20,651.51	19,630.90	952.1
Change w.r.t. 0% AVP	-3.53%	4.68%	7.36%	-	-3.53%	-2.47%	-5.30%
20 %	43,297,580.91	51,419,562.63	656,046.23	13,078.88	18,611.70	17,701.31	850.02
Change w.r.t. 0% AVP	-13.06%	3.25%	-0.62%	-	-13.05%	-12.06%	-15.46%
30 %	42,009,534.75	53,711,479.02	795,233.21	18,843.71	18,058.11	17,424.70	847.38
Change w.r.t. 0% AVP	-15.64%	7.86%	20.46%	-	-15.64%	-13.43%	-15.72%
40 %	30,409,088.78	48,107,445.42	434,155.36	28,499.77	13,071.49	12,356.10	601.52
Change w.r.t. 0% AVP	-38.94%	-3.40%	-34.23%	-	-38.94%	-38.61%	-40.17%
50 %	25,276,916.81	48,701,047.59	379,775.23	37,720.02	10,865.41	10,265.62	505.97
Change w.r.t. 0% AVP	-49.24%	-2.20%	-42.47%	-	-49.24%	-49.00%	-49.68%
60 %	18,878,161.50	50,667,156.06	276,765.34	51,190.01	8,114.87	7,602.79	379.86
Change w.r.t. 0% AVP	-62.09%	1.74%	-58.08%	-	-62.09%	-62.23%	-62.22%
70 %	13,837,822.66	53,281,806.43	198,920.67	63,516.88	5,948.26	5,535.61	279.48
Change w.r.t. to 0% AVP	-72.21%	6.99%	-69.87%	-	-72.21%	-72.50%	-72.20%
80 %	8,894,998.16	54,692,860.34	131,012.51	73,748.57	3,823.56	3,552.76	179.17
Change w.r.t. 0% AVP	-82.14%	9.83%	-80.15%	-	-82.14%	-82.35%	-82.18%
90 %	4,466,661.49	56,658,424.28	67,434.37	84,044.71	1,920.02	1,773.66	89.34
Change w.r.t. 0% AVP	-91.03%	13.77%	-89.79%	-	-91.03%	-91.19%	-91.11%
100 %	-	62,194,449.44	-	100,152.09	-	-	-
Change w.r.t. 0% AVP	-100.00%	24.89%	-100.00%	-	-100.00%	-100.00%	-100.00%

4.2.3. KNN and Decision Tree Regressor

The relationship between average speeds and CO2 emission will be discussed in the following models that are KNN Regressor and Decision Tree Regressor.

Initially, the K-Nearest Neighbor Regressor model is applied. The data given in the model contains two columns, which are average speed and CO2 emission values. The hyperparameter called “n-neighbors”, which is indicating the number of neighbors is selected to be 2. Then the model is split into train and test sets. Using the train set, the learning stage of the model is completed. To observe how successful the model is after the training, a test dataset is used. The scoring metric of the KNN-Regressor ranges between 0 and 1. Results show that the model had a score of 0.6540. In Figure 4.46, a visualization of the model is present.

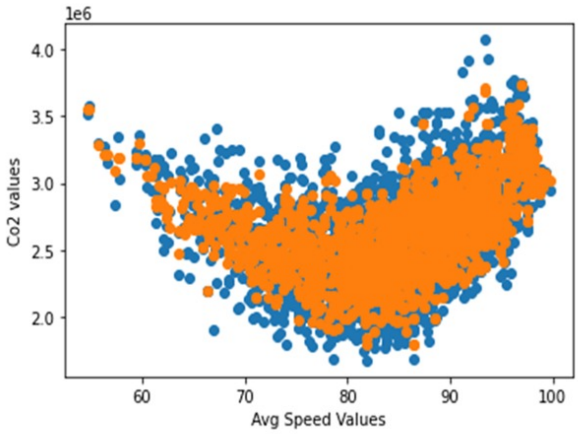

Figure 4.46. The Relationship between Avg Speed Values and CO2 based on KNN Regressor.

In addition to KNN-Regressor, one more model is trained to be able to compare them and select the best one in terms of their scores. The second model is a Decision Tree Regressor. Two hyperparameters are set, namely “max-depth” and “given-depth”, to be 51 and 20 respectively. After training the model and evaluating the success of the model with the test set, a score of 0.8358 is observed. Considering both models, the decision tree regressor had a higher score, which shows that for the same dataset, this model is more successful in means of learning the data. In Figure 4.47, the results of the model can be observed.

