A TIME-BASED INTUITIVE PATH PLANNING ON LARGE-SCALE CROWD SIMULATION MODELS

GENİŞ ÇAPLI KALABALIK BENZETİMİNDE ZAMAN ODAKLI SEZGİSEL YOL PLANLAMA

BERK ECER

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ABSTRACT

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Traditional management models of intersections, such as no-light intersections or signalized intersection, are not the most effective way of passing the intersections if the vehicles are intelligent. To this end, Dresner and Stone proposed a new intersection control model called Autonomous Intersection Management (AIM). In the AIM simulation, examining the problem from a multi-agent perspective, demonstrating that intelligent intersection control can be made more efficient than existing control mechanisms. In this study, autonomous intersection management has investigated. We extend their works and added a potential-based lane organization layer. In order to distribute vehicles evenly to each lane, this layer triggers vehicles to analyze near lanes and they change their lane if other lanes have advantage. We can observe this behavior in real life such as drivers change their lane by considering their intuitions. Basic intuition on selecting correct lane for traffic is selecting less crowded lane in order to reduce delay. We model that behavior without any change in AIM workflow. Experiment results shows us that intersection performance is directly connected with the vehicle distribution in lanes of roads of intersections We see the advantage of handling lane management with a potential approach in performance metrics such as average delay of intersection and

average travel time. Therefore, lane management and intersection management are problems that needs to be handled together. This study shows us that, the lane through which vehicles enter the intersection is an effective parameter for intersection management. Our study draws attention to this parameter and suggested a solution for it. We observed that the regulation of AIM inputs, which are vehicles in lanes, was as effective as contributing to aim intersection management. PLO-AIM model outperform AIM in evaluation metrics such as average delay of intersection and average travel time for reasonable traffic rates which is in between 600 vehicle/hour per lane to 1300 vehicle/hour per lane. Proposed model reduced the average travel time reduced in between %0.2 - %17.3 and reduced average delay of intersection in between %1.6 - %17.1 for 4-lane and 6-lane scenarios.

Keywords: AIM project, Autonomous intersection management, Lane organization, Potential-based approach

ÖZET

GENİŞ ÇAPLI KALABALIK BENZETİMİNDE ZAMAN ODAKLI SEZGİSEL YOL PLANLAMA

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Araçların akıllı olması durumunda, ışıksız kavşaklar veya sinyalize kavşaklar gibi geleneksel kavşak yönetim modelleri, kavşakları geçmenin en etkili yolu değildir. Bu amaçla, Dresner ve Stone, Otonom Kavşak Yönetimi (AIM) adı verilen yeni bir kavşak kontrol modeli önerdi. AIM simülasyonunda, problemi çok ajanlı bir perspektiften inceleyerek, akıllı kavşak kontrolünün mevcut kontrol mekanizmalarından daha verimli hale getirilebileceğini gösterir. Önerilen model üzerinde yapılan deneyler ve gözlemler sonucunda araçların kavşağa hangi şertitten girdiklerinin kavşak performansına doğrudan etkisi olduğunu gördük. Bu çalışmada, Stone ve Dresner'in sunduğu AIM modeli ile otonom kavşak yönetimi ele alınmış ve kavşak performansının arttırılması hedeflenmiştir. Yapılan geliştirmeler ve deneyler sonucunda Stone ve Dresner'in sundukları AIM modelini genişlettik ve potansiyele dayalı bir şerit organizasyon katmanı ekledik. Araçları her bir şeride eşit olarak dağıtmak için, bu katman araçları yakın şeritleri analiz etmeleri için tetikler ve diğer şeritlerin avantajı varsa şeritlerini değiştirirler. Sürücülerin sezgilerini dikkate alarak şerit değiştirmesi gibi gerçek hayatta da bu davranışı gözlemleyebiliriz. Trafik için doğru şeridi seçmenin temel sezgisi, gecikmeyi azaltmak için daha az kalabalık şeridi seçmektir. Bu davranışı AIM iş akışında herhangi bir değişiklik olmadan modelliyoruz. Deney sonuçları bize, kavşak performansının, kavşak yollarının şeritlerinde araç dağılımı ile doğrudan bağlantılı olduğunu göstermektedir. Ortalama kavşak gecikmesi ve ortalama seyahat süresi gibi performans ölçümlerinde potansiyel bir yaklaşımla şerit yönetimini ele almanın avantajını görüyoruz. Bu nedenle, şerit yönetimi ve kavşak yönetimi birlikte ele alınması gereken sorunlardır. Bu çalışma bize, araçların kavşağa girdiği şeridin kavşak yönetimi için etkili bir parametre olduğunu göstermektedir. Çalışmamız bu parametreye dikkat çekmekte ve bunun için bir çözüm önermektedir. Şeritlerdeki araçlar olan AIM girdilerinin düzenlenmesinin amaç kavşak yönetimine katkı sağlayacak kadar etkili olduğunu gözlemledik. PLO-AIM modeli, şerit başına 600 araç / saat ila şerit başına 1300 araç / saat arasındaki makul trafik oranları için ortalama kavşak gecikmesi ve ortalama seyahat süresi gibi değerlendirme ölçütlerinde AIM'den daha iyi performans gösterir. Önerilen model, 4 şeritli ve 6 şeritli senaryolarda ortalama seyahat süresini %0,2 - %17,3 arasında azaltmış ve ortalama kavşak gecikmesini% 1,6 -% 17,1 arasında azaltmıştır.

Anahtar Kelimeler: AIM project, Autonomous intersection management, Lane organization, Potential-based approach

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SYMBOLS AND ABBREVIATIONS

Symbols

A *	A Star Algorithm
Veh/hour	Vehicle count per hour
s	Second

Abbreviations

AIM	Autonomous Intersection Management
PLO-AIM	Potential-based Lane Organization in AIM
TP-AIM	Trajectory planning in AIM
DCL-AIM	Decentralized coordination learning in AIM
DOI	Delay of intersection
ATT	Average travel time
TT	Total Travel Time

1. INTRODUCTION

In today’s world, there are several problems that is affecting the World such as environmental pollution. One of the biggest reasons that the world is getting polluted is the traffic jams caused by millions of vehicles that we used to go to work, go to schools, shopping, holidays and etc. Mankind is trying to save the world by reducing pollution that is created by vehicles with the ways like electric powered vehicles which is not producing any pollution. In order to serve this purpose, vehicle usage could transform to a smarter and efficient version which eliminates the extra time spending on travelling by just increasing the traffic performance.

In this purpose, with the power of growing computer technology autonomous vehicles can be used to transform our well-known transportation sector into a more intelligent, safer, and more efficient version. With this transformation, the autonomous vehicles and autonomous transportation could reduce the pollution of the vehicles by just increasing vehicle performance during travelling. Autonomous vehicles could also decrease the travelling time with the control of autonomous systems. Therefore, the pollution and the vehicle usage could be decreased because there won’t be unnecessary movements and traffics. For this purpose, this study presents a new model for increasing autonomous vehicles performance in autonomous intersections. In order to understand the problem, history of transportation must be investigated.

Transportation is a problem that humanity has tried to solve throughout history and has produced different solutions about this issue and still tries to produce. The solutions and ideas produced by humanity on this subject have developed very rapidly from the past to the present. The transportation problem was tried to be solved by the invention of the wheel in the early ages and by developing mobile vehicles. Later, these vehicles are transformed into the tools we use today with the developing technology.

During this transformation, the transportation technologies we currently use have changed and developed over the years. Humanity has produced countless different vehicles for transportation and transportation. It has produced sophisticated vehicles such as vehicles, trains, ships, and airplanes that can be reached by air, land and sea. Humanity has had to improve itself in transportation in order to keep up with the developing technology and the requirements of the age. As a result of these developments, different types of transportation vehicles started to be produced from different sources. With the production of these vehicles, a problem arose before mankind, such as maintaining control and order during the transportation of these vehicles.

Today, cats are one of the most accessible and popular ways of transportation. In our daily life, we need to reach somewhere for our business and social life. They are land transportation vehicles developed for carrying passengers or cargo in cars. When we look at the development of cars, in the early days, machines were able to convert the energy in fuels into motion energy, that is, wheeled vehicles that move with motors.

Most of the vehicles are used in our age have become complex systems that can offer different technologies and functions, pay attention to consumption efficiency and environmental cleanliness, can be produced in different ways according to the passenger or load profile they carry, and carry security measures, with computers that can have their own system. Transportation to meet the needs of people is one of the giant sectors with many sub-topics such as the production, control and security of vehicles, technical maintenance, part production and technology research to further develop these vehicles. This sector, which we can call the transportation sector, has been affected by other sectors developed in our age and it looks like it will continue to be affected.

With the development of computers and technology, the technologies used on vehicles have also developed. Computers are now integrated into most of the vehicles. With this partnership, both the capabilities of the vehicles can be expanded, and the capabilities and possibilities that the vehicles can offer to their users and to the jobs they can do in line with their purposes can also be increased. For example, some of the vehicles that can park themselves, some of the vehicle systems that can follow lanes, GPS features that can be used to track the position of the vehicles, and the ability to detect the vehicle's environment and their own physical movements have gained many different functions.

Today, transportation vehicles, which are now called smart vehicles, are started to be used and developed. Smart vehicles are vehicles that have sensors that can perceive their movement and physical changes around them, and technologies that can communicate with other smart tools and systems like themselves. These tools have been developed and adapted to our age with the development of computer technology and its transformation into more portable small technological units. In other words, with the developments in many different sectors, vehicles can also be affected by these developments and have become structures that can offer more performance, comfort, and confidence to their users.

Thanks to the variety of functions and capabilities of smart vehicles, these vehicles can act on their own in today's technology. In fact, unmanned vehicles that can go beyond this movement and use it for many purposes are produced. Unmanned vehicles are vehicles that are managed by smart computer systems and can serve their users without requiring any manpower, with features such as direction finding, route planning and communication with other smart systems. These vehicles can be used in many areas such as transportation, military, trade, and health. Human beings assign smart vehicles to places that are dangerous for people to go to, jobs that need to be done with machine precision, or jobs that do not require manpower with developing technology.

One of the most important features of smart vehicles to operate are being aware of their environment, gathering information from their environment about their physical movements, processing and interpreting this information and acting as a result of this interpretation. Thanks to these features, smart vehicles are becoming capable of functioning on their own.

If we limit the smart vehicles to the transportation sector, for example, when we think of smart cars with land vehicles, they can plan routes according to their starting and ending points or follow their determined routes, can detect obstacles and other objects they encounter during their journey, so that they can travel without collision, on the route they will follow during their journey We can explain it as a smart system that can follow its lanes and change lanes, and receive information from other systems thanks to the communication technologies it contains.

With the rapidly spreading smart vehicles, concepts such as autonomous cars, autonomous driving, autonomous intersection, and road systems should be emerged today. Autonomous vehicles are one of the intelligent transportation units that offer a safe, comfortable and performance drive without the need for any driver. These vehicles should have different sensor systems that enable them to perceive their surroundings, for example, infrared, radar, or direct analysis through visual data.

By using the sensor systems, vehicles can perceive what is happening around them during their travels and can detect obstacles or objects that they encounter. These vehicles should able to access basic information about their physical movements such as speed, acceleration, and direction, thanks to their detective sensors. These tools, which can perceive their movement as well as their movements and positions in their surrounding objects, have the knowledge to model movements in the real world. As a result of these models, the vehicles have gained the ability to decide on their own actions and actions and update these decisions against instant situations.

Using these models, vehicles can estimate the positions of themselves and the objects around them over time, and using this position information, they can define the most appropriate route for them with physical information such as acceleration, speed, and direction. Autonomous driving can be expressed as the autonomous vehicles traveling on their own without human input. Autonomous driving can also be seen as a type of travel managed and maintained by smart vehicles. Due to the increase in the number of smart vehicles and the development of their usability, they are getting more popular.

The existence of vehicles that can travel on their own naturally created a need for smart systems for the control and management of these vehicles. In order to meet this need, smart intersection, and lane management mechanisms, which have smart management units, should be emerged. Thanks to these mechanisms, it has been ensured that many smart vehicles that can complete the travel task on their own are coordinated with each other and with these management systems throughout their travels, in other words, the travels of these vehicles are organized by individual vehicle agents or by intelligent management units that are a higher control unit. Smart intersections can be counted among these management units.

Smart intersections should provide a layout and management system for smart vehicles to pass through the intersection by communicating with them as they approach. This queuing problem, which can be solved with different approaches, can be handled by the smart intersection manager on the intersection. They can create a ranking structure for vehicles approaching the intersection and should allow the vehicles to pass through the intersection without colliding with other vehicles in this sequence. Intelligent intersection management can also be done by using a general manager such as the intersection manager or by enabling vehicles to individually follow certain protocols. Communication between objects plays an important role in both approaches. Coordination between vehicles can be provided by using vehicle-vehicle and vehicle-structure communications in smart traffic.

Developing technology and rapidly spreading smart traffic systems show us that in the future, the transportation sector could be changed completely and new transportation methods, where unmanned approaches are intense. For this reason, many studies are carried out around the world to make smart vehicles and smart traffic units more efficient, environmentally friendly, and more advantageous for the user. The development of the unmanned transportation concept in the future with the knowledge that develops with these studies is very important both environmentally and will help to create a better transportation sector with the decrease in the energy and time people spend for transportation.

Today, intersections are one of the most critical traffic points where vehicles lose the most time in traffic and generate fuel waste and environmental pollution. When intersections are managed with protocols such as intersections with lights or intersections with no lights, which are traditional intersection management methods, they show lower performance under the rate of heavy traffic. Considering the developing smart vehicle technology with this situation, the need for smart intersection management units could be increased.

This thesis is about intelligent intersection management. It aims to increase the performance of smart intersection management mechanisms. The structure presented in this thesis aims to reduce the amount of time and energy spent on transportation by reducing the delay that vehicles experience due to waiting times at intersections, in other words, due to junctions. As a natural result of saving time and energy, it aims to be effective in reducing nature pollution such as noise, air and water caused by traffic.

In order to increase the intersection performance, proposed model triggers the vehicles which are arriving to an intersection starts to check other possible lanes which may be more advantageous. For example, if a vehicle should change its lane to less crowded lanes it will arrive the intersection faster. Therefore, it will send its reservation request to the intersection manager sooner. As a result of this earlier registration to intersection queue, vehicles are served by intersection earlier. Therefore, the waiting time spending for the queue of the intersection will be decreased for this specific autonomous vehicle.

All of the vehicles perform this evaluation by potential calculation to the neighboring lanes and their current lane. The potential calculation based on the vehicle counts which are in front of the subject vehicle. The less potential valued lane means that it is the less crowded lane because potential calculation depends on the vehicle counts. This calculation is repeated until the arrival of intersection with 1 second interval. If vehicle finds a lane which is less crowded it changes its lanes.

When this behavior performed by all of the autonomous vehicles which are arriving to the intersection, all of them will try to reach to intersection in the most advantageous lane for them. In conclusion, this behavior provides earlier registrations to IM. The delay caused by the intersection will be decreased. This performance update will reduce the delay of intersection and average travel times which are performance metrics of autonomous intersection management systems.

In the advanced parts of the thesis, concepts such as smart traffic management systems, smart vehicles, road planning, collision-free traffic, lane management will be explained respectively in the second part and field information is given about these subjects. In the third part, a summarized field literature about the solutions produced about these issues covered by the thesis study is presented. In the fourth chapter, the potential-based lane management system for smart traffic management systems developed within the scope of the thesis study will be explained and the experiments performed will be shared. Finally, the results obtained in the thesis will be summarized, these results will be rocked with other studies and the implications that can be made from these results and comparisons are discussed.

2. BACKGROUND

2.1. Autonomous Vehicles

Autonomous vehicles are getting popular every day. They are used for military purposes such as field explorations, or civilian purposes such as traffic and transportation. Autonomous vehicles can used for anywhere that is dangerous for humans or does not require humans to operate. With the help of the computers, autonomous vehicles can serve the humanity and eliminate human responsibility in some of the routines for transportation such as travelling to work, schools, or houses.

Autonomous vehicles (AV), also known as self-driving cars is a vehicle that has ability to driving without any human who operates the vehicles through ability to sense its surroundings. Autonomous vehicles don't need any human drivers for travelling between the start and destination points of the travel. Also, they don't require even any passenger in it. They can be used for commercial transportation. Autonomous vehicles can travel wherever a conventional vehicle goes and can do anything an experienced human driver does without any human touch[1].

An automated vehicle system can only be termed as an "autonomous" system, when all the dynamic driving tasks, at all driving environment, can be performed by the vehicle's automated system. In order to, evaluate autonomous systems, SAE has presented the levels of automation. Throughout this paper, the term autonomous vehicle (AV) refers to the levels higher than 3 in levels of automation table described in the next chapter.

2.1.1. Models of Automation

Society of Automotive Engineers (SAE) presented the 5-level of automation in 2014 [1]. understanding Autonomous vehicles are separated into a six category by looking the level of automation. No driving automation is the level 0 of the categories which is the vehicles that is used manually. Level 0 vehicles contain automated systems such as breaking, or cruise control. The vehicles which has driver assistance is the level 1 of the categories.

Level 1 vehicles contain automated driving assisted systems such as lane control or cruise control which adapts the external changes. At level 3, vehicles contain partial automation such as accelerate, break or steering. At level 4, vehicles are highly automated. They contain self-driving mode which is not like fully autonomous vehicles. Because of the legislation and infrastructure which are not as advanced as the vehicles automated vehicles which can be seen in the real life are less than other vehicles.

Last level of automation is the full automation. At this level, vehicles are fully automated, and they are capable of handling all of the responsibilities during travel which is taken by the drivers.

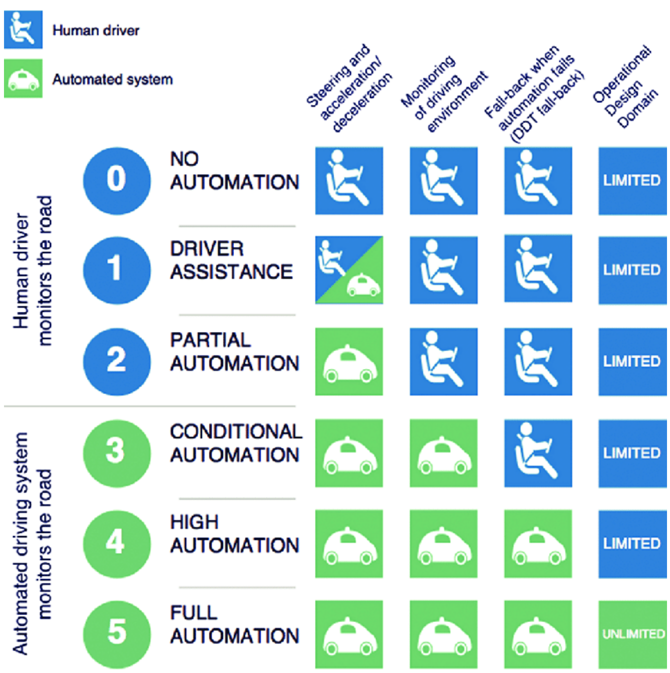

Figure 2.1.1 SAE J3016 levels of driving automation [1]

2.1.2. Abilities

Autonomous vehicles are the vehicles can operate and travel safe by sensing its surroundings and provide functions to operate the vehicle without any other human interaction. This type of vehicle requires different types of ability in order to operate independently. They need to sense the environment which they are in, they need to detect the obstacles before they reach in their way by using sensor, in order to achieve self-driving, firstly vehicle needs sensors[2].

Self-driving vehicles uses different types of sensors in order to perceive their surroundings, such as lidar, sonar, GPS, odometry and internal measurement systems. Sensed data is used for detecting the environment or obstacles are processed with for example computer vision techniques and as a result of this processing the vehicle know about its surrounding and obstacles. Vehicles use this knowledge to plan their path and actions during travelling in this path.

Sensor systems is the critical part of the autonomous vehicles because if the vehicles face with an obstacle or any other vehicle, it must be detected by the sensor systems. The environmental changes must also be detected such as traffic lights. Basically, sensor systems are the eyes and the ears of the autonomous vehicles. The detected data gathered from sensors are processed in the vehicle’s computer systems such as driver agent and trajectory planning systems.

In an example scenario, autonomous vehicles detects the change by using its sensors, it uses the data for computation of trajectories and determine that if it keeps on its movement or if it needs a change in its movement such at decelerating or accelerating. Therefore, autonomous vehicles must have a reasoning ability which is used with the data gathered from sensors in order to move independently by itself.

Autonomous vehicles must have a control system which is responsible for following the commands of the computation and decision-making systems. Converting the commands in the real-life actions such as breaking or turning is the job of the low-level control systems.

Autonomous vehicles must have a communication ability in order to share and collect the information about surroundings. The communication is one of the critical abilities that autonomous vehicles have. The communication is used to interact with the environment such that intelligent intersection managers and the other autonomous vehicles.

To sum up, an autonomous vehicle is the vehicle which can travel without collision and does not need any other human interaction rather than its decisions. In general, autonomous vehicles has sensors which provides the data, which is used to understand the environment, computation center which use the data, understands the environment, and calculate and plan the actions. They have communication ability to gather more information about surroundings. By using all of these abilities, autonomous vehicles can travel by their own.

2.2. Navigation of Autonomous Vehicles

Navigation of an autonomous vehicle is one of the biggest problems in this area. Navigation is a field that investigates, monitors and controls of the motion of a vehicle during their travels from their start point to their destination point[3]. All of the navigation methods use navigators' position and the known locations or patterns.

Due to the versatility of the environment, which is the real life basically, navigation of the vehicles becomes harder. In order to achieve that autonomous vehicle navigation, the data obtained by the sensor systems must processed because environmental changes are directly affecting the path and also effect the navigation.

In generally, navigation is determined by the roads because traffic infrastructure does not allow free movement. Vehicles must follow the lanes and roads and junctions. Therefore, navigation of the autonomous vehicles is determined by the path planning. Path planning methods are using the connections of the roads and intersections and applies specific path planning algorithms to generate a list of paths must be followed by vehicles.

2.2.1. Path Planning

The definition of the path planning problem can be defined as searching for a collision-free motion between start and end points within a specified environment. The simplest situation is when the path is to be planned in a static and known environment; however, more generally, the path planning problem can be formulated for any robotic system subject to kinematic constraints, in a dynamic and unknown environment[4]. The change in the environment directly effects that path planning because static path planning is not covering real time environment.

Autonomous vehicles must have collision-free path plan in order to travel safe. Path planning algorithms can be diverse but in the end collision-free path must be achieved by the path planning process. Traffic is a real life subject which actors and obstacles can change any time. Therefore, path planning methods that is used for autonomous vehicles must also work real time and must update the path by looking the environmental objects or situations such as other vehicles or traffic lights.

Because of the changing environment, path planning algorithm must be dynamic and every new event which has been captured by the sensors of the vehicles, must affect the dynamic path plan. For example, the planned path can be changed the road regulations or different events such that accidents, pedestrians, or obstacles must be considered by the path planning system in order to achieve collision-free path.

2.2.2. Collision-free Movement

Collision-free movement can be defined as travelling between the start and end points without any physical interaction with other objects and the autonomous vehicle [5]. Vehicles detect and sense their path with objects on top of it.

The other biggest problems in autonomous vehicles is the collision-free movement. Because of the safety issues, vehicles have to avoid from the collisions. Collision can be happening because of several factors such as other vehicles, obstacles, pedestrian, and other environmental objects. In order to prevent from the collisions, vehicles have to detect their roads and the other objects in their roads.

Detecting the environment is the first part of providing collision-free movement. In order to act about the environmental changes, first vehicle must sense or detect the environmental changes by using its sensor system such that cameras, radars, lidars and etc. When, vehicle detects a change in the environment, path planning and trajectory planning systems must immediately act and calculate the future position of the vehicle and the obstacles which can be mobile such that other vehicles or pedestrians or static such that infrastructural buildings.

Trajectory planning is the key to the collision-free movement. Which can be defined as calculating the future space-time occupancies of environmental objects and the vehicle itself [6]. Sensor systems provides the physical data about the movement or position of both environmental objects and the autonomous vehicles. Therefore, trajectory planning can be performed as simulation because system got definitions of the movements such that position, speed, acceleration, or deceleration.

By using this physical data about the movement, system can calculate the future positions of the objects. The system also calculates the future position of the autonomous vehicle. Therefore, if any of this calculated space-time trajectories collide, it means that if autonomous vehicle keeps the same movement, in the future it will collide with the object whose space-time trajectory intersects with the vehicle's trajectory.

Collisions can be detected by the sensors and trajectory planning, after that vehicles must act with the information gathered from trajectory calculations. If the system, detects a collision by comparing the space-time trajectories, the system must alter their movement such that stop, accelerate, decelerate.

Trajectory planning can be performed by the autonomous intersection managers as well as the the autonomous vehicles. In this case, all of the objects in the intersections such that autonomous vehicles desire to use the intersection shared their movement information to the intersection manager. Intersection manager calculated the trajectory plans for every object and provides a collision-free movement for every vehicle. If any future collision is detected by the intersection manager, intersection manager alters one of the vehicles which will have a future collision. For example, intersection manager stops on vehicle and let the other vehicle to pass. In general, the vehicle, which is arrived the intersection first, gets the transition priority. Therefore, intersection managers use queue mechanisms to handle transition priority problem.

2.3. Autonomous Intersection Management

Intersection management is the subject which can be described as the management of vehicles in the intersection whose will use the intersection. Traditional intersection management protocols such that traffic lights or no-light intersection protocol are used for controlling and scheduling the vehicles which need to travel through the intersection.

Traffic lights controls the roads of the intersection and with the configurated interval it allows the vehicles to enter the intersection. Traffic lights control the intersection by letting the vehicles of the roads in an order. In each light step, flow of the some of the roads stops and flow of some of the roads that will not create a collision starts. With this interval-controlled mechanism, vehicles can enter the intersection with road-based order.

No light intersection protocol is the way that vehicles that needs to use the intersection follow some rules and stop signs. For example, the vehicles must wait the other vehicles who is inside of the intersection. First comes first goes method is used and if two vehicles arrive to the intersection same time. Stop signs are used to manage lane priorities. If a vehicle in the road with stop sign in no light intersection, other lanes which have not stop sign have priority to use the intersection. With this protocol, vehicles are free to use intersection with following all of these rules.

With the growing technology and autonomous vehicle industry, new intersection management policies are appeared. Traditional models of intersection management are not really efficient when autonomous vehicles are in actors. Autonomous intersection management can be described as managing the intersection of autonomous vehicles without any human interaction.

When intersection protocols begin to be controlled by computer systems such that autonomous intersection managers, the flow of autonomous vehicles don’t need to be stopped like traffic light protocol and no-light protocol. The continuous flow will be achieved because of the intersection manager or autonomous vehicles calculates the future space-time trajectories of their and other vehicles in order to avoid collisions.

This study investigates autonomous intersection management and aims to improve the intersection performance. The performance of the autonomous intersection management can be measured by calculation the average travel time or delay of intersection values. In this study, on top of the autonomous intersection management, a new lane management model is proposed. Experiments revealed that the distribution of the vehicles in lanes of roads are directly affect the performance of the intersection. Therefore, proposed model provides a new potential based lane organization method which will be described in next chapters.

2.3.1. Actors

Smart and autonomous vehicles are the main actor of the autonomous traffic. Autonomous vehicles are the mobile part of the autonomous traffic. They are responsible for traveling through their entrance and destination points without any human effort. Autonomous vehicles are referred as connected which means that vehicle can communicate between other vehicles or other infrastructures such that intersection managers. Agents of autonomous traffics are directly connected to each other in order to achieve collision-free travel.

Static members of autonomous traffic are the stationary parts such that intersection manager systems. The intersection managers are in responsible for controlling the autonomous intersection usage. Autonomous vehicles communicate with the intersection managers in order to share their physical information about their movement.

Intersection manager uses the collected information shared by each autonomous vehicle and calculate space-time trajectories therefore, it will allow or reject the request of each vehicle. Intersection manager provides collision-free continuous flow of autonomous vehicles through intersection.

2.3.2. Communication Methods

Autonomous intersection management can be performed by different models and solutions. These models differ by their communication types. Vehicle-to-vehicle communication and vehicle-to-infrastructure communication methods are used in widely. Autonomous vehicles can be managed by themselves alone in the intersections by using vehicle-to-vehicle communication.

Vehicle-to-vehicle (V2V) communication means that all of the intelligent vehicles has communication systems in order to share physical information about their movement. With this information share, all of the autonomous vehicles can calculate both their position in future and other vehicles positions. With this calculation, and a queue mechanism such that first comes first served, autonomous vehicles can manage their intersection behaviors.

Vehicle-to-Infrastructure (V2I) communication means that all of the intelligent vehicles can communicate with the smart intersection manager (IM) of the intersection. In this case, calculation and collision-free movement are guaranteed by the intersection manager. Vehicles send their movement information and to the intersection manager. Intersection manager uses the information such that speed, acceleration, start point and destination to calculate future positions of all the vehicles in the intersection. Then intersection manager accepts or rejects the requests of the vehicles by looking calculations and the order of the vehicle arrivals.

If a vehicle won’t face with another vehicle in the intersection, in other words will have collision-free space and time trajectory in the intersection, IM will accept and let it move. If two space-time trajectory collides which means two vehicles will have collision if they keep moving, intersection manager will reject one of them and let the first arrived vehicle to use the intersection.

In both methods, the information which defines the movement of the vehicles must be shared between the actors of intersection. In both methods, continuous flow of the autonomous vehicles is succeeded. Proposed model in this study can be applied in both methods of autonomous intersection managements because the lane distribution effects the order of the vehicles which needs to use the intersection and eliminate unnecessary latencies generated by randomized traffic of autonomous vehicles.

2.3.3. Systems Design

Intersections are the most common source of traffic delays and accidents in traditional transportation systems. In order to ensure safety and collision-free transportation the intersection systems must be evolved to be intelligent for autonomous vehicles.

Traditional intersection control systems can be investigated in three categories. First layer is the coordination layer which is used for coordination between multiple intersections. This layer controls the flow of the roads between intersection. Maximization of the green band is very common application of this layer [8]. Second layer is the intersection management and trajectory planning layer which controls and organize the vehicle flow in the intersection. This layer can also be used for autonomous intersection management which will provide efficiency for transportation of autonomous vehicles.

Second layer in autonomous intersection management provides trajectory planning in order prevent collisions. Main goal of this trajectory planning is separation of the conflict movements of the vehicles. Third layer is the vehicle control layer which aims to motion control for each individual vehicle. Vehicle control can be managed by humans or in autonomous vehicles the control system is already operates the vehicle without any human interaction.

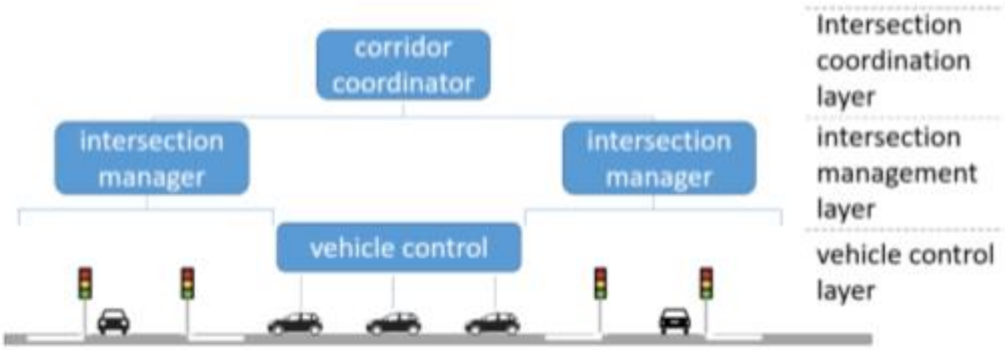

Figure 2.3.3.1 Intersection control layer [7]

Autonomous intersection management systems are more efficient and safer when it is compared with the traditional intersections. By using the properties of being intelligent and autonomous, new intersection management systems can be improved. Stone and Dresner noticed that when the subject of the transportation is autonomous and intelligent, traditional intersection management systems are not very effective [8].

Autonomous intersection management systems generally contain two individuals but communicating part. First of them is the driver agent which controls the vehicle and communicate with the environmental objects such as other vehicle agents or intersection manager agents. When the vehicles arrive to the intersection, driver agent starts to communicate and sends a reservation request in order to use the intersection. This process can be handled by communicating other autonomous vehicles.

The other individual part is the intersection manager (IM). This system controls the vehicle flow through the intersection and organize and manages the vehicle travels during the intersection. IM is responsible for deciding weather a vehicle enter or wait for the intersection. IM controls and operates the vehicle by calculation of the trajectory plans of each vehicle. By looking these plans, IM decides actions for each vehicle which has requested. In general, IM uses queue mechanisms to determine which vehicle will go first in conflicted vehicle movements.

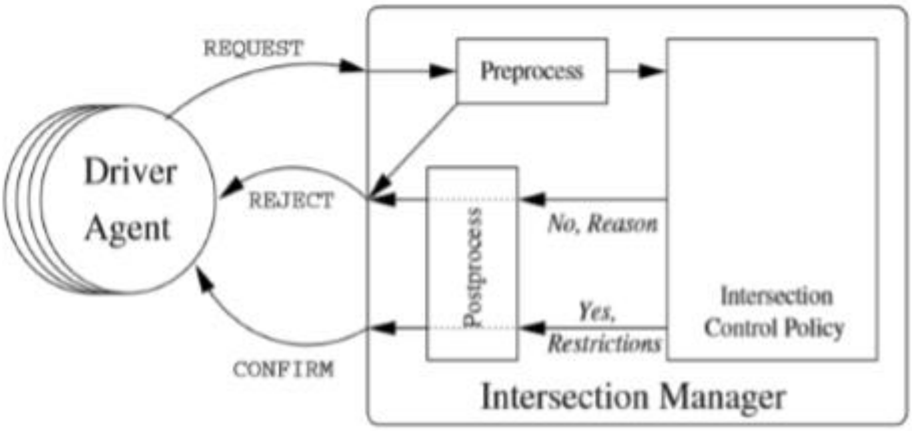

Figure 2.3.3.2 Intersection control layer [9]

Intersection management systems can be categorized in two as centralized and decentralized intersection managements. In centralized architecture, all of the intelligent vehicles are communicating with the central manager such that intersection manager which is an intelligent traffic infrastructure. In decentralized architecture, all of the autonomous vehicles are communicating with each other directly and plan their movement by regarding the information shared [10].

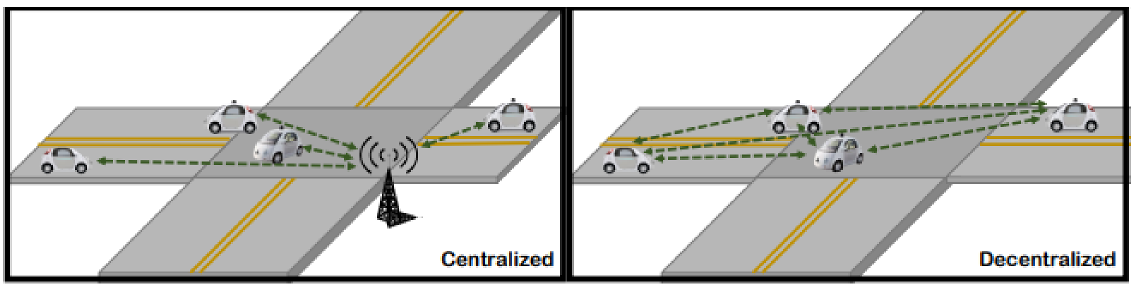

Figure 2.3.3.3 Centralized – Decentralized Architecture[10]

2.3.4. Performance Criteria

Performance criteria of autonomous intersections are directly related with the time spent during the travel through intersection. In this study, delay of intersection is used to determine intersection efficiency and performance. Delay of intersection can be described as the delay which is created by the intersection on the vehicles due to traffic management.

In order to evaluate efficiency, Stone and Dresner measured the delay of intersection, which can be described as the additional travel time caused by a vehicle as a result of passing through the intersection [8]. Delay of intersection (DOI) can be calculated as the time difference between travel times of the vehicle travelling without any other vehicles and vehicle travelling in traffic load.

Other performance metric which is investigated in this study is the average travel time (ATT). Average travel time can measure by taking the average of the travel times of each vehicle. Travel time is measured as time difference between entrance and exit of vehicles. Average travel time indicates that each vehicle can complete their travel through intersection on average travel time value.

2.4. Lane Management

Lane management can be described as organizing the vehicles in the lanes of roads therefore all of the lanes in roads shared equally distributed load. In other words, lane management can refer as traffic load balancer on lanes of roads. In general, lane management is used for big traffic networks or freeways in order to equalize the randomized traffic.

Lane management can be used for autonomous intersections to eliminate the jams created by randomized traffic. By organizing the vehicles at the entrance lanes of intersection, input lanes of intersection, provides a fully and evenly distributed intersection reservation line.

In this study, lane management model has used for improving autonomous intersection performance by prevent vehicles from piling up in a single lane due to randomized traffic. Lane management has proven its success on autonomous intersections in the experiments which is a part of this study. With the light of this study, it is seen that the lane management directly effect the performance of the autonomous intersection as same as traffic level. Therefore, in order to achieve lane management in autonomous intersections, potential based lane organization model is proposed in this study.

2.5. Path Planning Methods

Path planning is one of the complex problems in the autonomous vehicles. Every vehicle must have calculated collision-free path plan in order to follow through the intersection. Path planning is an important subject because of the meaning of autonomous vehicles refers travelling between destinations without any human interaction therefore, it requires autonomous path planning.

Path finding is the first part of the path planning which can be described as finding all of the possible paths between the points. Path finding provides all the possible paths to the path planning part. Path planning uses the paths and tries to determine the optimal path between start and end points from all of the paths provided by path finding operations [11].

Path planning can be described as generating a geometric path between start point and end point without any collisions. There are several types of path planning methods which can be categorized in three method [4].

Firstly, the roadmap techniques can be used for path planning which can be defined as union of curves in connected points between start and end points in free space. The roadmap is generated by a set of paths where every path is connected and collision-free area. The cell decomposition method is the second type of the path planning methods. In this method the area which is used to for path planning is divided with the adjacent cells.

The continuous path between cells is generated by considering obstacles. The potential filed method is the third type. In this case, goal point has attractive potential and the obstacles have a repulsive potential. Agents plan their path by this potential filed value [12].