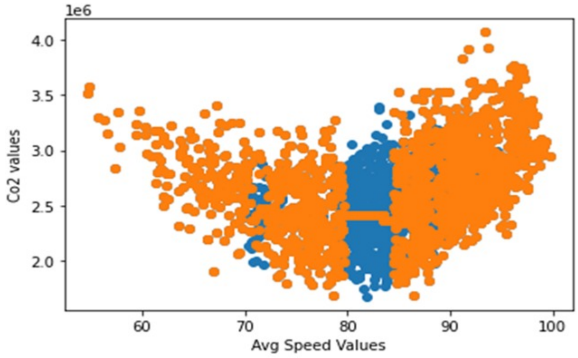

Figure 4.47. The Relationship between Avg Speed Values and CO2 based on Decision Tree Regressor Results.

5. CONCLUSION

In this thesis, 2 different real time traffic management methods, namely Lane Control Signals (LCS) and Variable Speed Limits (VSL), and 2 different traffic incident detection algorithms, which are Standard Normal Deviation (SND) and California, are combined to be simulated on SUMO Simulation Software. To do so, initially, a road network is created using “NetEdit”, which is a simulation network creation tool. The created network is a 3-lane road network, which is 10400 meters long with its first 200 meters being the entrance section and the last 200 meters being the exit section. Then, 2 different driver characteristics are defined representing human-driven and autonomous vehicles. Simulation scenarios, which are run on the created road network, contain various parameters such as traffic demand, autonomous vehicle penetration rate, and incident status. 3 different traffic demand values, which are 1200, 1350, and 1500 veh/hr/lane, are used. 11 different autonomous vehicle penetration rates, 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 100%, are determined. Incident status is either 1 or 0, which indicates if there is an incident in the scenario or not. In total 66 scenarios are created, and each scenario is run with 100 different seeds to be able to eliminate the factor of randomness. For each seed, incident location, incident duration, incident time and incident lane changes, so different incident scenarios can be analyzed. While running the simulations, density, speed, flow, and environmental aspect data is collected using the “e1 detectors” located on the simulation network. Considering the simulation study, SND and California algorithms, which are the incident detection algorithms, are simulated first, and data regarding these simulations are collected and stored. Afterward, traffic traffic management methods, namely LCS and VSL, are simulated. Then, incident detection and traffic management methods are integrated into the simulation environment, so that they can be simulated following each other. 4 different models, namely LCS-SND, LCS-CAL, VSL-SND, and VSL-CAL, are created and simulated with the predetermined incident scenarios. Both traffic and environmental data are collected and stored for each model to be analyzed. Then, 2 different regression models are trained with the collected environment and traffic data to be able to detect the relationships between these data [109, 110].

The contribution of this thesis to the literature is regarding the usage of autonomous vehicles in integrated incident detection and management models and the investigation of the effects of autonomous vehicles on these models. Since incidents occur in traffic inevitably, the application of incident detection and management algorithms is more than necessary. Implementation of incident detection methods reduces the time to detect the incident, which enables the authorities to act faster, whereas traffic management methods are used to reduce the severity of incident-induced congestion so that the traffic densities near the incident location are relieved. Implementing a model, which integrates incident detection and traffic management methods, has the potential to detect the incident in a very short duration and start managing the traffic before the traffic gets congested severely. Usage of autonomous vehicles in such operations is very promising since these vehicles can be used as in-traffic sensors to aid incident detection and they obey every instruction given to them in the name of the traffic management method. By implementing AVs in incident detection and management models, congestions will be managed more effectively and in a faster manner. Even though these vehicles are not used frequently in real-life traffic yet, autonomous vehicle technologies are developing very fast, so it is expected that they will be integrated into real-life traffic soon. Traffic congestions affect traffic in many ways. Increased stop-and-go motions, irregular speed patterns, and increased traffic delays are a few of these effects. One common aspect of these effects is that they negatively affect the environment by increasing fuel consumption and Greenhouse Gas (GHG) emissions. By collecting environmental data such as CO2 emission and fuel consumption during the simulations, investigation of the effects of autonomous vehicles and incident detection and management models on the environment can be analyzed clearly. Therefore, considering the results of this thesis, decision-makers and authorities of both traffic management and the department of environment can benefit by using this thesis as a guide while implementing autonomous vehicles in incident detection and management.

Considering the results of the simulation study, initially, incident detection algorithms are compared based on 3 performance criteria, namely detection rate (DR), false alarm rate (FAR), and mean time to detect (MTTD). Results indicate that the SND algorithm outperformed California algorithm in terms of better DR and MTTD values. Even though California algorithm had lower FAR results, overall results show that SND is more efficient and effective. Then, the results of integrated incident detection and management models, namely LCS-SND, LCS-CAL, VSL-SND, and VSL-CAL, are investigated. In addition to 4 integrated models, the case of the incident-only scenario is also inserted into the analysis to have a reference point.

The analysis is conducted on environmental data. Since the autonomous vehicles used in the simulation study are all-electric vehicles, electric consumption of AVs and fuel consumption of human-driven vehicles are recorded. However, electric consumption of vehicles yields very small amounts of GHG, but the generation of the consumed electricity by burning coals, petroleum, etc. yields high amounts of GHG. To categorize countries based on their greenness in electricity generation, 4 different clusters are created. Analyses are done according to these clusters' CO2-Electricity conversion coefficients and so, the CO2 emission in electricity generation is taken into account. Results indicate that at the traffic demand of 1350 veh/hr/lane, 50% AVP, and small CO2-Electric coefficient clusters, integrated models emitted less CO2 compared with the incident-only scenarios. However, at high CO2-Electric coefficient clusters, integrated models emitted more CO2 compared with the incident-only scenario. Additionally, for all clusters, in the presence of an incident, the LCS-CAL model emitted less carbon compared with other models, whereas the other 3 models showed similar and close patterns. After the recovery phase, LCS-CAL started emitting more carbon than the other models. Considering the results according to changing traffic demands, it is observed that at high demand (1500 veh/hr/lane) and low CO2-Electric coefficient clusters, all models showed the most improvement in means of reduced CO2 emission. On the other hand, comparing the effects of autonomous vehicle penetration rates on CO2 emission for the cluster of high CO2-Electric coefficient, which contains Turkey, it is observed that VSL-CAL and LCS-CAL models showed their best performance at 40% AVP. For the VSL-SND model, results indicate that 50% AVP outperforms other penetration rates. Overall results indicate that 40% is the most optimum autonomous vehicle penetration rate means of reducing the CO2 emissions in Turkey's electricity generation conditions. Finally, the relationship between traffic data and CO2 data was examined using KNN-Regressor and Decision Tree models. Considering these 2 models, it is seen that there is a high correlation between average speed and CO_2 emission. Traffic incidents can occur not only on uninterrupted road networks but also on interrupted road networks. Since the simulation study of this thesis is carried out on a 10-kilometer uninterrupted road network, the results corresponding to interrupted road networks are not known, which is a limitation. Efficient and effective estimation of the environmental contributions to be obtained from integrated incident detection and management models utilizing autonomous vehicles is only possible by carrying out this study on other road networks [109, 110].

For future works, integrated models can be implemented in a predetermined pilot project area. This implementation has the potential to show the actual benefits of the study. Also, as mentioned before, this study is carried out on only an uninterrupted road network. To observe the improvements of the study on interrupted road networks, the study can be further expanded to contain interrupted road network analysis.

REFERENCES

1. Steg, L. and R. Gifford, "Sustainable Transportation and Quality of Life", *J. Transp. Geogr.*, Vol. 13, No. 1, pp. 59–69, 2005.

2. Gokasar, I., "Kaza-olay Algılama Algoritmalarının Mikroskobik Benzetim ile Bodellenmesi ve Değerlendirilmesi: D 100 Karayolu örneği, İstanbul", *Akıllı Ulaşım Sistemleri ve Uygulamaları Dergisi*, Vol. 1, No. 2, pp. 87–107, 2018.

3. Gokasar, I., "Şerit Kontrol Sistemleri: D 100 Karayolu, İstanbul Örneği", *Teknik Dergi*, Vol. 27, No. 4, 2016.

4. Council, N. R., *The Congestion Mitigation and Air Quality Improvement Program, assessing 10 years of experience*, Transportation Research Board., Washington, DC, 2002.

5. Zhao, H. and . Daniel Sperling, "Traffic Emission Pollution Sampling And Analysis On Urban Streets With High-rising Buildings", *Transportation Research Part D:Transport and Environment*, Vol. 6, 1997.

6. Coelho, M. F., J. M. Bandeira and M. C. Coelho, "Impact of Road Traffic Incidents on Pollutant Emissions", *2011 IEEE Forum on Integrated and Sustainable Transportation Systems*, pp. 312–316, 2011.

7. Corcoba Magaña, V. and M. Muñoz-Organero, "WATI: Warning of Traffic Incidents for Fuel Saving", *Mobile Information Systems*, pp. 1–16, 2016.

8. Owczarzak, Ł. and J. Żak, "Design of Passenger Public Transportation Solutions Based on Autonomous Vehicles and Their Multiple Criteria Comparison with Traditional Forms of Passenger Transportation", *Transp. res. procedia*, Vol. 10, pp. 472–482, 2015.

9. Csiszár, C. and A. Zarkeshev, "Demand-capacity Coordination Method in Autonomous Public Transportation", *Transportation research procedia*, Vol. 27, pp. 784–790, 2017.

10. Lam, A. Y. S., Y.-W. Leung and X. Chu, "Autonomous Vehicle Public Transportation System", *2014 International Conference on Connected Vehicles and Expo (ICCVE)*, IEEE, 2014.