3. RELATED WORKS

Intersections are the most common point of accidents in the traffic. With the help of the autonomous vehicles and other intelligent infrastructures, this critical accident cause may be safer and more efficient. Autonomous intersection management is a major problem about travelling with autonomous vehicles. Also, these two topics triggers each other. Developments in intelligent vehicles causes new developments in management systems of intelligent vehicles.

As the vehicles are getting smarter, the management systems are also getting smarter. Because of that different solutions from multiple disciplines can be applied for this topic. This study investigates that the effects of doing lane organization by using potential approach on autonomous intersection management. Therefore, autonomous intersection management models have been investigated in this study.

The most relevant studies about autonomous intersection management are listed in four different categories. Relevant studies have been investigated under these four main topics. Space-Time reservation and priority determination is the key elements of the autonomous intersection management which is handled by trajectory planning. Third category is the centralization which can be centralized and decentralized. Centralization basically defines the communication and management method. In the fourth category, the studies, and developments about vehicle control for autonomous intersection management is presented. Lastly, AIM project will be described in detail.

3.1. Space-Time Reservation

Trajectory planning which is directly connected with the Space-Time reservation is a method which is used to determine rotation and future positions of the vehicles. By calculation this trajectory, the management units of autonomous traffic such as intersection managers can predict weather a collision will arise or not.

Trajectories and conflict points determined by finding the intersections between trajectory plans of each vehicle is presented in the figure below. In autonomous intersection management this trajectory planning is performed at vehicle level. Trajectory planning is executed for each individual autonomous vehicle [7].

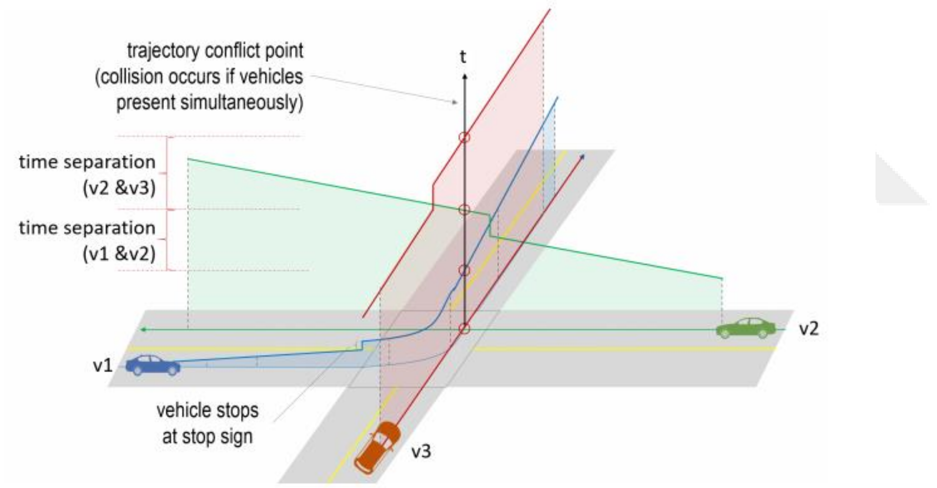

Figure 3.1 Trajectory and conflict points [7]

These trajectory plans are used for collision-free autonomous driving. In autonomous intersections all of the vehicles are planning their usage of intersection by reservation-based methods which are determining which vehicle will move first in case of conflict points.

There are four different reservation methods in order to solve conflicts in AIM. First of them is the intersection-based reservation [13] which allows one and only one vehicle within an intersection in order to prevent from collisions. Secondly tile-based reservation [9] is the method that free space is divided into a grid of tiles. Manager rejects if two vehicles occupy the same tile at the same time which means a collision. In some of the studies these ties can be grouped into bigger regions in order to decrease the computation load and complexities for reservation [14].

Thirdly conflict point-based reservation [15] which is performed by conflict point determination by using all of the space in the intersection. The last one is vehicle-based reservation [16] system which guides and manages all of the autonomous vehicles within an intersection space without any collision. The vehicle-based reservation method is required computational expense in order to solve collision avoidance constraints.

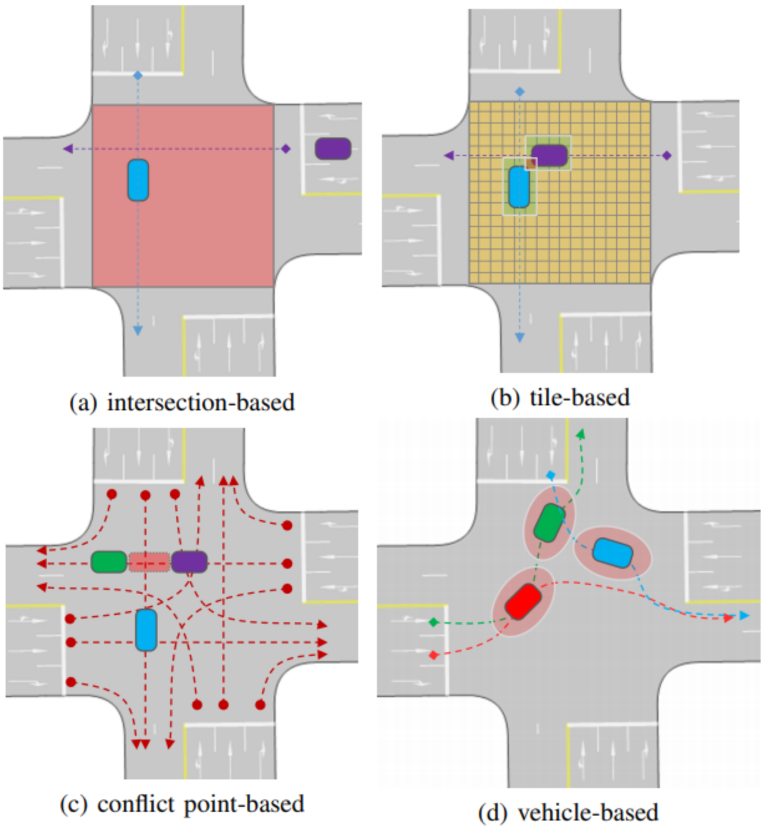

Figure 3.2 Reservation Models [7]

3.2. Priority Determination

All of the autonomous intersection management systems requires a priority policy due to decide which vehicle will move first when a collision or trajectory intersection occurs. In AIM, as well as the trajectory planning, priority determination is performed for each individual vehicle [7].

Firstly, autonomous intersection management systems are using first-come-first-serve (FCFS) policy which is fair as it’s in the real-life queues. Although vehicles are autonomous, equality is an issue for everything. Therefore, this real-life behavior of humans is applied on most the AIM research.

Secondly, system-optimal policy is the second most common policy. In the system-optimal policy, vehicle queues are determined based on system-level performance therefore, intersection manager always try to do the best when it comes to intersection performance. It will not consider the order of the vehicle arrivals. In the system-optimal policy, the priority is determined by considering system evaluation metrics such as overall delay, vehicle throughput and travel times.

There are several other priority policies which have been tried and experimented on priority determination in autonomous intersection management systems such as longest-queue-first policy [17]. In the longest-queue-first policy the order of priority is determined by considering the longest queues in the intersections. Vehicle type-based policy [18] is used by Dresner and Stone in order to give higher priority to the important or special vehicles during emergencies.

Custom-priority score-based policy[19] determines the priority by regarding the scores which is generated by other previous vehicles in order to provide a fair and efficient priority. The last one is the auction-based policy [20] which determines priority with auctions. Auctions are used to determine which vehicle should enter the intersection next. First vehicles of each lane are the participants of the auctions because no other vehicle in their lane can move before of them.

The other vehicles which are not participants, they bid on the first vehicle on their lane. Therefore, the waiting vehicles back of the first vehicle add value to the first vehicles bid. All of the vehicles in the same lanes are working together to get the priority.

Game theoretic priority policy [21, 22] is one of the most common method among the heuristic methods. In some of the research, platoon-based performance evaluators [23, 24] which are also one of the heuristic methods are used to determine priority.

The FCFS is investigated in many of research about autonomous intersection management. In this policy the arrival times of the vehicles are the first important point of determining the order of the vehicles which is about to use the intersection. Therefore, the intersection manager uses the time which a vehicle start communication to the manager. The vehicles which are in front of the lanes send communication request earlier to the other vehicles which are behind.

The second important point of determining the order is the intersection rules which is defined for traditional intersection management method named stop signs policy. These rules are working when more than one vehicle arrive and communicate with the IM at the same time. At this point, the vehicle on the right-off-lane has the priority.

Stone and Dresner proposed an enhanced version of FCFS which considers the emergency vehicles such as ambulances and firetrucks. Proposed FIFS-EMERG model increase the priority of the special vehicles[18]. Proposed model tries to decrease average delay of the emergency vehicles.

In the system-optimal priority policies, the system considers the over all performance of the intersection. FCFS policy produce fair priority but it is not the optimal solution for prioritizing the order of the vehicles. It is not optimizing the global intersection performance[25].

In the work of Lee and Park [26], a trajectory management layer for all intersection is added in order to decrease the load of FCFS policy. In the proposed model, all of the vehicles whose trajectories are conflicting are assigned individual trajectory in order to reduce the overlapping trajectories.

3.3. Type of Centralization

Centralization is the structure of the autonomous intersection management which determines how the organization is. The organization of the AIM determines the communication schemes as well as the operation. Three types of centralization method have been used in autonomous intersection management[7].

Centralized autonomous intersection management has one main coordinator which generally named as intersection manager. Vehicles are sharing their information to the one manager and the manager use this information for decision making about intersection processes. In general, autonomous intersection management models are rely on central coordinator but this method is expensive to built and operate and there are several bottlenecks like communication performance[27].

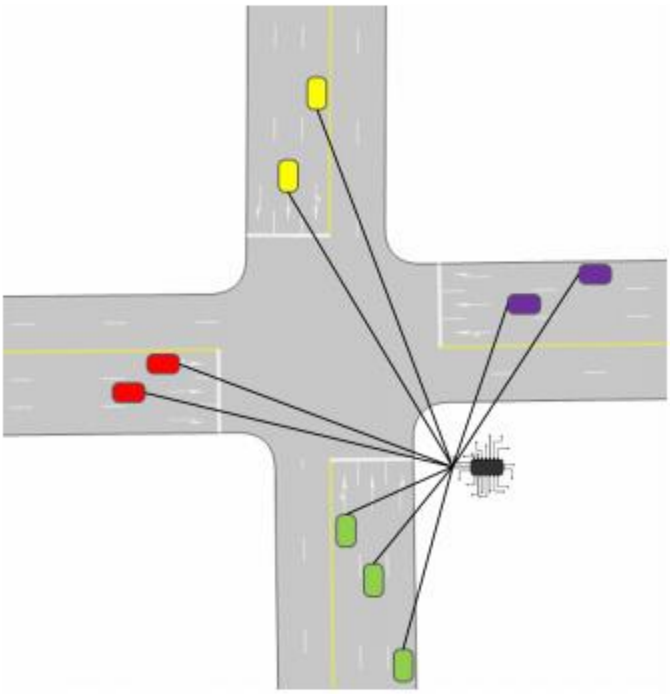

Figure 3.3.1 Centralized Communication AIM [7]

Decentralized autonomous intersection management has multiple group coordinators in the intersection system. The information is shared to all of the nodes and also the processing load is decentralized between nodes. In the platoon-based autonomous intersection managements [23, 24] platoon leader acts like a decentralized coordinator node which communicate the intersection manager except all of the vehicles.

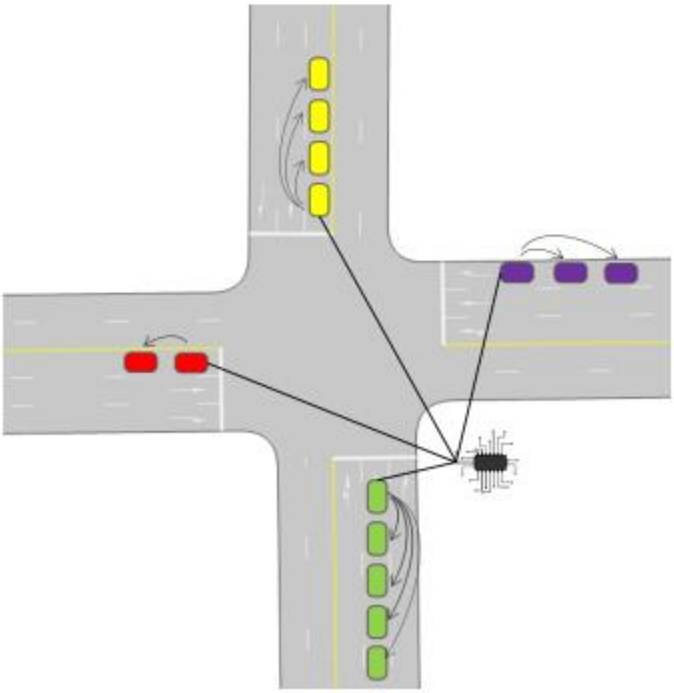

Figure 3.3.2 Decentralized Communication AIM [7]

Distributed autonomous intersection management is the extended version of decentralization which means all of node are making decisions for their own behaviors. All of the nodes are communicating with each other in order to gather information for decision making.

In Hassan and Rakha's work [27] fully distributed model is proposed. In their work vehicles are categorized in four label which are out, last, mid, and head in order to reduce the communication load of distributed system.

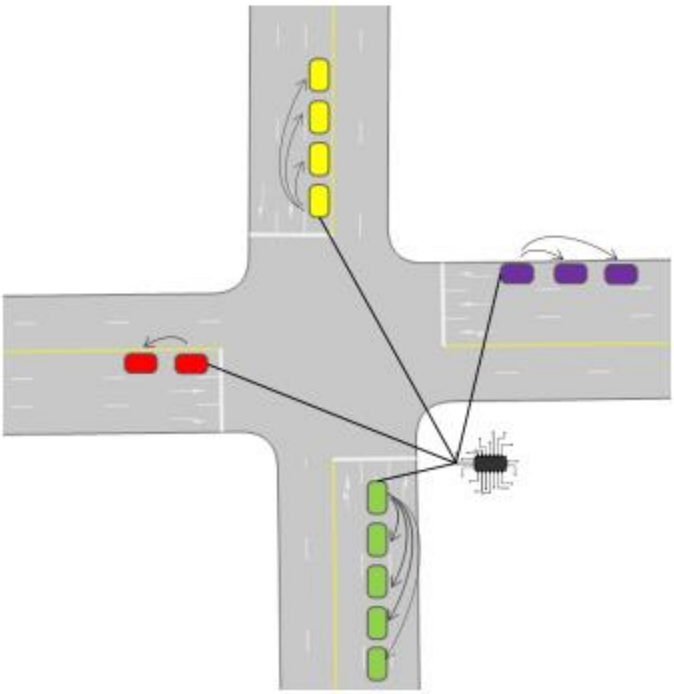

Figure 3.3.3 Distributed Communication AIM [7]

3.4. Significant Works

In the study of C Yu, W Sun and X Yang, a reservation-based method with simple policies, such as First-come-first-served Service (FCFS), has been proposed in the literature to manage connected automated vehicles (CAV) at isolated intersections, but there is a comprehensive analysis of intersection capacity and vehicle delays in FCFS [28]. In order to solve the problem of lack of underlying control, especially in high traffic demand situation, to solve this problem, adopt queuing theory to analytically show that this method cannot meet the high demand where traffic flow overlaps, and provide optimal service. Proposed an optimization model for CAV reaching the intersection to minimize delay.

This study compares the performance of the predicted optimization-based control at various demand levels for conventional vehicle drive control and reservation-based control. It shows the best performance in the proposed optimization and has a noticeable advantage over the other two controls. The advantages of reservation-based control are insignificant over demanding vehicle operation control.

M Khayatian and M Mehrabian proposed a time and space sensitive technique for managing the intersections of autonomous vehicles that are rugged against external disturbances and model mismatches in their study about RIM [29]. In their method, IM is responsible for assigning the oncoming vehicles safe Time of Arrival (TOA) and Arrival Speed (VOA) without any conflict, and vehicles are responsible for selecting and following a trajectory to reach the intersection and driving in VOA. Since the vehicles follow a position trajectory, the effect of limited pattern mismatch and external disturbances can be compensated. Also, vehicles that want to turn at the intersection do not need to drive at low speed before entering the intersection. Results from experiments show that improvements shorten the average times.

In the article of B Liu, Q Shi, Z Song and A El Kamel a collaborative timing mechanism for autonomous vehicles passing through an intersection called TP-AIM has been proposed [19]. The main purpose of this research is to ensure safe driving while minimizing delay at an intersection without traffic lights. First, an intersection management system used as an information gathering-editing center assigns reasonable priorities for all available vehicles and thus plans their trajectories. Secondly, a window search algorithm is performed to find backup windows as well as an input window that can create a collision-free trajectory with minimal delay.

Finally, vehicles can individually edit their trajectories by applying dynamic programming to calculate the speed profile to pass the intersection. MATLAB / Simulink and SUMO based simulations are created between three types of traffic mechanisms with different traffic flows. The results show that the proposed TP-AIM mechanism significantly reduced the average evacuation time and increased efficiency by over 20% . The article also explores delay, which can be reduced to less than 10% compared to conventional light management systems. Both safety and efficiency can be guaranteed in the proposed mechanism.

In the study of R Chen, J Hu, MW Levin and D Rey, they propose an autonomous intersection management algorithm called AIM-pad that considers both vehicles and pedestrians to provide optimal efficiency when combined with maximum pressure control [30].This study analyzes the stability properties of the algorithm based on a simpler version of AIM-pad, the conflict zone model of autonomous intersection management. To apply the proposed algorithm in the simulation, this study the maximum pressure control current trajectory optimization algorithm to calculate optimal vehicle trajectories. Simulations were conducted to test the effects of pedestrian demand on intersection efficiency. The simulation results show that the delays of pedestrians and vehicles are negatively correlated, and the proposed algorithm can adapt to the change in pedestrian demand and enable conflicting trajectory vehicle movements.

Y Wu, H Chen and F Zhu modeled CAVs as Markov Decision Processes (MAMDPs), using communication and computational technologies, in which sequential movements of vehicles from intersection points work together to minimize deceleration of vehicle factors with non-collision constraints in their study DCL-AIM [17]. From the structural features of the AIM problem and using a decentralized coordinated multi-factor learning approach (DCL), it is divided into an independent part and a coordinated part. AIM) is recommended to solve the problem efficiently by leveraging both global and localized agent coordination requirements in AIM. The main feature of the proposed approach is to clearly identify the coordination needs of representatives in the learning process and adapt them dynamically, so that the dimensional and non-stationary problems of the environment can be alleviated while learning with more than one tool.

The effectiveness of the proposed method has been demonstrated under various traffic conditions. Comparative analysis is based on the LQFAIM guide (Longest Queue-First) and Webster’s method (Signal) between DCL-AIM and first-come-first-service-based AIM (FCFSAIM). as comparison. Experimental results show that DCL-AIM’s sequential decisions outperform other control directives.

3.5. AIM Project

Developments in autonomous vehicles and smart transportation systems point to a rapidly approaching future where smart vehicles can automatically manage the travel process, become aware of their environment, make decisions with this awareness, and implement the decisions they make. When K Dresner and P Stone consider the increasing traffic and number of active vehicles, they saw that smart solutions will need to be implemented in the field of transportation. In order to increase the efficiency of transportation infrastructure, more intelligent traffic control mechanisms that work hand in hand with smart vehicles are needed to include into our lives.

To this end, Dresner and Stone proposed a new junction control mechanism called Autonomous Intersection Management (AIM), and in the simulation, examining the problem from a multi-agent perspective, it showed that intersection control could be made more efficient than existing control mechanisms such as traffic signals or stop signs [8]. AIM is an open-source intersection management framework that generates an intersection model based on simulation configurations. AIM also generate vehicles, drivers, and operate them during intersections. All of the vehicles can turn left and right or keep moving forward after the intersection.

This multi-agent systems-based intersection management strategy, introduced by Dresner and Stone, follows a protocol for reservation for every vehicle. Arriving vehicles to the intersection will inform the Intersection Manager (IM) agent. The IM is responsible for controlling that intersection by reserving a trajectory for vehicles through intersection space-time. The IM process every reservation request and determines requests whether confirm or reject by regarding intersection control policy [8].

General communication between vehicles and intersection manager is ordered below.

(a) The vehicle approaching the intersection informs the intersection manager that it is approaching along with required information such as vehicle size, estimated time of arrival, speed, acceleration, the lane it is in and the lane it wants to pass.

(b) The intersection manager simulates the road that the vehicle will follow inside the intersection using the information shared by the vehicle. The IM checks whether the road that the previous vehicles will follow at the intersection and the road that the new vehicle wants to follow does not conflict.

(c) The intersection manager confirms a reservation if there is no interference with the path in times the vehicles will use. After this point, it becomes the vehicle's task to reach the intersection and pass through the intersection.

(d) Vehicles must receive their successful reservation message from IM, in order to use intersection and pass to their desired lanes.

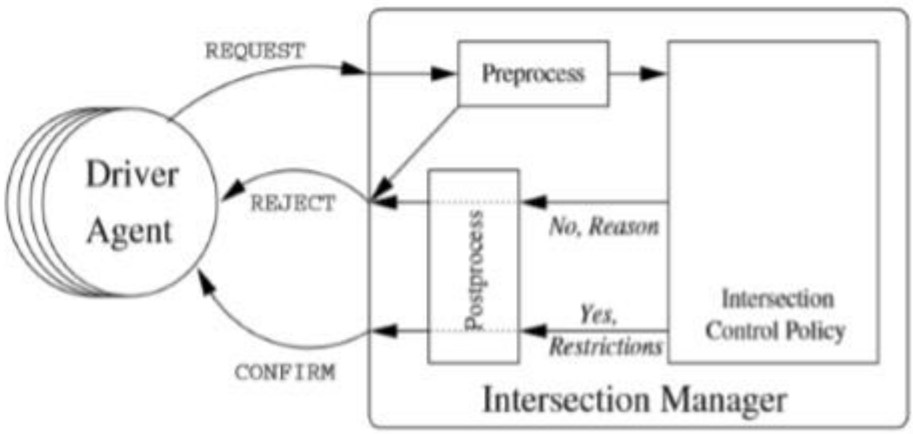

Figure 3.2 AIM workflow [9]

After the response of the intersection manager, vehicle performs the IM decision or wait and re-sent reservation request for successful message. It is vehicles' duty to move as the intersection manager accepted.

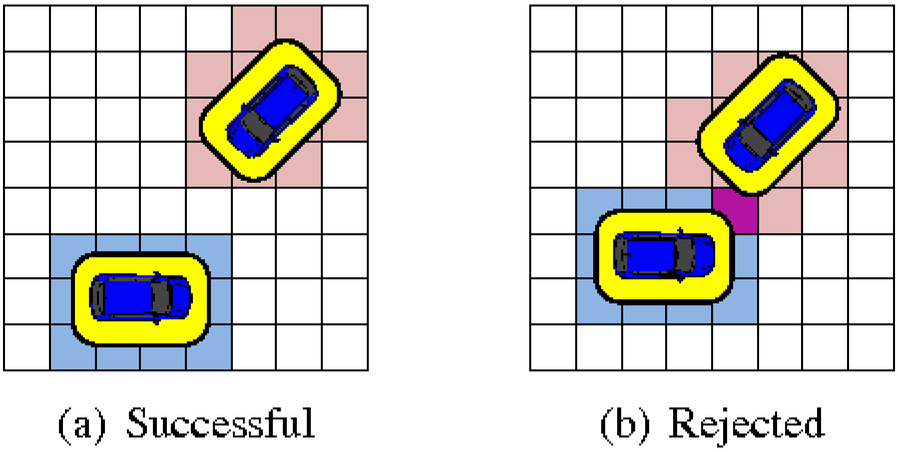

Figure 3.3 Successful and rejected situations in simulation [9]

M Hausknecht, TC Au and P Stone extended the work of Stone and Dresner beyond the situation of a single intersection and examine the unique consequences and capabilities of using AIM-based agents to control an interconnected network of intersections [8]. They explore various navigation rules that autonomous vehicles can use to dynamically change their planned routes, observe an example of the Braess Paradox, and explore the new possibility of dynamically reversing traffic flow across lanes in response to minute-by-minute traffic conditions. By examining this multi-agent system in simulation, they measure the significant efficiency improvements that can be achieved with this tool-based traffic control methods.

4. POTENTIAL-BASED LANE MANAGEMENT SYSTEM

The aim of this study is to improve autonomous intersection management performance by decreasing average travel time of vehicles and delay of the intersection. In order to achieve this goal, proposed model enables vehicles to adjust their lanes in order to arrive earlier to the intersection and as a result of this vehicle sends the intersection reservation earlier. This lane adjustment uses potential based approach in order to select the most advantageous lane for every vehicle.

Proposed model is a potential based lane organization module which triggers the vehicles to reconsider their lanes and analyze neighboring lanes. When the vehicles pass through the beginning data collection line, lane organization module is triggered. Once vehicle is triggered, it calculates potential values for its current lane and neighboring left and right lanes. When the vehicle has potential values of its own lane and neighboring lanes, it compares the results and select the lowest potential lane which means most advantageous lane. Then vehicle change its own current lane in order to reach the intersection earlier.

Vehicles calculate the lane potentials by looking frontier vehicles of each lane. In another words, calculated lane potentials are based on vehicle counts in front of the current vehicle in each lane. Therefore, the lowest potential lane will be the less crowded lane for the vehicle.

This approach and potential calculation triggering occur on every vehicle that enters the simulation. Therefore, all of the vehicles are trying to change their lanes to the lowest potential lane which refers as less crowded lane. Also, when a vehicle triggered to calculate potential, it repeats that calculation and decision making for every 1 second until they stop or arrived at the intersection. This behavior is performed by every other vehicle in the system.

This common behavior provides benefits for the system and for each single vehicle. In the perspective of the vehicle, vehicle will be arrived earlier to the intersection therefore its total travel time and delay of intersection is decreased. In the system perspective, all of the vehicles are trying to change their lane to the less crowded lanes therefore, problems caused by randomized traffic such as single lane jams or lane blockings will be reduced and eliminated. With this common behavior, it is ensured that the vehicles are evenly distributed to the lanes on the roads.

Potential approach was used in Cumhur Y. Ozcan's path-based study of crowd simulation for path planning [31]. They proposed a system using the Reciprocal Speed Barriers [32] (RVO) model as the basic routing algorithm, which provides macro information computed by a modified A * algorithm.

The main feature of the proposed system is the modification of cost function of the A * algorithm to consider the current and possible future positions of other agents and path calculations. For this purpose, after a path calculation is made for an agent, they store the information about the calculated path (ie potential value) on the grid that other agents will use when determining their paths. Cumhur Y. Ozcan used potential approach in comparison with machine learning methods in his time-based global path planning study [33].

These studies show that the potential approach can compete with machine learning approaches. Because, in fact, moving in the crowd and driving in the crowd as a very similar problem are actions based on learned reflexes that people perform with their intuition. For this reason, it is very plausible that heuristic algorithms modeling human intuition are successful.

In addition, collecting the volume and variety of data required by machine learning is a research problem in itself. While collecting even this data, data must be collected from intersections where there are intuitive approaches to actually reflect the context, because people drive intuitively. For this reason, we cannot collect data as if all drivers behave in the same way because we do not drive our cars that way. In order for machine learning data to work, it must be based on real life. In real life, people are already driving intuitively.

People actually predict who will turn, who will not turn, and which vehicle will turn where even if it does not signal. This is a very important issue because we choose the most advantageous lane according to these estimates. What we are trying to do with potential is to be able to model this intuitive behavior and prediction that people exhibit.

In this study, crowd management problem is investigated, and proposed model uses potential base crowd navigation by calculating position potentials of each agent. Lane management of autonomous vehicle agents as sharing the same problem as the crowd management of Cumhur Y. Özcan. All of the agents in this case vehicles add potential to the positions which they will arrive in their path. Navigation system uses this potential information for calculating possible paths.

With the help of the potential information enhanced A Star Algorithm calculate the optimal path for the agents. The proposed A Star algorithm considers the potential information as well as the standard A * algorithm [33]. Therefore, it considers both the path and the potential which is generated individual values by the crowd.

In this study, potential based method is used to organize vehicle positions in the lanes of roads. Autonomous vehicles are the agents that calculate potential information for their current and neighboring lanes. Each vehicle adds potential value to its current lane. Therefore, vehicles can determine the least potential lane by calculating the potentials of the lanes.

After that point, vehicle can change their lane in order to be in a lane which is more advantageous or if the current lane of the vehicles is the most advantageous, the vehicle will keep its movement on that lane. All of the autonomous vehicles are triggered to potential calculation and the following lane change consideration. When the process is triggered, every vehicle which is triggered for lane management starts to calculate potential values for lanes. After the calculation complete, they compare the potential their lane and the others, and they decide weather change the lane or not. This procedure is repeated at a specified time interval which is 1 second in this study.

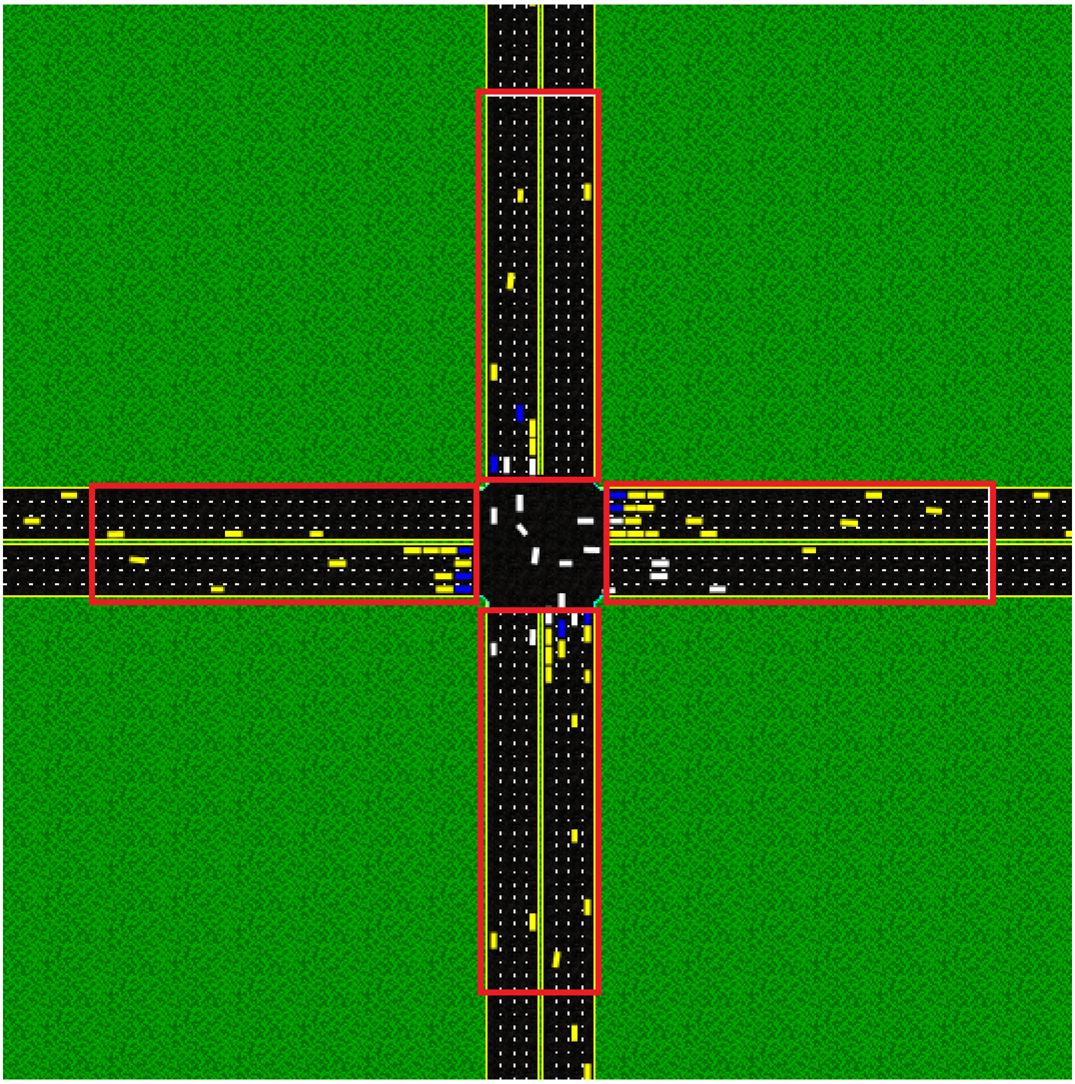

Figure 4.1 PLO-Layer Areas

PLO layer is triggering the vehicles when they intersect with the data collection lines and they perform potential calculation until they arrive the intersection. The area which is shown in the Figure 4.1 is representing the PLO layer operation region.

Every vehicle which enters the systems, evaluate the neighboring lanes of it in every 1 second by using potential approach. With the procedure executed several times, all of the vehicles adjust their lanes to the most advantageous one for them.

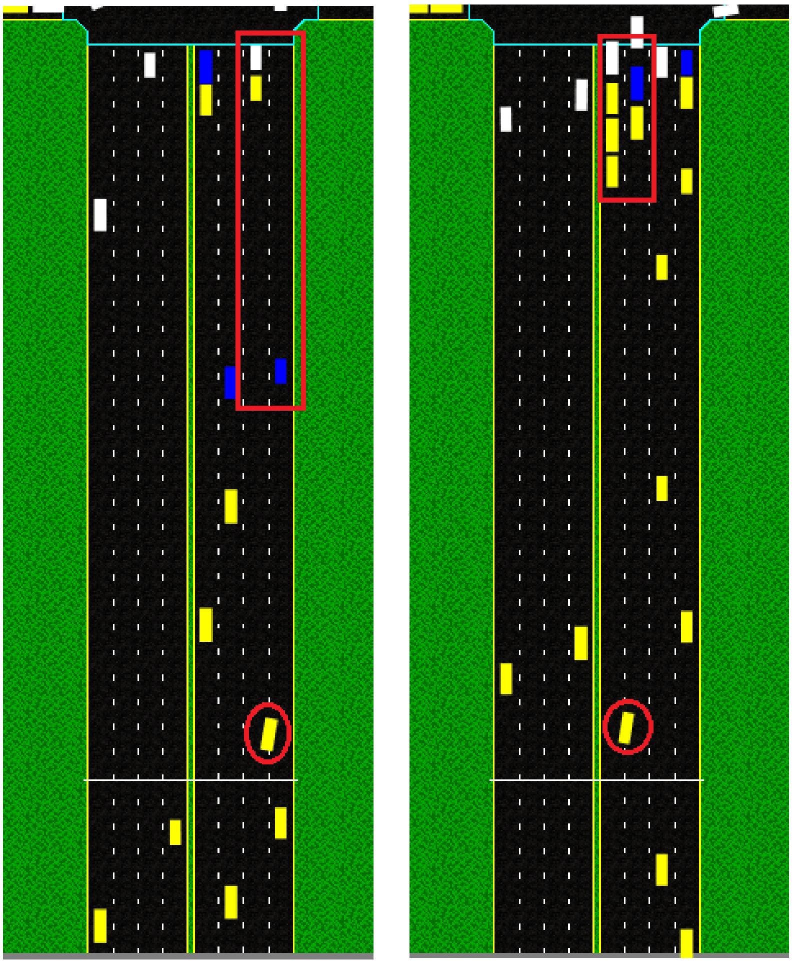

Figure 4.2 Lane changing vehicles

Vehicles in the Figure 4.2 are performing lane changes depending on the comparison of the potential values of the neighboring lanes and their current lane. After the potential calculation, the vehicles know that which lane has lowest potential value. As a result of this, the vehicles are performing lane changes.

5. EXPERIMENTS

5.1. Experimental Setup

This study uses AIM open source software for autonomous intersection management system and AIM simulation tool for experimenting and observations. AIM contains a built-in simulator which can be used for testing and visualizing traffic motion. We used this simulator in order to analyze AIM performance. After that, proposed model has been applied to the AIM source code without changing the flow of AIM. Proposed model which can be denoted as PLO-AIM has been tested and performance metrics has been gathered by using this simulation tool.

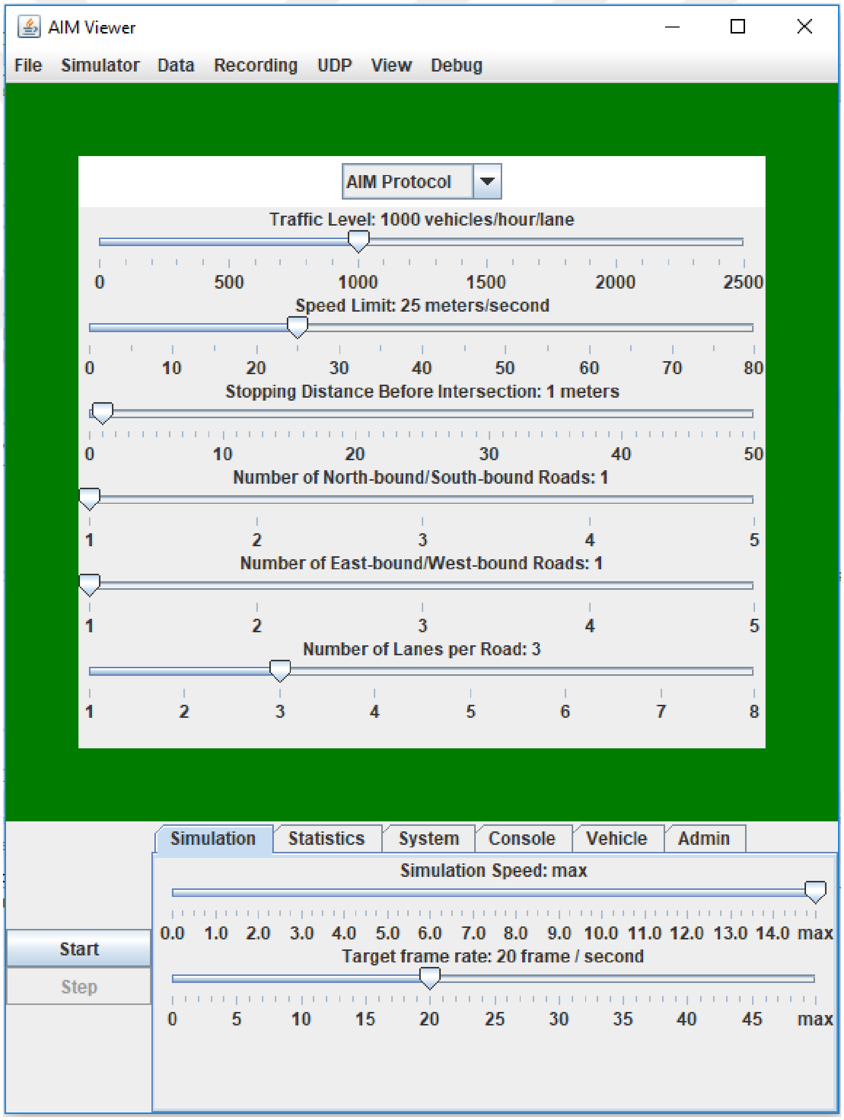

Figure 5.1.1 AIM configuration panel

AIM simulator has several options in it. In the configuration part of simulator, required traffic parameters such as traffic rate, lane counts, etc. can be set. Different models of intersection can be simulated. By using this configuration panel, complex systems of intersection can also be simulated.