11. Lam, A. Y. S., Y.-W. Leung and X. Chu, "Autonomous-vehicle Public Transportation System: Scheduling and Admission Control", *IEEE Trans. Intell. Transp. Syst.*, Vol. 17, No. 5, pp. 1210–1226, 2016.

12. Eden, G., B. Nanchen, R. Ramseyer and F. Evéquoz, "Expectation and Experience: Passenger Acceptance of Autonomous Public Transportation Vehicles", Lecture notes in computer science, pp. 360–363, Springer International Publishing, Cham, 2017.

13. Hilgarter, K. and P. Granig, "Public Perception of Autonomous Vehicles: A Qualitative Study Based on Interviews After Riding an Autonomous Shuttle", *Transp. Res. Part F Traffic Psychol. Behav.*, Vol. 72, pp. 226–243, 2020.

14. Salonen, A. and N. Haavisto, "Towards Autonomous Transportation. Passengers' Experiences, perceptions and feelings in a driverless shuttle bus in Finland", *Sustainability*, Vol. 11, No. 3, p. 588, 2019.

15. Shen, Y., H. Zhang and J. Zhao, "Integrating Shared Autonomous Vehicle in Public Transportation System: A Supply-side Simulation of the First-mile Service in Singapore", *Transp. Res. Part A Policy Pract.*, Vol. 113, pp. 125–136, 2018.

16. Iclodean, C., N. Cordos and B. O. Varga, "Autonomous Shuttle Bus for Public Transportation: A Review", *Energies*, Vol. 13, No. 11, p. 2917, 2020.

17. Karsan, "Karsan, Otonom Atak Electric'in Üretimine Başladı!",

https://www.karsan.com/tr/, accessed on May, 2022.

18. Gurtas, S., *Otonom Araç Sürüş Destek Sistemleri ve Yapay Zeka Uygulamaları*, Master's Thesis, Bursa Uludag University, 2021.

19. Sener, E., *Otonom ve Paylaşımlı Araç Yönetim Sistemi*, Master's Thesis, Bursa Uludag University, 2021.

20. Basargan, H., "Driver and Pedestrian Trust Analysis on Integration of Autonomous Vehicles to Infrastructure of Turkey", *Alphanumeric j.*, pp. 25–36, 2019.

21. Namazi, E., J. Li and C. Lu, "Intelligent Intersection Management Systems Considering Autonomous Vehicles: A systematic Literature Review", *IEEE Access*, Vol. 7, pp. 91946–91965, 2019.

22. Kang, J. and D. Lin, "DASH: A Universal Intersection Traffic Management System for Autonomous Vehicles", *2020 IEEE 40th International Conference on Distributed Computing Systems (ICDCS)*, IEEE, 2020.

23. Martin-Gasulla, M. and L. Elefteriadou, "Traffic Management with Autonomous and Connected Vehicles at Single-lane Roundabouts", *Transp. Res. Part C Emerg. Technol.*, Vol. 125, No. 102964, p. 102964, 2021.

24. Rubin, I., A. Baiocchi, Y. Sunyoto and I. Turcanu, "Traffic Management and Networking for Autonomous Vehicular Highway Systems", *Ad Hoc Netw.*, Vol. 83, pp. 125–148, 2019.

25. Lu, Q. and K.-D. Kim, "Autonomous and Connected Intersection Crossing Traffic Management Using Discrete-time Occupancies Trajectory", *Appl. Intell.*, Vol. 49, No. 5, pp. 1621–1635, 2019.

26. Amirgholy, M., M. Shahabi and H. Oliver Gao, "Traffic Automation and Lane Management for Communicant, Autonomous, and Human-driven Vehicles",

Transp. Res. Part C Emerg. Technol., Vol. 111, pp. 477–495, 2020.

27. Mushtaq, A., I. U. Haq, M. U. Imtiaz, A. Khan and O. Shafiq, "Traffic Flow Management of Autonomous Vehicles Using Deep Reinforcement Learning and Smart Serouting", *IEEE Access*, Vol. 9, pp. 51005–51019, 2021.

28. Wagner, P., "Traffic Control and Traffic Management in a Transportation System with Autonomous Vehicles", *Autonomous Driving*, pp. 301–316, Springer Berlin Heidelberg, Berlin, Heidelberg, 2016.

29. Ashtiani, F., S. A. Fayazi and A. Vahidi, "Multi-intersection Traffic Management for Autonomous Vehicles via Distributed Mixed Integer Linear Programming", *2018 Annual American Control Conference (ACC)*, IEEE, 2018.

30. Lu, G., Y. Nie, X. Liu and D. Li, "Trajectory-based Traffic Management Inside an Autonomous Vehicle Zone", *Trans. Res. Part B: Methodol.*, Vol. 120, pp. 76–98, 2019.