In the configuration panel, user can select intersection management protocol as the first parameter. Protocol can be set on of the three pre-defined protocols such that standard traffic light protocol, no light protocol and finally AIM protocol which is directly design for autonomous intersection management. In this AIM protocol, autonomous vehicles and autonomous intersection manager organize vehicle flow inside the intersection. This study uses AIM protocol in order to experiment and develop new model for autonomous intersection management.

Speed limit parameter can be set in this configuration. Which directly controls the speed limit of autonomous vehicles. In this study, 25 meters/second speed (90 km/h) has used in all experiments. Speed limit is fixed for the entire experiment in order to eliminate the effects of the parameter differences.

Stopping Distance Before Intersection is one of the other configuration parameters. It defines the distance that vehicles should stop before entering the intersection. This parameter is fixed as 1 meter same as default configuration of AIM. Same stopping distance is used for entire experiment.

In the configuration panel, user can set number of roads in North-South direction and East-West direction. This parameter defines the number of roads which contains lanes that enters the intersections. In this experiment, 4-way intersection model has been used, in order to simulate this Number of North-bound/South-bound roads parameter and Number of East-bound/West-bound roads parameter kept 1 as the default.

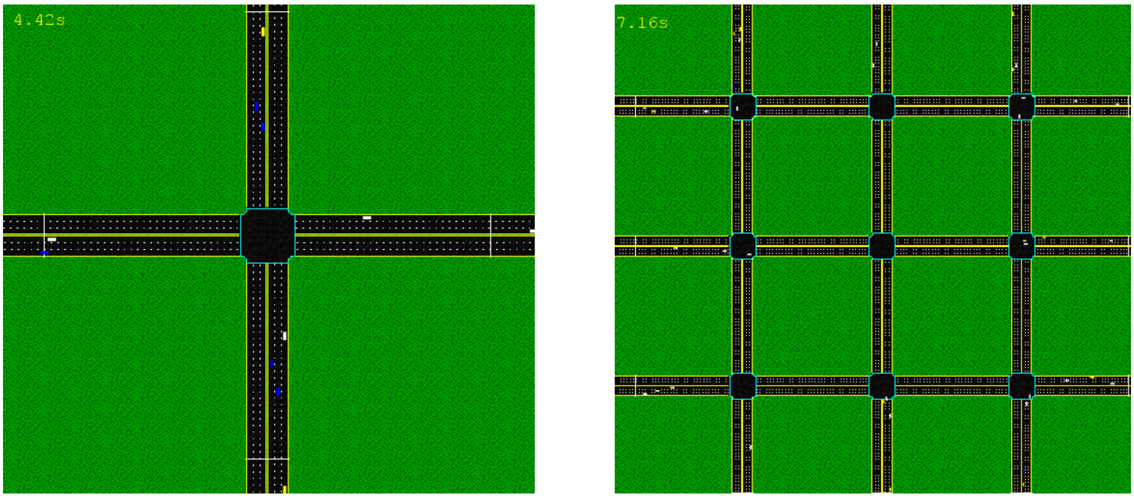

Figure 5.1.2 Single intersection and Multiple intersection systems

Last parameter is the Number of Lanes per Road which defines the lane count of each road contains. In this experiment, AIM and proposed model PLO-AIM has been analyzed, tested for both 4 lanes per road and 6 lanes per road. Therefore, this parameter takes values either 4 or 6.

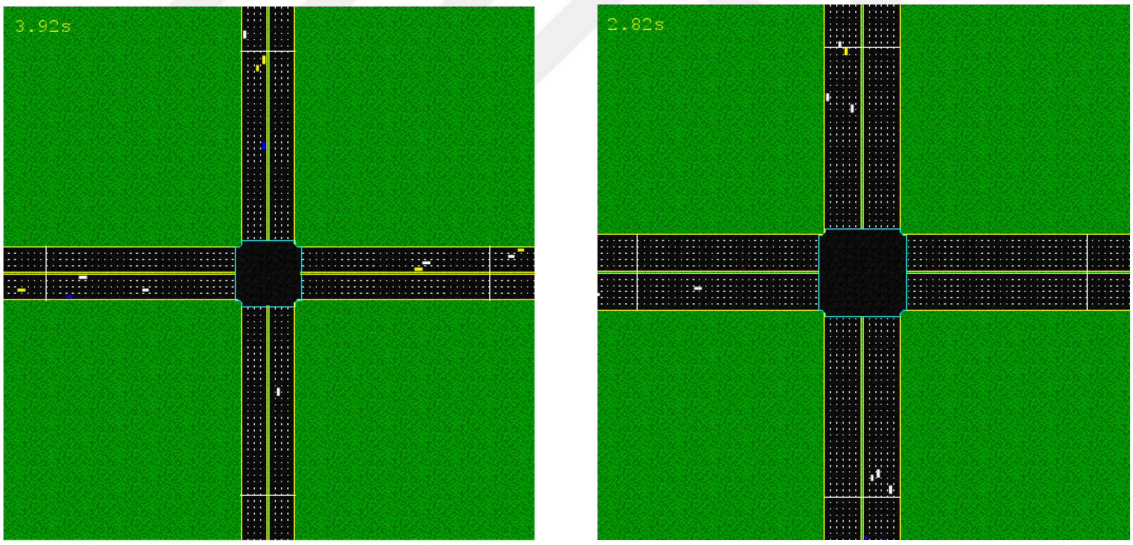

Figure 5.1.3 4-lane and 6-lane intersection models

To sum up, in this study all of the configuration parameters kept as what is set in AIM as default except traffic level and number of lanes per road. The effects of the traffic level are investigated by increasing the values from 600 veh/hour to 200 veh/hour by 200. Also, the effects of lane count of road are investigated by changing value either 4 or 6.

In order to extract data from simulation, AIM has data collection lines at the beginning and end of all roads. Data required for this study, is gathered by modifying these data collection lines. Added a timestamp collector in order to get when the vehicle enter the system and when they left the system of intersection.

Every vehicle pass through this data collection lines twice in the system. First pass happens when they have entered the system and second pass happens when they exit the system. Each time, with the modified data collection line, timestamp and vehicles identifier is stored and exported to the database.

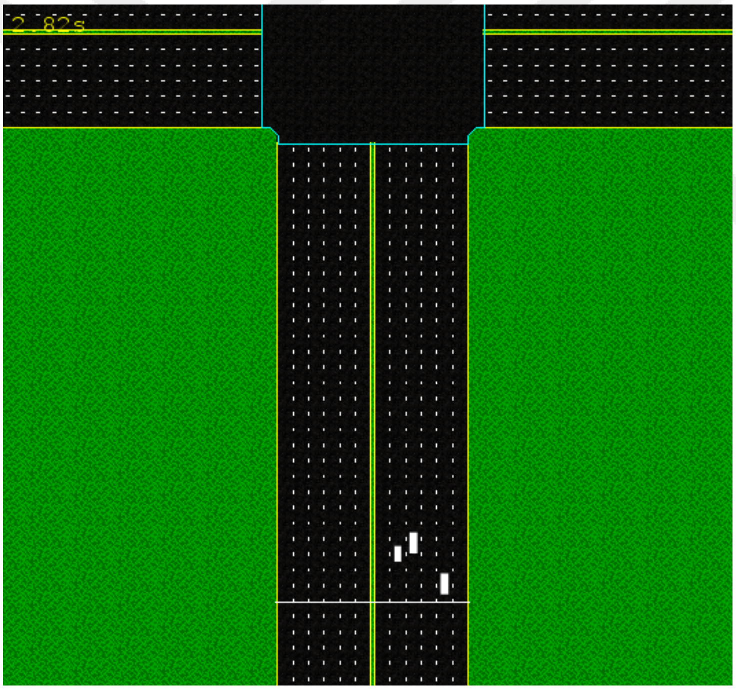

Figure 5.1.4 Data collection line.

In this study, these entering and exiting timestamps of vehicle data has been used for calculating metrics such as delay of intersection (DOI) and average travel time (ATT) as performance evaluators. This part will be present with more detail in following section.

5.2. Measurement Data

In order to determine efficiency, Dresner and Stone measured delay of intersection, which can be presented as the additional travel time caused by a vehicle as a result of passing through the intersection. Delay of intersection can be denoted as the time difference between travel times of the vehicle passing through the same intersection without any other cars and vehicle passing through the intersection with in traffic load.

In this study, delay of intersection and average travel time is measured by using the timestamps that is gathered by data collection lines. After the simulation ends, the timestamp data is exported to a database table in order to prepare calculations.

Exported data contains vehicle identifiers which is denoted as vehicle identifier and timestamps. Therefore, for each vehicle, two different timestamps have collected from simulation. One timestamp is for entrance and second timestamp for the exit. By using these timestamps, we can calculate the time difference between entrance and exit of each vehicle. Calculated difference refers total travel time of vehicle.

By using this difference method, travel time of every vehicle is calculated. After these calculations, vehicle identifiers and total travel times are inserted to different database table which is used for determining DOI and ATT. Average of total travel time values will reveal average travel time(ATT) which is one of the performance metrics that this study investigates.

Second performance metric that this study investigates is delay of intersection(DOI). In order to calculate this metric, calculations have designed as Stone and Dresner description. Therefore, in order to calculate additional travel time caused by a vehicle as a result of passing through the intersection, firstly the time spent for travelling between data collection lines without traffic is measured. This measurement is performed by just spawning one vehicle at once. Therefore, spawned vehicle will arrive their destination without any delay cause by traffic and intersection.

At this point, total travel times of each vehicle has calculated, and the time required for travel without any traffic has measured. By using Stone and Dresner description, the difference calculation between total travel time and time without traffic provides the delay that intersection cause on the vehicles which is main performance metric that this study investigates. The calculation results which is delay of intersection values are inserted in the same database table near the total travel time values. The average value of delay of intersections provides us average delay of intersection value.

These ATT and DOI calculations have done for every vehicle in every simulation for five times. Also, this procedure has completed for each configuration setup for both AIM and proposed model PLO-AIM. Results of this measurements and comparison between AIM and PLO-AIM will be presented in the next section.

5.3. AIM and PLO-AIM Experiments

In this study, several of experiments has done for both base AIM system in order to analyze and measure AIM performance. After AIM experiments has completed, proposed model has been implemented without changing workflow of base AIM. Then, same experiments that has been investigated with base AIM product, has executed again for proposed PLO-AIM model.

In this section of this study, all the experiments has done for five times for each configuration for both AIM and proposed PLO-AIM model, in order to calculate average total travel time and average delay of intersection, this five experiment results has been used. In each time, data collection and extracting, ATT and DOI calculation is repeated. Therefore, for each experiment, five result has been calculated. In the end, the average value of these five results is calculated for ATT and DOI. The results are the average travel time and average delay of intersection is the performance metrics for that experiment.

This procedure of ATT and DOI calculation has been performed for all of the different simulation configurations which is described in Experimental Setup section has performed. This procedures and experiments have performed for base AIM product in order to analyze its performance and results of AIM is the base performance value that proposed model must improve. After the proposed model PLO-AIM has implemented, all the performance evaluation procedure has repeated for PLO-AIM. The results of this PLO-AIM experiments are used to measure the PLO-AIM results and compare it with base AIM product.

This study aims to improve autonomous intersection management performance by reducing travel time and delay of intersections. In order to achieve this, potential based lane management system that is described in the third section, has been implemented on top the AIM product. In the following sections, the results of ATT and DOI calculations will be presented for every simulation configuration. All the parameters except lane count and traffic level has kept default as AIM predefined. In each experiment, traffic level is increasing by 200 from 600 veh/hour to 200 veh/hour. All of these different traffic level scenarios has been tested and measured for both 4 lane and 6 lane intersections.

5.3.1. 4 Lane Experiments

In this study, two different intersection model has been investigated. All of the experiments have been performed for both 4 lane intersections and 6 lane intersections. Number of lanes in roads parameter, directly effects the vehicle count that intersection manager must handle. Therefore, in this study, first the 4-lane intersection model has been tested.

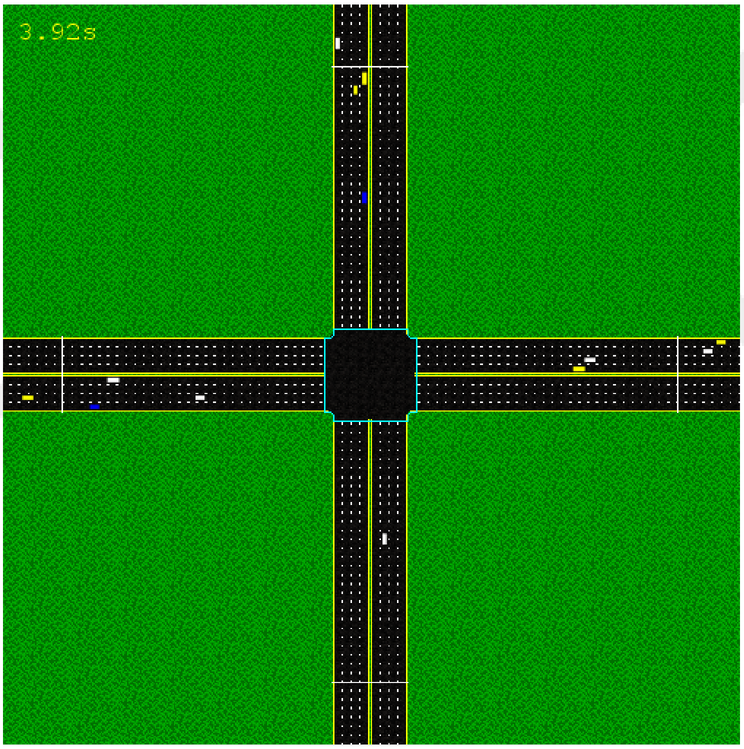

Figure 5.3.1 4-lane intersection

In this infrastructure, intersection is created by 4-way roads which all roads contain four lanes. Therefore, intersection has 16 lanes as input lanes which provide vehicle flow to the intersection and it also has 16 lanes which vehicle exits the intersection and travel to the out of the intersection.

In the following sections, the average travel time(ATT) and delay of intersection(DOI) calculations has been presented for both AIM product and proposed model PLO-AIM.

Presented results has been achieved by performing every simulation five times. All of the simulation results will be described in detailed for both models.

In this study, second configuration parameter is the traffic rate. Traffic rate means that the vehicle spawn rate of each lane. Traffic rate parameter is changing between 600 and 2000 by 200. In another words, 600 veh/hour means that in every lane 600 vehicles will be spawned in one hour. By changing this parameter, the effects of the increasing traffic rate is observed for both AIM and PLO-AIM.

5.3.1.1. 600 veh/hour

First, AIM model and PLO-AIM model is used to simulate 4 lane intersection model with 600 veh/hour vehicle spawn rate. Measurements are gathered and ATT and DOI calculations has performed for five times.

Table 5.3.1.1. ATT and DOI calculations for 4 lane 600 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	18.039	4.549	15.525	4.396
2	19.671	6.181	15.191	4.062
3	17.966	4.476	15.795	4.666
4	19.191	5.701	16.954	5.825
5	19.183	5.693	14.987	3.858

After performing the same simulation for five times with both AIM and proposed PLO-AIM model, calculated average travel times and delay of intersections presented above. Proposed model PLO-AIM outperformed AIM in all experiments that performed for this configuration setup.

5.3.1.2. 800 veh/hour

In this experiment, traffic level is increased by 200 to 800 veh/hour. Calculation results are presented below. AIM model and PLO-AIM model is used to simulate 4 lane intersection model with 800 veh/hour vehicle spawn rate.

Table 5.3.1.2. ATT and DOI calculations for 4 lane 800 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	27.796	14.306	24.968	13.839
2	31.954	18.464	24.902	13.773
3	33.210	19.720	28.149	17.020
4	29.597	16.107	24.661	13.532
5	31.050	17.560	24.318	13.189

Proposed model PLO-AIM outperformed AIM in all experiments that performed for this configuration setup. PLO-AIM model has decreased the delay of intersection and average travel times for all the experiments.

5.3.1.3. 1000 veh/hour

In this experiment, traffic level is increased by 200 to 1000 veh/hour. Calculation results are presented below. AIM model and PLO-AIM model is used to simulate 4 lane intersection model with 1000 veh/hour vehicle spawn rate.

At this traffic rate, the intersection begins to get full due to increased level of traffic. Therefore, the effect of the lane management system begins to decrease. When we examine the difference between, AIM and PLO-AIM, the effect of lane management still can be seen.

Table 5.3.1.3. ATT and DOI calculations for 4 lane 1000 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	52.907	39.417	43.285	32.156
2	45.498	32.008	49.485	38.356
3	47.247	33.757	42.845	31.716
4	53.044	39.554	41.803	30.674
5	48.656	35.166	37.399	26.270

Proposed model PLO-AIM outperformed AIM in all experiments that performed for this configuration setup. Above table show us that, the performance improvement of the proposed model still observed in the performance metrics.

5.3.1.4. 1200 veh/hour

In this experiment, traffic level is increased by 200 to 1200 veh/hour. Calculation results are presented below. AIM model and PLO-AIM model is used to simulate 4 lane intersection model with 1200 veh/hour vehicle spawn rate.

By increasing the traffic level, intersection begins to get full faster. In case of intersection gets full, the effect of lane management module will decrease because there will be no advantage between the lanes. When all of the lanes are fully occupied, lane management is not making change between the lanes because all of the lanes are equally full.

Table 5.3.1.4. ATT and DOI calculations for 4 lane 1200 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	69.764	56.274	65.630	54.501
2	70.190	56.700	61.295	50.166
3	57.403	43.913	58.933	47.804
4	64.579	51.089	66.409	55.280
5	73.202	59.712	66.762	55.633

Propsed model PLO-AIM outperformed AIM in all experiments that performed for this configuration setup.

5.3.1.5. 1400 veh/hour

In this experiment, traffic level is increased to 1400 veh/hour. After this point of 1300 veh/hour, intersection becomes fully occupied more rapidly. Therefore, no other lane has advantage to any other lane because every lane of intersection is full.

Table 5.3.1.5. ATT and DOI calculations for 4 lane 1400 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	85.552	72.062	84.106	72.977
2	82.860	69.370	83.461	72.332
3	85.906	72.416	81.072	69.943
4	75.981	62.491	79.574	68.445
5	82.379	68.889	82.513	71.384

When the intersection is full, lane management does not produce any advantage. Therefore, the calculation results are now similar with the base AIM product. The decrease of the effect of lane management can be seen in the table above.