31. Gora, P., "Simulation-based Traffic Management System for Connected and Autonomous Vehicles", *Road Vehicle Automation 4*, pp. 257–266, Springer International Publishing, Cham, 2018.

32. El Hamdani, S. and N. Benamar, "Autonomous Traffic Management: Open Issues and New Directions", *2018 International Conference on Selected Topics in Mobile and Wireless Networking (MoWNeT)*, IEEE, 2018.

33. Hasebe, K., K. Kato, H. Abe, R. Akiya and M. Kawamoto, "Traffic Management for Last-mile Public Transportation Systems Using Autonomous Vehicles", *2017 International Smart Cities Conference (ISC2)*, IEEE, 2017.

34. Zambrano-Martinez, J., C. Calafate, D. Soler, L.-G. Lemus-Zúñiga, J.-C. Cano, P. Manzoni and T. Gayraud, "A Centralized Route-management Solution for Autonomous Vehicles in Urban Areas", *Electronics (Basel)*, Vol. 8, No. 7, p. 722,

2019.

35. Farradyne, P. B., "Traffic Incident Management Handbook. Prepared for Federal Highway Administration", , 2000.

36. NHTSA, "Automated Vehicles for Safety", https://www.nhtsa.gov/, accessed on May, 2022.

37. "Traffic Congestion and Reliability: Linking Solutions to Problems", *Federal Highway Administration*, Washington, D.C, 2005.

38. Petrović, D., R. Mijailović and D. Pešić, "Traffic Incidents with Autonomous Vehicles: Type of Collisions, Manoeuvres and Errors of Conventional Vehicles' Drivers", *Transportation research procedia*, Vol. 45, pp. 161–168, 2020.

39. IIHS-HLDI, "Crash Avoidance Technologies", http://www.iihs.org/iihs/topics/t/crash-avoidance-technologies/hldiresearch, accessed on May, 2022.

40. Gutesa, S., J. Lee and D. Besenski, "Development and Evaluation of Cooperative Intersection Management Algorithm under Connected and Automated Vehicles environment", *Transp. Res. Rec.*, Vol. 2675, No. 7, pp. 94–104, 2021.

41. Tachet, R., P. Santi, S. Sobolevsky, L. I. Reyes-Castro, E. Frazzoli, D. Helbing and C. Ratti, "Revisiting Street Intersections Using Slot-based Systems", *PLoS One*, Vol. 11, No. 3, p. e0149607, 2016.

42. BELFER-CENTER, "Attacking AI - Artificial Intelligence", https://www.studocu.com/row/document/jamaa%D8%A9-almnsor%D8%A9/mathematics-2/attacking-ai-artificial-intelligence/9201756, accessed on May, 2022.

43. Stephanedes, Y. J. and A. P. Chassiakos, "Application of Filtering Techniques for

Incident Detection", *J. Transp. Eng.*, Vol. 119, No. 1, pp. 13–26, 1993.

44. Stephanedes, Y. J. and A. P. Chassiakos, "Freeway Incident Detection through Filtering", *Transp. Res. Part C Emerg. Technol.*, Vol. 1, No. 3, pp. 219–233, 1993.

45. Hellinga, B. and G. Knapp, "Automatic Vehicle Identification Technology-based Freeway Incident Detection", *Transp. Res. Rec.*, Vol. 1727, No. 1, pp. 142–153, 2000.

46. Mercader, P. and J. Haddad, "Automatic Incident Detection on Freeways Based on Bluetooth Traffic Monitoring", *Accid. Anal. Prev.*, Vol. 146, No. 105703, p. 105703, 2020.

47. Wang, J., X. Li, S. S. Liao and Z. Hua, "A Hybrid Approach for Automatic Incident Detection", *IEEE Trans. Intell. Transp. Syst.*, Vol. 14, No. 3, pp. 1176–1185, 2013.

48. Nikolaev, A. B., Y. S. Sapego, A. M. Ivakhnenko, T. E. Mel'nikova and V. Y. Stroganov, *Analysis of he Incident Detection Technologies and Algorithms in Intelligent Transport Systems*, 2017.

49. Martin, P. T., J. Perrin, B. G. Hansen, R. K. Kump and D. Moore, "Incident Detection Algorithm Evaluation", pp. 1–46, 2001.

50. Asakura, Y., T. Kusakabe, L. X. Nguyen and T. Ushiki, "Incident Detection Methods Using Probe Vehicles with On-board GPS equipment", *Transp. Res. Part C Emerg. Technol.*, Vol. 81, pp. 330–341, 2017.

51. Williams, B. M. and A. Guin, "Traffic Management Center Use of Incident Detection Algorithms: Findings of a Nationwide Survey", *IEEE Trans. Intell. Transp. Syst.*, Vol. 8, No. 2, pp. 351–358, 2007.

52. Wang, W., S. Chen and G. Qu, "Incident Detection Algorithm Based on Partial

Least Squares Regression", *Transp. Res. Part C Emerg. Technol.*, Vol. 16, No. 1, pp. 54–70, 2008.

53. Srinivasan, D., W. H. Loo and R. L. Cheu, "Traffic Incident Detection Using Particle Swarm Optimization", *Proceedings of the 2003 IEEE Swarm Intelligence Symposium. SIS'03 (Cat. No.03EX706)*, IEEE, 2004.

54. Zhu, L., F. Guo, R. Krishnan and J. W. Polak, "A Deep Learning Approach for Traffic Incident Detection in Urban Networks", *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, IEEE, 2018.

55. Li, L., Y. Lin, B. Du, F. Yang and B. Ran, "Real-time Traffic Incident Detection Based on a Hybrid Deep Learning Model", *Transp. Transp. Sci.*, pp. 1–21, 2020.

56. Ki, Y.-K., N.-W. Heo, J.-W. Choi, G.-H. Ahn and K.-S. Park, "An Incident Detection Algorithm Using Artificial Neural Networks and Traffic Information", *2018 Cybernetics & Informatics (K&I)*, IEEE, 2018.

57. Ivan, J. N., *Real-time Data Fusion For Arterial Street Incident Detection Using Neural Networks*, Ph.D. Thesis, Microfilms International University, 1994.

58. Assidiq, A. A. M., O. O. Khalifa, M. R. Islam and S. Khan, "Real Time Lane Detection for Autonomous Vehicles", *2008 International Conference on Computer and Communication Engineering*, IEEE, 2008.

59. Imani, H. N., *The Use of Real-time Connected Vehicles and Data in Developing an Automated Freeway Incident Detection Algorithm*, Ph.D. Thesis, University of North Florida, 2019.

60. Coelho, M. F., J. M. Bandeira and M. C. Coelho, "Impact of Road Traffic Incidents on Pollutant Emissions", *2011 IEEE Forum on Integrated and Sustainable Transportation Systems*, IEEE, 2011.

61. Songchitruksa, P. and K. N. Balke, "Assessing Weather, Environment, and Loop Data for Real-time Freeway Incident Prediction", *Transp. Res. Rec.*, Vol. 1959, No. 1, pp. 105–113, 2006.

62. Fontes, T., A. Lemos, P. Fernandes, S. R. Pereira, J. M. Bandeira and M. C. Coelho, "Emissions Impact of Road Traffic Incidents Using Advanced Traveller Information Systems in a Regional Scale", *Transp. res. procedia*, Vol. 3, pp. 41–50, 2014.

63. Tupper, L. L., M. A. Chowdhury, L. Klotz and R. N. Fries, "Measuring Sustainability: How Traffic Incident Management Through Intelligent Transportation Systems Has Greater Energy and Environmental Benefits than Common Construction-phase Strategies for "Green" Roadways", *Int. J. Sustain. Transp.*, Vol. 6, No. 5, pp. 282–297, 2012.

64. Xu, L., X. Xu, C. Ding, J. Liu, Y. Zhao, K. Yu, J. Chen, J. Liu and M. Qiu, "Spatial-temporal Prediction of the Environmental Conditions Inside an Urban Road Tunnel During an Incident Scenario", *Build. Environ.*, Vol. 212, No. 108808, p. 108808, 2022.

65. de Barros Baltar, M. L., V. H. S. de Abreu, G. M. Ribeiro and A. S. Santos, "Evaluating Impacts of Traffic Incidents on CO2 Emissions in Express Roads", *LCA Based Carbon Footprint Assessment*, pp. 35–53, Springer Singapore, Singapore, 2021.

66. Karioti, E., S. Basbas, E. Mintsis, G. Mintsis and C. Taxiltaris, "Traffic and Environmental Impacts of Traffic Incidents on Thessaloniki's Inner Ring Road", *Transp. res. procedia*, Vol. 24, pp. 288–295, 2017.

67. Avetisyan, H. G., E. Miller-Hooks, S. Melanta and B. Qi, "Effects of Vehicle Technologies, Traffic Volume Changes, Incidents and Work Zones on Greenhouse Gas Emissions Production", *Transp. Res. D Transp. Environ.*, Vol. 26, pp. 10–19, 2014.

68. Wirtz, J. J., J. L. Schofer and D. F. Schulz, "Using Simulation to Test Traffic Incident Management Strategies", *Transp. Res. Rec.*, Vol. 1923, No. 1, pp. 82–90, 2005.

69. Dudek, C. L., C. J. Messer and N. B. Nuckles, "Incident Detection on Urban Freeways", *Transportation Research Record*, Vol. 495, pp. 12–24, 1974.