5.3.1.6. 1600 veh/hour

In this experiment, traffic level is increased to 1600 veh/hour. Calculation results are presented below table.

Table 5.3.1.6. ATT and DOI calculations for 4 lane 1600 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	90.451	76.961	89.947	78.818
2	92.696	79.206	92.183	81.054
3	90.275	76.785	97.846	86.717
4	96.262	82.772	85.671	74.542
5	96.510	83.020	95.472	84.343

When the traffic level reaches the 1600 veh / hour, as well as the other traffic levels which are greater than 1300, the lanes of intersections are getting full in a short period of time. Therefore, the lane change is not providing any advantage.

Because of the input of the intersection and lane is huge, the lane management module works for a short period of time until the lanes are full. But in this case, lane changing can be expensive if the vehicle which is about to change their lane has lots of other vehicles waiting for it. In this case, the lane changing is not providing any advantage.

5.3.1.7. 1800 veh/hour

In this experiment, traffic level is increased to 1800 veh/hour. Calculation results are presented below table.

Table 5.3.1.7. ATT and DOI calculations for 4 lane 1800 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	98.572	85.082	97.218	86.089
2	98.701	85.211	103.745	92.616
3	99.618	86.128	103.141	92.012
4	100.556	87.066	95.914	84.785
5	99.186	85.696	102.436	91.307

5.3.1.8. 2000 veh/hour

In this experiment, traffic level is increased to 1200 veh/hour. Calculation results are presented below table.

Table 5.3.1.8. ATT and DOI calculations for 4 lane 2000 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	102.241	88.751	104.405	93.276
2	104.722	91.232	106.892	95.763
3	108.735	95.245	101.356	90.227
4	103.855	90.365	108.958	97.829
5	103.196	89.706	99.840	88.711

5.3.2. 6 Lane Experiments

In this infrastructure, intersection is created by 4-way roads which all roads contain six lanes. Therefore, intersection has 24 lanes as input lanes which provide vehicle flow to the intersection and it also has 24 lanes which vehicle exits the intersection and travel to the out of the intersection.

In the following sections, the average travel time(ATT) and delay of intersection(DOI) calculations has been presented for both AIM product and proposed model PLO-AIM. Presented results has been achieved by performing every simulation five times. All of the simulation results will be described in detailed for both models.

In this study, second configuration parameter is the traffic rate. Traffic rate means that the vehicle spawn rate of each lane. Traffic rate parameter is changing between 600 and 2000 by 200. In another words, 600 veh/hour means that in every lane 600 vehicles will be spawned in one hour. By changing this parameter, the effects of the increasing traffic rate is observed for both AIM and PLO-AIM.

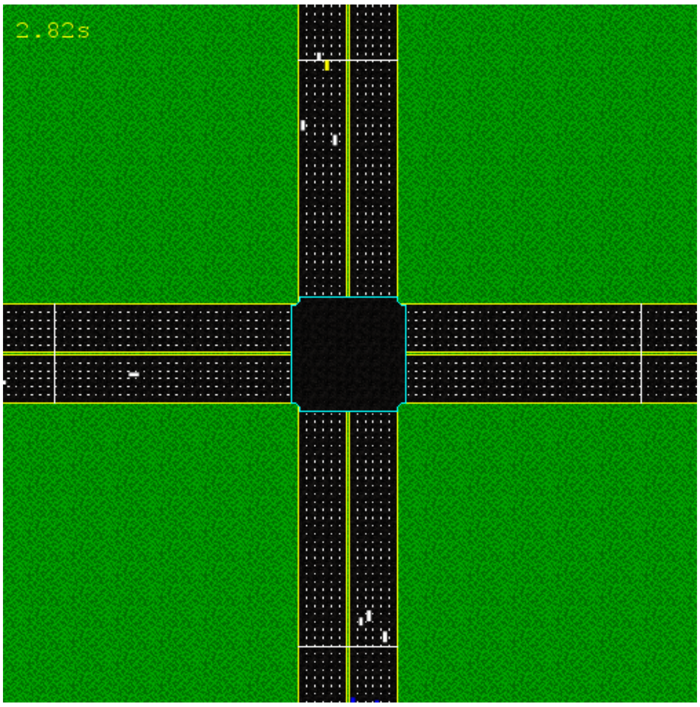

Figure 5.3.2 6-lane intersection

5.3.2.1. 600 veh/hour

First, AIM model and PLO-AIM model is used to simulate 6 lane intersection model with 600 veh/hour vehicle spawn rate. Measurements are gathered and ATT and DOI calculations has performed for five times.

Table 5.3.2.1. ATT and DOI calculations for 6 lane 600 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	25.159	11.669	19.552	8.423
2	25.222	11.732	22.288	11.159
3	23.621	10.131	18.732	7.603
4	26.272	12.782	21.171	10.042
5	27.569	14.079	23.943	12.814

After performing the same simulation for five times with both AIM and proposed PLO-AIM model, calculated average travel times and delay of intersections presented above. Proposed model PLO-AIM outperformed AIM in all experiments that performed for this configuration setup.

5.3.2.2. 800 veh/hour

In this experiment, traffic level is increased by 200 to 800 veh/hour. Calculation results are presented below. AIM model and PLO-AIM model is used to simulate 4 lane intersection model with 800 veh/hour vehicle spawn rate.

Table 5.3.2.2. ATT and DOI calculations for 6 lane 800 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	38.006	24.516	36.140	25.011
2	39.168	25.678	38.184	27.055
3	38.455	24.965	34.351	23.222
4	33.489	19.999	30.910	19.781
5	47.862	34.372	38.310	27.181

Proposed model PLO-AIM outperformed AIM in all experiments that performed for this configuration setup.

5.3.2.3. 1000 veh/hour

In this experiment, traffic level is increased by 200 to 1000 veh/hour. Calculation results are presented below.

Table 5.3.2.3. ATT and DOI calculations for 6 lane 1000 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	61.911	48.421	56.116	44.987
2	63.795	50.305	58.417	47.288
3	57.891	44.401	51.865	40.736
4	54.095	40.605	59.360	48.231
5	61.304	47.814	56.590	45.461

At this traffic rate, the intersection begins to get full due to increased level of traffic. Therefore, the effect of the lane management system begins to decrease. When we examine the difference between, AIM and PLO-AIM, the effect of lane management still can be seen.

5.3.2.4. 1200 veh/hour

In this experiment, traffic level is increased by 200 to 1200 veh/hour. Calculation results are presented below. AIM model and PLO-AIM model is used to simulate 4 lane intersection model with 1200 veh/hour vehicle spawn rate.

By increasing the traffic level, intersection begins to get full faster. In case of intersection gets full, the effect of lane management module will decrease because there will be no advantage between the lanes. When all of the lanes are fully occupied, lane management is not making change between the lanes because all of the lanes are equally full.

Table 5.3.2.4. ATT and DOI calculations for 6 lane 1200 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	86.145	72.655	77.283	66.154
2	79.446	65.956	82.064	70.935
3	85.638	72.148	75.917	64.788
4	76.952	63.462	71.728	60.599
5	78.520	65.030	77.068	65.939

Proposed model PLO-AIM outperformed AIM in all experiments that performed for this configuration setup.

5.3.2.5. 1400 veh/hour

In this experiment, traffic level is increased to 1400 veh/hour. After this point of 1300 veh/hour, intersection becomes fully occupied more rapidly. Therefore, no other lane has advantage to any other lane because every lane of intersection is full.

Table 5.3.2.5. ATT and DOI calculations for 6 lane 1400 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	90.787	77.297	98.910	87.781
2	98.416	84.926	97.385	86.256
3	95.200	81.710	93.462	82.333
4	92.272	78.782	87.479	76.350
5	93.468	79.978	98.864	87.735

When the intersection is full, lane management does not produce any advantage. Therefore, the calculation results are now similar with the base AIM product. The decrease of the effect of lane management can be seen in the table above.

5.3.2.6. 1600 veh/hour

In this experiment, traffic level is increased to 1600 veh/hour. Calculation results are presented below table. In this case, the traffic load of intersection is getting bigger, all of the lane's spawns 1600 vehicles in hour.

Intersection system suffers from the fully crowded lanes, all of the lanes gets full very rapidly. Lane management system works for a very short time which begins with the simulation starts and ends when the intersection is full.

Table 5.3.2.6. ATT and DOI calculations for 6 lane 1600 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	107.229	93.739	102.634	92.505
2	110.752	97.262	103.142	93.013
3	113.268	99.778	107.720	97.591
4	114.058	100.568	116.066	105.937
5	106.480	92.990	108.105	97.976

The calculation results are now similar with the base AIM product. The decrease of the effect of lane management can be seen in the table above.

5.3.2.7. 1800 veh/hour

In this experiment, traffic level is increased to 1800 veh/hour. Calculation results are presented below table.

Table 5.3.2.7. ATT and DOI calculations for 6 lane 1800 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	118.903	105.413	116.601	105.472
2	110.288	96.798	117.349	106.220
3	114.080	100.590	117.578	106.449
4	115.451	101.961	110.389	99.260
5	121.323	107.833	117.644	106.515

5.3.2.8. 2000 veh/hour

In this experiment, traffic level is increased to 2000 veh/hour. Calculation results are presented below table.

Table 5.3.1.8. ATT and DOI calculations for 6 lane 2000 veh/hour experiment

	AIM		PLO-AIM	
Experiment No	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
1	123.996	110.506	123.663	112.534
2	120.577	107.087	123.789	112.660
3	119.517	106.027	123.873	112.744
4	118.415	104.925	128.998	117.869
5	122.847	109.357	122.542	111.413

The results of the higher traffic levels, the effect of the lane change is totally vanished. Due to high traffic level, the intersection immediately gets full of all of its input lanes. After that point, nothing can improve the performance of the intersection because all of the lanes in all of the roads are full filled.

At this point, all of the processes are dependent to the queue mechanism which determines which vehicle will use the intersection first and the trajectory planning systems. When all of the lanes in the all of roads are full, the system acts as a closed-system and all of the measurements are getting similar because there is nothing to solve or change.

5.4. Comparison and Results

In this section present results have been compared and summarized. All of the calculations presented in the previous section is used to get following average values of each traffic level. Therefore, in the following tables presents the average values of each experiment which is performed five times.

Average Travel time and Average Delay of Intersection values are used as performance metrics that is used for comparison between AIM and PLO-AIM.

5.4.1 4 Lane Comparison

Table 5.4.1. ATT and DOI comparisons between AIM and PLO-AIM in 4 lanes

	AIM		PLO-AIM	
Traffic Level	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
600	18.810	5.320	15.690	4.561
800	30.721	17.231	25.400	14.271
1000	49.470	35.980	42.963	31.834
1200	67.028	53.538	63.806	52.677
1400	82.536	69.046	82.145	71.016
1600	93.239	79.749	92.224	81.095
1800	99.327	85.837	100.491	89.362
2000	104.550	91.060	104.290	93.161

By looking the above comparison between AIM and proposed model PLO-AIM, PLO-AIM outperformed AIM for reasonable traffic rates which is 600 veh/hour to 1300 veh/hour. Above this traffic rate intersections gets full very rapidly therefore, there is not enough time for lane management. Without lane management, the performance gets similar with the AIM.

The measurement data of 4-lane delay of intersection for bot AIM and PLO-AIM models are displayed in the following figure.

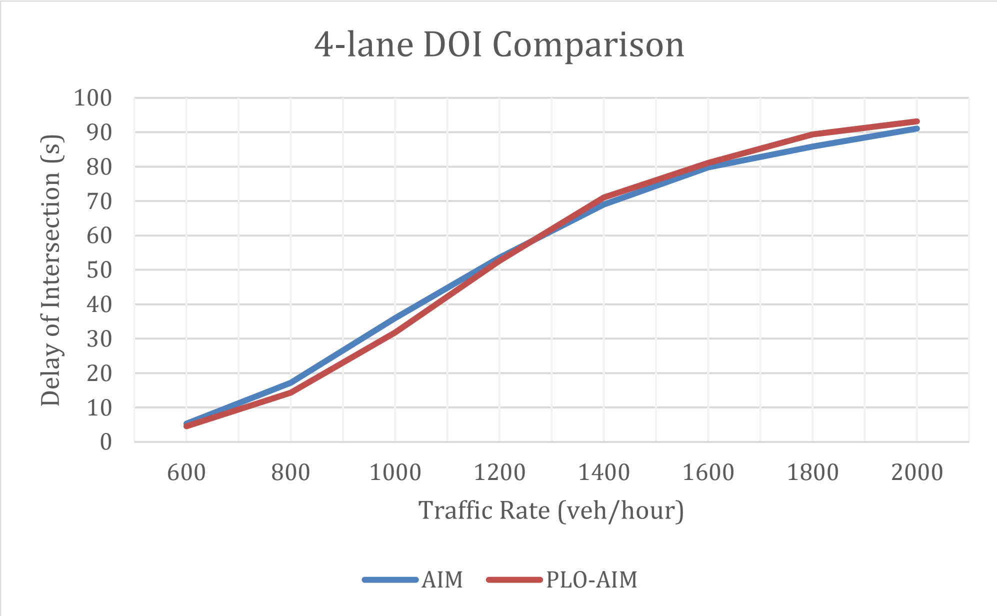

Figure 5.4.1.1 4-lane Delay of Intersection Comparison

The measurement data of 4-lane average travel time for bot AIM and PLO-AIM models are displayed in the following figure.

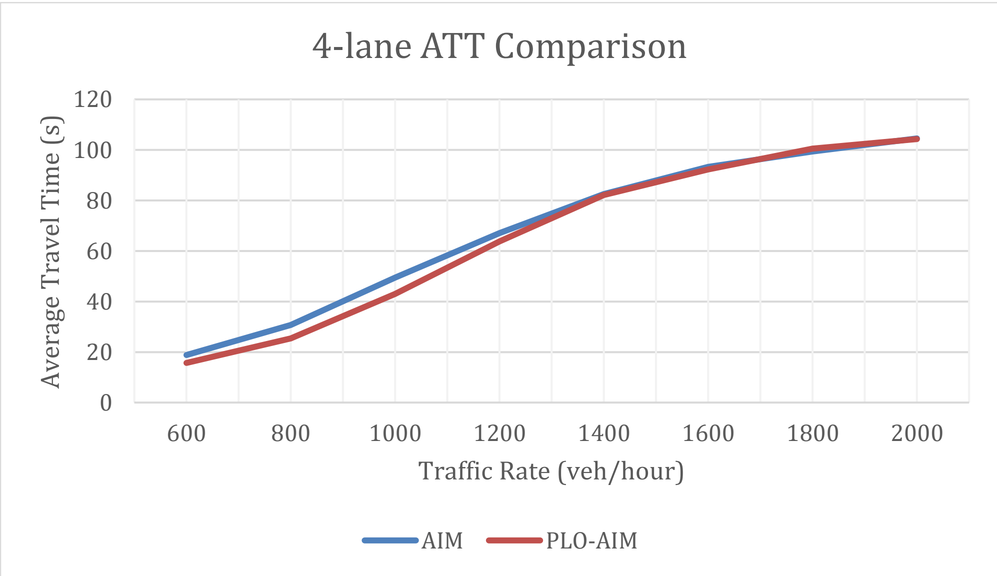

Figure 5.4.1.2 4-lane Average Travel Time Comparison

5.4.2 6 Lane Comparison

In this chapter, the results of 6 lane experiments are compared with the base AIM product. Following table, presents the average values of delay of intersections of each traffic level, and presents the average travel time for each traffic level.

These average values of the performance metrics are generated by using all of the five trials of each experiment. Therefore, in the below table, performance metrics of autonomous intersections such that delay of intersection and average travel times are listed for both AIM and proposed PLO-AIM model for 6-lane experiments.

Table 5.4.2. ATT and DOI comparisons between AIM and PLO-AIM in 6 lanes

	AIM		PLO-AIM	
Traffic Level	Average Travel Time	Delay of Intersection	Average Travel Time	Delay of Intersection
600	25.569	12.079	21.137	10.008
800	39.396	25.906	35.579	24.450
1000	59.799	46.309	56.470	45.341
1200	81.340	67.850	76.812	65.683
1400	94.029	80.539	95.220	84.091
1600	110.357	96.867	107.533	97.404
1800	116.009	102.519	115.912	104.783
2000	121.070	107.580	124.573	113.444

4 lane results are repeating themself also in the 6 lane experiments. By looking the comparison table, PLO-AIM outperformed AIM for reasonable traffic rates. Same behavior caused by increasing traffic observed also in 6 lane experiments. PLO-AIM outperformed AIM for reasonable traffic rates which is 600 veh/hour to 1300 veh/hour. After that point, because of intersection being full, lane management does not provide any advantage to vehicles. Therefore, results are getting similar with the base AIM.

The measurement data of 6-lane delay of intersection for bot AIM and PLO-AIM models are displayed in the following figure.

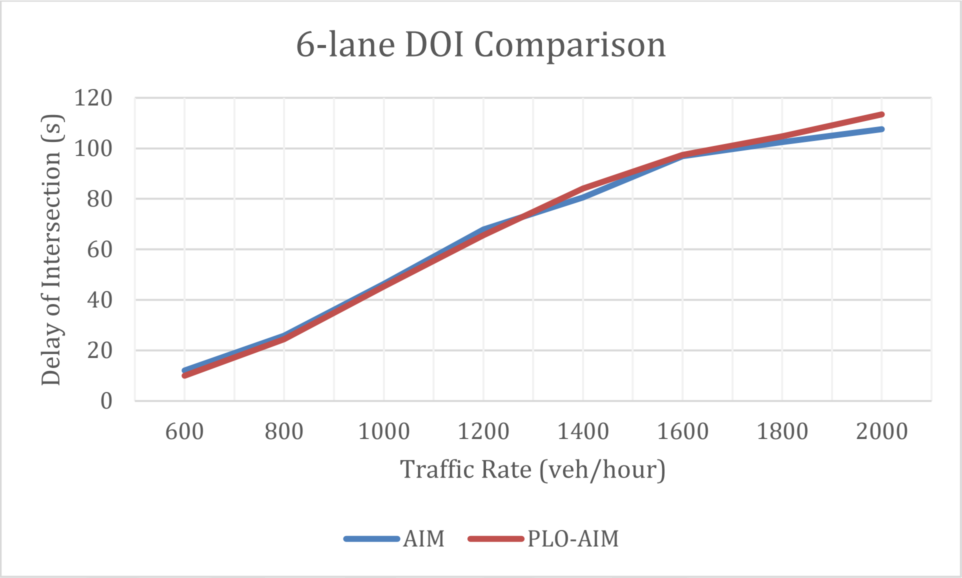

Figure 5.4.2.1 6-lane Delay of Intersection Comparison

The measurement data of 4-lane delay of intersection for bot AIM and PLO-AIM models are displayed in the following figure.