70. Payne, H. J., E. D. Helfenbein and H. C. Knobel, "Development and Testing of Incident Detection Algorithms.", `https://trid.trb.org/view/91809`, 1976.

71. Payne, H. J. and S. C. Tignor, "Freeway Incident-detection Algorithms Based on Decision Trees with States", *Transp. Res. Rec*, Vol. 682, pp. 30–37, 1978, accessed on May, 2022.

72. Queensland-Government, "Traffic and Road Use Management Manual", `https://www.tmr.qld.gov.au/business-industry/Technical-standards--publications/Traffic-and-Road-Use-Management-manual`, 2009.

73. SUMO, "EmissionOutput - SUMO Documentation", `https://sumo.dlr.de/docs/Simulation/Output/EmissionOutput.html`, accessed on May, 2022.

74. Gounni, A., N. Rais and M. A. Idrissi, "New Solutions to Reduce the Environmental Impact of Road Traffic Emissions, Using Sumo", *Proceedings of the 2nd International Conference on Networking, Information Systems & Security - NISS19*, ACM Press, New York, New York, USA, 2019.

75. Validi, A., N. Polasek, L. Alabi, M. Leitner and C. Olaverri-Monreal, "Environmental Impact of Bundling Transport Deliveries Using SUMO : Analysis of a cooperative approach in Austria", *2020 15th Iberian Conference on Information Systems and Technologies (CISTI)*, IEEE, 2020.

76. Krajzewicz, D., M. Behrisch, P. Wagner, R. Luz and M. Krumnow, "Second

Generation of Pollutant Emission Models for SUMO", *Modeling Mobility with Open Data*, pp. 203–221, Springer International Publishing, Cham, 2015.

77. Cappiello, A., I. Chabini, E. K. Nam, A. Lue and M. Abou Zeid, "A Statistical Model of Vehicle Emissions and Fuel Consumption", *Proceedings. The IEEE 5th International Conference on Intelligent Transportation Systems*, IEEE, 2003.

78. SUMO, "Emissions - SUMO Documentation", `https://sumo.dlr.de/docs/Models/Emissions.html`, accessed on May, 2022.

79. Stutzer, B. and . Zürich, "HBEFA - Handbook Emission Factors for Road Transport", `https://www.hbefa.net/e/index.html`, accessed on May, 2022.

80. SUMO, "HBEFA3-based - SUMO Documentation", `https://sumo.dlr.de/docs/Models/Emissions/HBEFA3-based.html`, accessed on May, 2022.

81. Song, Y., J. Liang, J. Lu and X. Zhao, "An Efficient Instance Selection Algorithm for K Nearest Neighbor Regression", *Neurocomputing*, Vol. 251, pp. 26–34, 2017.

82. Batra, M. and R. Agrawal, "Comparative Analysis of Decision Tree Algorithms", *Nature Inspired Computing*, Advances in intelligent systems and computing, pp. 31–36, Springer Singapore, Singapore, 2018.

83. Behrisch, M., L. Bieker, J. Erdmann and D. Krajzewicz, "SUMO – Simulation of Urban MObility: An Overview", Proceedings of SIMUL 2011, The Third International Conference on Advances in System Simulation, Spain, 2011.

84. Krauß, S., *Microscopic Modeling of Traffic Flow: Investigation Collision Free Vehicle Dynamics*, Ph.D. Thesis, Koln University, 1998.

85. Krajzewicz, D., *Fundamentals of Traffic Simulation," International Series in Op-*

erations Research and Management Science, Springer, 2010.

86. Papaleondiou, L. G., “TrafficModeler: A Graphical Tool for Programming Microscopic Traffic Simulators through High-Level Abstractions””, *Proceedings of the 69th IEEE Vehicular Technology Conference*, Hilton Diagonal Mar, Barcelona, Spain, 2009.

87. Tonguz, O. K., “How Vehicle-to-Vehicle Communication Could Replace Traffic Lights and Shorten Commutes”, *IEEE Spectrum*, 2018.

88. Krajzewicz, D., E. Brockfeld, J. Mikat, J. Ringel, C. Rössel, W. Tuchscheerer, P. Wagner and R. Woesler, “Simulation of Modern Traffic Lights Control Systems Asing the Open Source Traffic Simulation SUMO””, *Proceedings of the 3rd Industrial Simulation Conference 2005, Seiten 299-302. EUROSIS-ETI. 3rd Industrial Simulation Conference*, Berlin (Germany, 2005.

89. Bieker, L., “Emergency Vehicle Prioritization Using Vehicleto-Infrastructure Communication”, *Researchers Seminar 2011 (YRS2011)*, Denmark, 2011.

90. Barbecho Bautista, P., L. Urquiza-Aguiar and M. Aguilar Igartua, “Evaluation of Dynamic Route Planning Impact on Vehicular Communications with SUMO”, ACM, USA, 2020.

91. Brockfeld, E. and P. Wagner, “Calibration and Validation of Microscopic Traffic Flow Models”, *Traffic and Granular Flow ’03*, pp. 67–72, Springer Berlin Heidelberg, Berlin, Heidelberg, 2007.

92. Brockfeld, E. and P. Wagner, “Testing and Benchmarking of Microscopic Traffic Flow Models”, *Proceedings of the 10th World Conference on Transport Research*, pp. 775–776, Istanbul, 2004.

93. Brockfeld, E. and P. Wagner, “Calibration and Validation of Microscopic Traffic Flow Models”, *Traffic and Granular Flow ’03*, pp. 67–72, Springer Berlin Heidel-

berg, Berlin, Heidelberg, 2007.

94. Treiber, M. and D. Helbing, “Realistische Mikrosimulation von Strassenverkehr Mit Einem Einfachen Modell”, *Symposium Simulationstechnik (ASIM)*, 2002.

95. Wiedemann, R., *Simulation des Strassenverkehrsflusses. Schriftenreihe des Instituts für Verkehrswesen der Universität Karlsruhe*, Vol. 8, Karlsruhe, Germany, 1974.

96. Wegener, A., M. Piórkowski, M. Raya, H. Hellbrück, S. Fischer and J.-P. Hubaux, “TraCI: An Interface for Coupling Road Traffic and Network Simulators”, *Proceedings of the 11th communications and networking simulation symposium*, 2008.

97. Lu, Q., T. Tettamanti, D. Hörcher and I. Varga, “The Impact of Autonomous Vehicles on Urban Traffic Network Capacity: An Experimental Analysis by Microscopic Traffic Simulation”, *Transp. lett.*, Vol. 12, No. 8, pp. 540–549, 2020.

98. Song, J., Y. Wu, Z. Xu and X. Lin, “Research on Car-following Model Based on SUMO”, IEEE, 2014.

99. Li, Z., Q. Wu, H. Yu, C. Chen, G. Zhang, Z. Z. Tian and P. D. Prevedouros, “Temporal-spatial Dimension Extension-based Intersection Control Formulation for Connected and Autonomous Vehicle Systems”, *Transp. Res. Part C Emerg. Technol.*, Vol. 104, pp. 234–248, 2019.

100. Ibrahim, A., M. Cicic, D. Goswami, T. Basten and K. H. Johansson, “Control of Platooned Vehicles in Presence of Traffic Shock Waves”, *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, IEEE, 2019.

101. Do, W., O. Rouhani and L. Miranda-Moreno, “Simulation-Based Connected and Automated Vehicle Models on Highway Sections: A Literature Review”, *Journal of Advanced Transportation*, pp. 1–14, 2019.

102. May, A. D., *Traffic Flow Fundamentals*, Prentice Hall, 1990.

103. Gokasar, I., "Kaza-Olay Tespit Algoritmalarina Genel Bakis", *Dokuz Eylul Universitesi Muhendislik Fakultesi Fen ve Muhendislik Dergisi*, 2010.

104. Electricity-Maps, "ElectricityMaps", https://app.electricitymap.org/zone/SE, accessed on May, 2022.

105. Eurostat, "Passenger Cars Per 1000 Inhabitants", https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=road$_e qs_c$ $arhablang = en, accessedonMay,$ 2022.

106. Sõidukite, "Sõidukite statistika", https://transpordiamet.ee/soidukite-statistikat, accessed on May, 2022.

107. EIA, "Frequently Asked Questions (FAQs) - U.S.Energy Information Administration)", https://www.eia.gov/tools/faqs/faq.php?id=74t=11:%7E:text=In%202020%2C%20total%20U.S.%20electricity,CO2%20emissions%20per%20kWh, accessed on May, 2022.

108. Statista, "Turkey: Electricity Generation 2021", https://www.statista.com/statistics/450378/electricity-generation-turkey/:%7E:text=Electricity%20generation%20in%20Turkey%20amounted,comparison%20with%20the%20previous%20year., accessed on May, 2022.

109. Gokasar, Ilgın, "Baglı Otonom Araclarla Kesintisiz Trafik Akımında Kaza-Olay Yonetimi", https://www.tubitak.gov.tr/en, 2022, hibe Numarasi: 120M574, TUBITAK 1. Ara Rapor.

110. Gokasar, Ilgın, "Baglı Otonom Araclarla Kesintisiz Trafik Akımında Kaza-Olay Yonetimi", https://www.tubitak.gov.tr/en, 2022, hibe Numarasi: 120M574, TUBITAK 2. Ara Rapor.