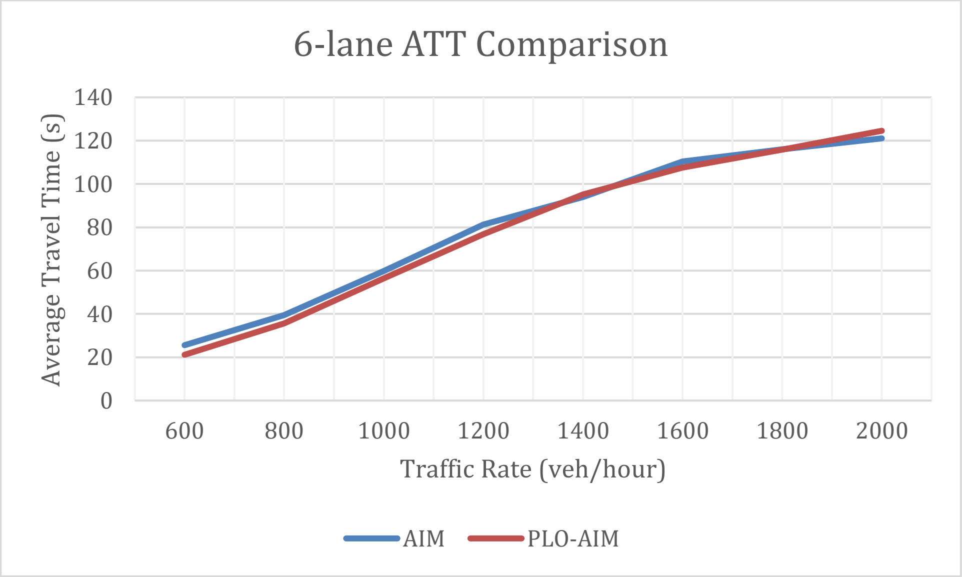

Figure 5.4.2.2 6-lane Average Travel Time Comparison

6. RESULTS AND DISCUSSIONS

After completing experiments about proposed model, organizing the autonomous vehicle distribution approaching the intersection in every lane is directly affecting the performance of the intersection. By triggering the autonomous vehicles to adjust their lane by looking the potential values regulates the inputs of intersections. This regulation provides time savings to each vehicle until they arrive to the intersection. Each vehicle changes their lane to most advantageous lane for themselves which means less crowded lanes. Therefore, autonomous vehicles arrive intersection earlier.

All of the vehicles try to adjust their lane, with this common behavior, all of the time required for vehicles to arrive intersection is decreased. Therefore, managing the lane distribution of autonomous vehicles improved the performance of the intersection and made the passing through the intersection is more efficient at acceptable traffic densities.

In this study, average intersection delay and average travel time criteria is used to evaluate the performance of autonomous intersections. With the vehicles using the potential approach to organize their own lanes, traffic flow has been managed in a more balanced form. Since the accumulations are balanced on the lanes, it has been observed that both the total travel time of the vehicles and the intersection delays have decreased.

PLO-AIM model improves the evaluation metrics such as average delay of intersection and average travel time for reasonable traffic rates, which is in between 600 vehicle/hour per lane to 1300 vehicle/hour per lane. The proposed model reduced the average travel time reduced in between %0.2 - %17.3 and reduced the average delay of intersection in between %1.6 - %17.1 for 4-lane and 6-lane scenarios for reasonable traffic rates, which is in between 600 vehicle/hour per lane to 1300 vehicle/hour per lane.

As a result of the development and experiments were carried out in this study, it is observed that lane management is a parameter that directly affects autonomous intersection management performance. The solution that is proposed has increased the performance of autonomous intersection management compared to the base AIM structure for acceptable traffic densities.

Additionally, it is observed that at high traffic densities, the effect of the potential based lane arrangement layer gradually diminished. However, this is not a problem with the potential approach. Since the intersection reaches its maximum capacity very quickly at high traffic rates, no lane has an advantage over other lanes. For this reason, there is no benefit in changing lanes. Therefore, the effect of a lane management and potential based lane changes can only be observed in a short time until the intersection is full. Since this time is too short, the effect of the PLO layer is not be observed at high traffic densities.

By decreasing the travel times and delays, the wasted time and energy for transportation will also be decreased. Proposed model will increase the autonomous intersection performance therefore, it will decrease the time spent. Intersections are the bottleneck of the efficient autonomous transportation. Therefore, increasing the performance of the intersections are directly increase the performance of the autonomous transportation. By saving time and energy, transportation of autonomous vehicles will be more efficient and will reduce the side effects of the transportations such as air pollution and noise pollution.

In future studies, proposed potential based method can be used not only to reorganize the lanes, but also to plan all the routes of autonomous vehicles with potential-based intuitive choices. With this approach, it is aimed to create a potential-based autonomous vehicle management strategy different from the existing methods in the literature.

The scope of decisions taken by autonomous vehicles can be expanded by adding additional parameters that will express the different intentions and preferences of the vehicles or passengers to the potential calculation is used in this study. Intentions means that each vehicle has destination points in autonomous driving therefore, they have intention to reach their destination. In order to use this intention, additional parameters can be added to the potential calculation. By considering the intention, destination relevant lane changing can be achieved. Therefore, autonomous vehicles will try to change their lane by considering their destinations. The vehicles need to turn right, will not go to the left lanes unless there is not a huge advantage difference. This approach will make the potential based lane changing more efficient.

By adding additional parameters to the potential calculation such as representing different types of actors such that ambulances, fire trucks and police vehicles can be prioritized in lanes. With this concept, real-life intuitive driving will be modeled more accurately by autonomous vehicles.

7. COMMENTS AND CONCLUSIONS

In conclusion, autonomous intersection management is one of the popular subjects about autonomous vehicles. Also, these two areas trigger each other to expand. Developments in intelligent vehicles feeds the developments in management of intelligent vehicles. As the vehicles are getting smarter, the management systems are also getting smarter. Because of that different solutions from multiple disciplines can be applied for this topic.

This study presents the effects of lane organization by using potential approach in order to improve performance of autonomous intersection management. In light of the results achieved, managing the lanes of vehicles entering intersections has a significant impact on determining autonomous intersection management performance. By managing the lanes, intersection delay and travel times of vehicles for specified traffic rates is decreased. This study showed that performance of autonomous intersection management is directly related with the lane management and by organizing the lanes, the intersection performance, output, has increased.

Proposed model allows the vehicles to manage their lanes by potential calculation. There is no central moderator, but as the vehicles switched the most advantageous lane for themselves as a result of potential-based decisions. Therefore, proposed model can be applied to all of the autonomous vehicles which will eventually use the intersection.

The proposed model does not even require an intersection. Lane management can be used in free ways or long roads. Therefore, lane management ability can be used for every where during the autonomous travels because proposed model gave the ability to vehicles not a central moderator.

With the increasing traffic rate, intersections are getting crowded faster than ever. This study also showed that, lane management in the fully crowded intersections does not provide any performance benefits because no other lane has advantage to each other. Therefore, vehicles must follow their lane to the intersection.

8. REFERENCES

[1] Serban, Alexandru Constantin, Erik Poll, and Joost Visser. "A standard driven software architecture for fully autonomous vehicles." 2018 IEEE International Conference on Software Architecture Companion (ICSA-C). IEEE, 2018.

[2] Kato, Shinpei, et al. "An open approach to autonomous vehicles." IEEE Micro 35.6 (2015): 60-68.

[3] Nearchou, Andreas C. "Adaptive navigation of autonomous vehicles using evolutionary algorithms." Artificial Intelligence in Engineering 13.2 (1999): 159-173.

[4] Gasparetto, Alessandro, et al. "Path planning and trajectory planning algorithms: A general overview." Motion and operation planning of robotic systems (2015): 3-27

[5] Llorca, David Fernández, et al. "Autonomous pedestrian collision avoidance using a fuzzy steering controller." IEEE Transactions on Intelligent Transportation Systems 12.2 (2011): 390-401.

[6] Gasparetto, Alessandro, et al. "Path planning and trajectory planning algorithms: A general overview." Motion and operation planning of robotic systems (2015): 3-27.

[7] Zhong, Zijia, Mark Nejad, and Earl E. Lee. "Autonomous and Semi-Autonomous Intersection Management: A Survey." arXiv preprint arXiv:2006.13133 (2020).

[8] Dresner, Kurt, and Peter Stone. "Multiagent traffic management: An improved intersection control mechanism." Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems. 2005.

[9] Dresner, Kurt, and Peter Stone. "A multiagent approach to autonomous intersection management." Journal of artificial intelligence research 31 (2008): 591-656.

[10] Khayatian, Mohammad, et al. "A survey on intersection management of connected autonomous vehicles." ACM Transactions on Cyber-Physical Systems 4.4 (2020): 1-27.

[11] Sathyaraj, B. Moses, et al. "Multiple UAVs path planning algorithms: a comparative study." Fuzzy Optimization and Decision Making 7.3 (2008): 257.

[12] Šeda, Miloš. "Roadmap methods vs. cell decomposition in robot motion planning." Proceedings of the 6th WSEAS international conference on signal processing, robotics and automation. 2007.

[13] Zhang, Yue J., Andreas A. Malikopoulos, and Christos G. Cassandras. "Optimal

control and coordination of connected and automated vehicles at urban traffic intersections." 2016 American Control Conference (ACC). IEEE, 2016.

[14] Bichiou, Youssef, and Hesham A. Rakha. "Real-time optimal intersection control system for automated/cooperative vehicles." International Journal of Transportation Science and Technology 8.1 (2019): 1-12.

[15] Kamal, Md Abdus Samad, et al. "A vehicle-intersection coordination scheme for smooth flows of traffic without using traffic lights." IEEE Transactions on Intelligent Transportation Systems 16.3 (2014): 1136-1147.

[16] Li, Bai, et al. "Near-optimal online motion planning of connected and automated vehicles at a signal-free and lane-free intersection." 2018 IEEE Intelligent Vehicles Symposium (IV). IEEE, 2018.

[17] Wu, Yuanyuan, Haipeng Chen, and Feng Zhu. "DCL-AIM: Decentralized coordination learning of autonomous intersection management for connected and automated vehicles." Transportation Research Part C: Emerging Technologies 103 (2019): 246-260.

[18] Dresner, Kurt, and Peter Stone. "Human-usable and emergency vehicle-aware control policies for autonomous intersection management." Fourth International Workshop on Agents in Traffic and Transportation (ATT), Hakodate, Japan. 2006.

[19] Liu, Bing, et al. "Trajectory planning for autonomous intersection management of connected vehicles." Simulation Modelling Practice and Theory 90 (2019): 16-30.

[20] Carlino, Dustin, Stephen D. Boyles, and Peter Stone. "Auction-based autonomous intersection management." 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013). IEEE, 2013.

[21] Zohdy, Ismail H., and Hesham Rakha. "Game theory algorithm for intersection-based cooperative adaptive cruise control (CACC) systems." 2012 15th International IEEE Conference on Intelligent Transportation Systems. IEEE, 2012.

[22] Elhenawy, Mohammed, et al. "An intersection game-theory-based traffic control algorithm in a connected vehicle environment." 2015 IEEE 18th international conference on intelligent transportation systems. IEEE, 2015.

[23] Bashiri, Masoud, and Cody H. Fleming. "A platoon-based intersection management system for autonomous vehicles." 2017 IEEE Intelligent Vehicles Symposium (IV). IEEE, 2017.

[24] Bashiri, Masoud, Hassan Jafarzadeh, and Cody H. Fleming. "Paim: Platoon-based autonomous intersection management." 2018 21st International Conference on

Intelligent Transportation Systems (ITSC). IEEE, 2018.
[25] Zohdy, Ismail H., and Hesham A. Rakha. "Intersection management via vehicle connectivity: The intersection cooperative adaptive cruise control system concept." Journal of Intelligent Transportation Systems 20.1 (2016): 17-32.
[26] Lee, Joyoung, Byungkyu Park, and Ilsoo Yun. "Cumulative travel-time responsive real-time intersection control algorithm in the connected vehicle environment." Journal of Transportation Engineering 139.10 (2013): 1020-1029.
[27] Hassan, Abdallah A., and Hesham A. Rakha. "A fully-distributed heuristic algorithm for control of autonomous vehicle movements at isolated intersections." International Journal of Transportation Science and Technology 3.4 (2014): 297-309.
[28] Yu, Chunhui, et al. "Managing connected and automated vehicles at isolated intersections: From reservation-to optimization-based methods." Transportation research part B: methodological 122 (2019): 416-435.
[29] Khayatian, Mohammad, Mohammadreza Mehrabian, and Aviral Shrivastava. "RIM: Robust intersection management for connected autonomous vehicles." 2018 IEEE Real-Time Systems Symposium (RTSS). IEEE, 2018.
[30] Chen, Rongsheng, et al. "Stability-based analysis of autonomous intersection management with pedestrians." Transportation research part C: emerging technologies 114 (2020): 463-483.
[31] Ozcan, Cumhur Yigit, and Murat Haciomeroglu. "A path-based multi-agent navigation model." The Visual Computer 31.6 (2015): 863-872.
[32] Van Den Berg, Jur, et al. "Reciprocal n-body collision avoidance." Robotics research. Springer, Berlin, Heidelberg, 2011. 3-19.
[33] Ozcan, Cumhur Yigit, Ebru Akcapinar Sezer, and Murat Haciomeroglu. "A time-based global path planning strategy for crowd navigation." Computer Animation and Virtual Worlds 30.2 (2019): e1864.

APPENDIX

EK 1 – Tezden Türetilmiş Bildiriler

PLO-AIM: Potential-based Lane Organization in Autonomous Intersection Management

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Abstract—Traditional management models of intersections, such as no-light intersections or signalized intersection, are not the most effective way of passing the intersections if the vehicles are intelligent. To this end, Dresner and Stone proposed a new intersection control model called Autonomous Intersection Management(AIM).In the AIM simulation, they were examining the problem from a multi-agent perspective, demonstrating that intelligent intersection control can be made more efficient than existing control mechanisms. In this study, autonomous intersection management has been investigated. We extended their works and added a potential-based lane organization layer. In order to distribute vehicles evenly to each lane, this layer triggers vehicles to analyze near lanes, and they change their lane if other lanes have an advantage. We can observe this behavior in real life, such as drivers, change their lane by considering their intuitions. Basic intuition on selecting the correct lane for traffic is selecting a less crowded lane in order to reduce delay. We model that behavior without any change in the AIM workflow. Experiment results show us that intersection performance is directly connected with the vehicle distribution in lanes of roads of intersections. We see the advantage of handling lane management with a potential approach in performance metrics such as average delay of intersection and average travel time. Therefore, lane management and intersection management are problems that need to be handled together. This study shows us that the lane through which vehicles enter the intersection is an effective parameter for intersection management. Our study draws attention to this parameter and suggested a solution for it. We observed that the regulation of AIM inputs, which are vehicles in lanes, was as effective as contributing to aim intersection management. PLO-AIM model outperforms AIM in evaluation metrics such as average delay of intersection and average travel time for reasonable traffic rates, which is in between 600 vehicle/hour per lane to 1300 vehicle/hour per lane. The proposed model reduced the average travel time reduced in between %0.2 - %17.3 and reduced the average delay of intersection in between %1.6 %17.1 for 4-lane and 6-lane scenarios.

Keywords— AIM project, Autonomous intersection management, Lane organization, Potential-based approach

I. INTRODUCTION

In this study, research and developments and experiments have been made on models related to intersection management of autonomous vehicles. The basis of our problem is to ensure that autonomous vehicles pass through intersections collision-free and with as little delay as possible.

Autonomous intersection management systems are systems established to manage the passage of connected and autonomous vehicles (CAV) through intersections without collision. For this purpose, different approaches have been adopted. Intersection management is provided by the communication between smart vehicles or with a central moderator. In this approach, smart vehicles coming to the intersection share physical parameters such as speed, position, acceleration, direction, source, target with each other and become aware of each other. As a result of the calculations made with these data defining the movement, they enable them to pass through the intersection without collision. Another approach is in the structures where these smart vehicles communicate with an intersection manager or moderator placed on the intersection and plan their passage through the intersection. There are approaches that create learning models over the movements of vehicles using machine learning or even more complex systems using fuzzy logic with machine learning to make decision to move together or individually.

One of the most outstanding studies in this field is AIM, the autonomous intersection management system presented by Stone and Dresner in 2004 and developed in 2008 with a multi-agent approach [1]. AIM offers a multi-agent model and simulator that communicates with an intersection manager of autonomous vehicles to pass the intersection without collision. There are many successful studies in the literature based on this AIM simulator developed by Stone and Dresner. In our study, we used this AIM simulator to implement our own approach. In studies on this subject, approaches are generally seen with the movements of the vehicles.

During our experiments on AIM, we saw that how the vehicles approach the intersection and which lane they go from have a significant effect on the delay values caused by the intersection. We said that the vehicles do not proceed to the intersection randomly, after a control mechanism and evaluation mechanism calculate which lane is more advantageous for them and enter the intersection over that lane. In this way, we reduce the delay applied by the intersection, namely the delay of Intersection. This means reducing the time spent by vehicles at intersections.

About this problem, we aim to enable autonomous vehicles to change the lanes from which they enter intersections to be the most advantageous lane for them. With this approach, it is aimed that vehicles can overcome the accumulation of random traffic. It is aimed to reduce the travel time of vehicles and reduce intersection delays by enabling them to approach the intersection from the most suitable lane. In our study, instead of dealing with the movements of the vehicles, we ensure that the filling of intersections is out of randomness and filled in a balanced way by determining the most appropriate lane in which the vehicles can move. While doing this, we ensure that the vehicles calculate the potential values for their own and adjacent lanes, and according to these potential values, they switch to the most convenient and most advantageous lane.

As a result, we have shown that the lane from which the vehicles enter the intersections and the delays that the intersections cause on autonomous vehicles are interrelated. We will present with our experimental results that this delay can be reduced by a correct lane management. Lane management will increase the performance of autonomous intersections and reduce the duration of autonomous travels. As a natural consequence of this, traffic created by autonomous vehicles will decrease in the final case. While supporting the positive environmental changes that occur with the decrease in traffic, it will save energy and time when evaluated specifically for autonomous vehicles.

II. LITERATURE SUMMARY

Autonomous intersection management is a common problem about autonomous vehicles. Also, these two topics triggers each other. Developments in intelligent vehicles feeds the developments in management of intelligent vehicles. As the vehicles are getting smarter, the management systems are also getting smarter. Because of that different solutions from multiple disciplines can be applied for this topic. This study investigates that the effects of doing lane organization by using potential approach on autonomous intersection management. Therefore, we researched about autonomous intersection management. The most relevant studies have listed in the table below.

In the study of C Yu, W Sun and X Yang, a reservation-based method with simple policies, such as First-come-first-served Service (FCFS), has been proposed in the literature to manage connected automated vehicles (CAV) at isolated intersections, but there is a comprehensive analysis of intersection capacity and vehicle delays in FCFS [2]. In order to solve the problem of lack of underlying control, especially in high traffic demand situation, to solve this problem, adopt queuing theory to analytically show that this method cannot meet the high demand where traffic flow overlaps, and provide optimal service. Proposed an optimization model for CAV reaching the intersection to minimize delay. This study compares the performance of the predicted optimization-based control at various demand levels for conventional vehicle drive control and reservation-based control. It shows the best performance in the proposed optimization and has a noticeable advantage over the other two controls. The advantages of reservation-based control are insignificant over demanding vehicle operation control.

M Khayatian and M Mehrabian proposed a time and space sensitive technique for managing the intersections of autonomous vehicles that are rugged against external disturbances and model mismatches in their study about RIM [3]. In their method, IM is responsible for assigning the oncoming vehicles safe Time of Arrival (TOA) and Arrival Speed (VOA) without any conflict, and vehicles are responsible for selecting and following a trajectory to reach the intersection and driving in VOA. Since the vehicles follow a position trajectory, the effect of limited pattern mismatch and external disturbances can be compensated. Also, vehicles that want to turn at the intersection do not need to drive at low speed before entering the intersection. Results from experiments show that improvements shorten the average times.

In the article of B Liu, Q Shi, Z Song and A El Kamel a collaborative timing mechanism for autonomous vehicles passing through an intersection called TP-AIM has been proposed [4]. The main purpose of this research is to ensure safe driving while minimizing delay at an intersection without traffic lights. First, an intersection management system used as an information gathering-editing center assigns reasonable priorities for all available vehicles and thus plans their trajectories. Secondly, a window search algorithm is performed to find backup windows as well as an input window that can create a collision-free trajectory with minimal delay. Finally, vehicles can individually edit their trajectories by applying dynamic programming to calculate the speed profile to pass the intersection. MATLAB / Simulink and SUMO based simulations are created between three types of traffic mechanisms with different traffic flows. The results show that the proposed TP-AIM mechanism significantly reduced the average evacuation time and increased efficiency by over 20% . The article also explores delay, which can be reduced to less than 10% compared to conventional light management systems. Both safety and efficiency can be guaranteed in the proposed mechanism.

In the study of R Chen, J Hu, MW Levin and D Rey, they propose an autonomous intersection management algorithm called AIM-pad that considers both vehicles and pedestrians to provide optimal efficiency when combined with maximum pressure control [5].This study analyzes the stability properties of the algorithm based on a simpler version of AIM-pad, the conflict zone model of autonomous intersection management. To apply the proposed algorithm in the simulation, this study the maximum pressure control current trajectory optimization algorithm to calculate optimal vehicle trajectories. Simulations were conducted to test the effects of pedestrian demand on intersection efficiency. The simulation results show that the delays of pedestrians and vehicles are negatively correlated, and the proposed algorithm can adapt to the change in pedestrian demand and enable conflicting trajectory vehicle movements.

Y Wu, H Chen and F Zhu modeled CAVs as Markov Decision Processes (MAMDPs), using communication and computational technologies, in which sequential movements of vehicles from intersection points work together to minimize deceleration of vehicle factors with non-collision constraints in their study DCL-AIM [6]. From the structural features of the AIM problem and using a decentralized coordinated multi-factor learning approach (DCL), it is divided into an independent part and a coordinated part. AIM) is recommended to solve the problem efficiently by leveraging both global and localized agent coordination requirements in AIM.

The main feature of the proposed approach is to clearly identify the coordination needs of representatives in the learning process and adapt them dynamically, so that the dimensional and non-stationary problems of the environment can be alleviated while learning with more than one tool. The effectiveness of the proposed method has been demonstrated under various traffic conditions. Comparative analysis is based on the LQF-AIM guide (Longest Queue-First) and Webster's method (Signal) between DCL-AIM and first-come-first-service-based AIM (FCFS-AIM). as comparison. Experimental results show that DCL-AIM's sequential decisions outperform other control directives.

Developments in autonomous vehicles and smart transportation systems point to a rapidly approaching future where smart vehicles can automatically manage the travel process, become aware of their environment, make decisions with this awareness and implement the decisions they make. When K Dresner and P Stone consider the increasing traffic and number of active vehicles, they saw that smart solutions will need to be implemented in the field of transportation. In order to increase the efficiency of transportation infrastructure, more intelligent traffic control mechanisms that work hand in hand with smart vehicles are needed to include into our lives.

To this end, Dresner and Stone proposed a new junction control mechanism called Autonomous Intersection Management (AIM), and in the simulation, examining the problem from a multi-agent perspective, it showed that intersection control could be made more efficient than existing control mechanisms such as traffic signals or stop signs [1]. AIM is a open source intersection management framework that generates an intersection model based on simulation configurations. AIM also generate vehicles, drivers, and operate them during intersections.

This multi-agent systems-based intersection management strategy, introduced by Dresner and Stone, follows a protocol for reservation for every vehicle. Arriving vehicles to the intersection will inform the Intersection Manager (IM) agent. The IM is responsible for controlling that intersection by reserving a trajectory for vehicles through intersection space-time. The IM process every reservation request and determines requests whether confirm or reject by regarding intersection control policy [1].

General communication between vehicles and intersection manager is ordered below.

(a) The vehicle approaching the intersection informs the intersection manager that it is approaching along with required information such as vehicle size, estimated time of arrival, speed, acceleration, the lane it is in and the lane it wants to pass.
(b) The intersection manager simulates the road that the vehicle will follow inside the intersection using the information shared by the vehicle. The IM checks whether the road that the previous vehicles will follow at the intersection and the road that the new vehicle wants to follow does not conflict.
(c) The intersection manager confirms a reservation if there is no interference with the path in times the vehicles will use. After this point, it becomes the vehicle's task to reach the intersection and pass through the intersection.
(d) Vehicles must receive their successful reservation message from IM, in order to use intersection and pass to their desired lanes.

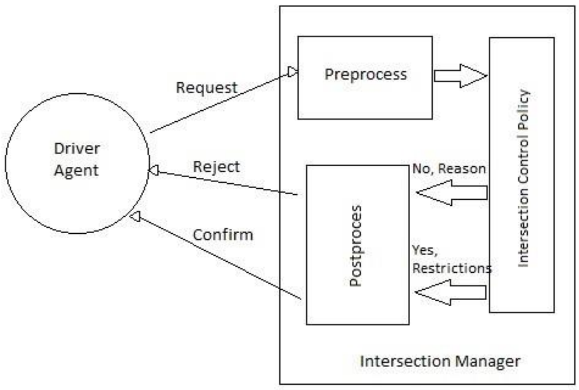

Fig. 1. Diagram of Intersection workflow.

After the response of the intersection manager, vehicle performs the IM decision or wait and re-sent reservation request for successful message.

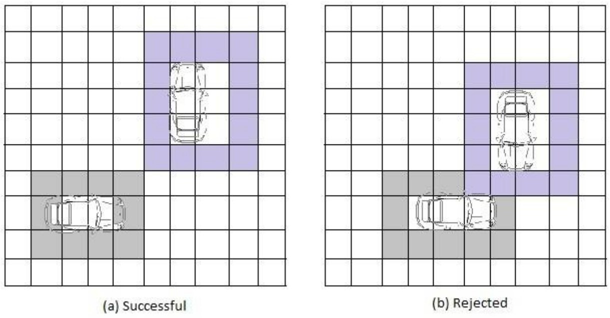

Fig. 2. Successful and rejected situations in simulation.

M Hausknecht, TC Au and P Stone extended the work of Stone and Dresner beyond the situation of a single intersection and examine the unique consequences and capabilities of using AIM-based agents to control an interconnected network of intersections [7]. They explore various navigation rules that autonomous vehicles can use to dynamically change their planned routes, observe an example of the Braess Paradox, and explore the new possibility of dynamically reversing traffic flow across lanes in response to minute-by-minute traffic conditions. By examining this multi-agent system in simulation, they measure the significant efficiency improvements that can be achieved with this tool-based traffic control methods.

III. METHOD

The main problem that we focus on this study is to reduce the intersection delays and the maximum travel time by reorganizing the lane distributions of autonomous vehicles in autonomous intersection management. We have observed in our experiments that reorganizing the lanes from which vehicles enter the intersections to the density of their neighboring lanes and allowing the vehicles to move to the less dense lanes from their own lanes, reduces the delays that the vehicles are exposed to.

To this end, the solution we proposed is to create a lane management line that will trigger autonomous vehicles to evaluate other lanes in order to change their lanes to the most advantageous lane. Vehicles change their lanes by making assessment according to the condition of the neighbor lanes repeatedly at a certain interval. Vehicles uses potential approach for evaluation of the other lanes.

At this point, we are managing autonomous intersections using the AIM project presented by Stone and Dresner [1]. AIM is a simulation tool for autonomous intersection management. AIM creates a intersection or system of intersections using preselected parameters in configuration panel. Then, it starts to produce vehicles at the rate determined by the configuration parameters. These vehicles begin to move from the lane they spawned to the intersection. When vehicles enter the intersection, zone determined dynamically by IM, if they are the first vehicle in their lane, they send a reservation request to IM.

Reservation requests thrown by the foremost vehicle of all lanes are kept in a queue structure. Vehicles whose turn is in the queue enter the intersection for turning and are removed from the queue. The first vehicle just behind the vehicle that has entered the intersection and started the turning process, as it is now the first in that lane, sends a reservation request to IM and is included in the queue structure. In this way, vehicles cross the intersection with the principle of first come, first out.

For vehicles that send reservation requests, the intersection manager runs a simulation and calculates the space-time trajectory of these vehicles. As long as the results of the calculation do not intersect with the space-time trajectory of the vehicles at the intersection, the intersection manager sends permission to pass these vehicles. If there is an intersection, the intersection manager sends a rejection response and triggers the vehicle to request a reservation again. In this way, all vehicles complete the intersection crossing within a queue structure without collision.

With the traffic density parameter selected during configuration, vehicles begin to spawn from all lanes and move towards the intersection. At this point, we can observe the situation that we consider as a problem. Since the vehicles are moving in the lanes they are formed, they are not stacked in a balanced way on the intersection. This means that instead of entering the intersection from an emptier lane and queuing up and out faster, they only have to wait for the vehicles in front of them because they comes from the lane they were created in. This increases the intersection delay and total travel time, which are our evaluation criteria.

Our solution is to use the potential approach to move vehicles into the lane that is most advantageous for them. As a natural consequence of this, vehicles will enter the intersection in the least crowded lane and the distribution of vehicles at the intersection on the lanes will be balanced. Ultimately, the efforts of vehicles to reach the intersection in the most advantageous lane based on lane density will reduce their junction delay and overall travel time.

Potential approach was used in Cumhur Y. Ozcan's path-based study of crowd simulation for path planning [8]. They proposed a system using the Reciprocal Speed Barriers [9] (RVO) model as the basic routing algorithm, which provides macro information computed by a modified A * algorithm.

The main feature of the proposed system is the modification of cost function of the A * algorithm to consider the current and possible future positions of other agents and path calculations. For this purpose, after a path calculation is made for an agent, they store the information about the calculated path (ie potential value) on the grid that other agents will use when determining their paths. Cumhur Y. Ozcan used potential approach in comparison with machine learning methods in his time-based global path planning study [10].

These studies show that the potential approach can compete with machine learning approaches. Because, in fact, moving in the crowd and driving in the crowd as a very similar problem are actions based on learned reflexes that people perform with their intuition. For this reason, it is very plausible that heuristic algorithms modeling human intuition are successful.

In addition, collecting the volume and variety of data required by machine learning is a research problem in itself. While collecting even this data, data must be collected from intersections where there are intuitive approaches to actually reflect the context, because people drive intuitively. For this reason, we cannot collect data as if all drivers behave in the same way because we do not drive our cars that way. In order for machine learning data to work, it must be based on real life. In real life, people are already driving intuitively.

People actually predict who will turn, who will not turn, and which vehicle will turn where even if it does not signal. This is a very important issue because we choose the most advantageous lane according to these estimates. What we are trying to do with potential is to be able to model this intuitive behavior and prediction that people exhibit.

We achieved the lane management using the potential approach to organize AIM inputs by keeping the core business logic of AIM. Lane management means regulating the distribution of vehicles on a road over lanes. We solved this problem by enabling the vehicles to calculate the potential for their lane and neighboring lanes at certain time intervals and to choose the most advantageous lane according to these potential values and change lanes.

With this potential calculation, we enable vehicles entering from a random lane to determine which lane they should be in by evaluating their lane and the density of neighboring lanes. During this assessment, vehicles calculate the total potential for the right adjacent lane, left adjacent lane and the current lane. While doing this calculation, the vehicles give potential values to the vehicles ahead of them, in other words closer to the intersection, according to their distance from them.

Vehicles obtains the potential values of the lanes by summing up these potential values by lane. With this logic, the lane with the lowest potential means the most advantageous lane for that vehicle. If the lane with the lowest potential value is the current lane of the vehicle, the vehicles do not change its movement, but if the lane with the lowest potential value is the right and left adjacent lane, the vehicle changes lane. Repeating this process every second until they reach the intersection, they enter this intersection in the most advantageous lane for them. Since this approach is made by all vehicles, a balanced distribution of vehicles on lanes is ensured. This increases the performance of the intersection by reducing the intersection delay and travel time, which are performance metrics as described in the previous sections.

IV. EXPERIMENTS

In this section, there will be detailed information about what experiments we have done for research. We firstly analyze the base AIM system. After that, we implement our lane organization layer to distribute vehicles more intuitive with the potential based approach. We did all the tests and experiments we did on the base AIM version in this version as well in order to comparison of performances. We compared our PLO-AIM version with standard AIM version and listed the results. Finally, in the discussion subsection we present summary information about findings of this study, strengths and weaknesses of our development, and possible future works.

A. Measurement Data

This study aims to decrease the delay of intersection(DOI) and average travel time in order to increase the efficiency of intersection. We implement a structure to collect time and space data about vehicles. Data collection lines, triggers the measurement methods, and outputs every time vehicle passes. Therefore, we can determine the timestamps of each vehicle entered and also the timestamps of each vehicle exit the intersection.

Measurement layer produce timestamp data indexed by vehicle identifiers and ready to import local database. After we import the data to oracle database, we calculate timestamp differences of each vehicles data. This difference corresponds to the time differences between the vehicles entering and exiting the intersection.

B. Experimental Setup

AIM project has built-in simulator. We used this tool for experimenting base AIM project and also experimenting our version of AIM with potential based approach. In this simulator you can configure, some key parameters to build and simulate autonomous intersection. We can set traffic management protocol (aim, traffic lights, etc.), traffic level (vehicles /hour) per lane, vehicle speed(meters/second), stopping distance before intersection, number of north-bound/southbound roads, number of east-bound/west-bound roads, intersection count. In this study, all the configurations kept as default except traffic level rate will change by 200 from 600 veh/hour to 2000 veh/hour. Also, we execute same scenarios for 4 lane per road and 6 lane per road.

We collect the data from base AIM product and after that we execute the same simulations with AIM with potential based approach. In order to evaluate performances of both systems, we calculate delay of intersection (DOI) and average travel time as performance evaluators. Travel time means that total time of vehicle. We measure this by taking timestamps in entering and exiting points of roads.

In order to determine efficiency, Dresner and Stone measured delay of intersection, which can be presented as the additional travel time caused by a vehicle as a result of passing through the intersection. Delay of intersection can be denoted as the time difference between travel times of the vehicle passing through the same intersection without any other cars and vehicle passing through the intersection within traffic load. We measured the same criteria in order to compare. Results of these calculations and comparisons between AIM and PLO-AIM is shared in following section.

C. Results

In order to analyze and observe base AIM system times, we run five simulation for each traffic rate and intersection size. We calculated average delay of intersection (Average DOI) and average travel time for each configuration. In this case, our experiments use same configuration, but we use two different intersection model. First one has 4 road entry in each direction, we call this 4-lane intersection. Second one has 6 road entry in each direction, we call this 6-lane intersection. Also, traffic rate (veh/hour) is changing. We defined a wide set of traffic rates in order to extend our research from sparse traffic situations to dense traffic situations. Therefore, we observe the performance of AIM in crowded or non-crowded traffic situations.

TABLE I
AIM: AVERAGE TRAVEL TIME - DOI FOR 4-LANES

Vehicle Count	4-lane Max-Min DOI (s)	4-lane Average Travel Time (s)	4-lane Average DOI (s)
600	1.7052	18.8099	5.3199
800	5.4143	30.7213	17.2313
1000	7.546	49.4704	35.9804
1200	15.7993	67.0275	53.537
1400	9.9248	82.5357	69.0457
1600	6.2349	93.2388	79.7488
1800	1.9842	99.3265	85.8365
2000	6.494	104.5498	91.0598

In the first table above, we analyze the change of average travel time and average delay of intersection for 4-lane intersection. We can see that delay and travel time increases while the traffic rate increase. As the data show us, while vehicle rate is increasing, travel time and delay will perform logarithmic growths because of the capacity of intersection. When all the lanes are full, maximum delay rate achieved. We called this as maximum intensity point of intersection. After that point, delay time and travel time convergence for same values.

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TABLE II
AIM: AVERAGE TRAVEL TIME - DOI FOR 6-LANES

Vehicle Count	6-lane Max -Min DOI (s)	6-lane Average Travel Time (s)	6-lane Average DOI (s)
600	3.9486	25.5685	12.0785
800	14.3727	39.3960	25.9060
1000	9.7	59.7993	46.3093
1200	9.1927	81.3401	67.8501
1400	7.6292	94.0286	80.5386
1600	7.578	110.3573	96.8673
1800	11.0349	116.0088	102.5188
2000	5.5807	121.0703	107.5803

In the 6-lane scenario, average travel time and delay starts with greater values compare to 4-lane values as expected. Because total vehicle density increased. Also 6-lane statistics shows us AIM performs same behavior for 6-lane intersections. Average delay time and travel time performs logarithmic growth and they also keep converging.

At this point, we collected enough data for evaluating base AIM system. Then we implement our solution in order to organize AIM inputs which are vehicles in lane. In order to make comparison between AIM and PLO-AIM, we had repeated the same analyzing and data collection process that we done for AIM with PLO-AIM model.

TABLE III
PLO-AIM: AVERAGE TRAVEL TIME - DOI FOR 4-LANES

Vehicle Count	4-lane Max -Min DOI (s)	4-lane Average Travel Time (s)	4-lane Average DOI (s)
600	1.967	15.6904	4.5614
800	3.831	25.3996	14.2706
1000	12.08665	42.96333	31.8343
1200	7.82874	63.80585	52.6768
1400	4.531592	82.14534	71.0163
1600	12.175	92.22365	81.0946
1800	7.830872	100.4908	89.3618
2000	9.118	104.2902	93.1612

Table 3 shows us that, AIM with potential-based lane organization layer performs better until the intersection is full. Because it distributes vehicles more evenly to each lane vehicles sent reservation to intersection manager faster. Therefore, they act faster. We can observe the improvement until the intersection capacity be full. If the traffic rate increase, time to full fill the intersection decreases. Therefore, the effect of PLO layer also decreases.

TABLE IV
PLO-AIM: AVERAGE TRAVEL TIME - DOI FOR 6-LANES

Vehicle Count	6-lane Max -Min DOI (s)	6-lane Average Travel Time (s)	6-lane Average DOI (s)
600	5.211	21.1372	10.0082
800	7.4	35.579	24.45
1000	7.4945	56.4695	45.3405
1200	10.3359	76.8117	65.6827
1400	11.4311	95.2200	84.0910
1600	13.4313	107.5334	97.4044
1800	7.25450	115.9122	104.7832
2000	6.456	124.573	113.444

In the 6-lane scenario of PLO-AIM, we observed the same improvement in times in Table 4. PLO layer decrease times until intersection becomes full and until there is no advantage for lane changing.

In both intersection model (4-lane or 6-lane), PLO layer proved its effect on time measurements. PLO layer reduce the times for each vehicle by adjusting their lanes to less crowded lanes. Results shows us that PLO layer decrease the average travel time and average delay of intersection for intersections which lanes are not fully occupied.

We saw that PLO layer is more effective in for acceptable traffice rates. In our vehicle traffic rates, PLO layer affects and reduce the measurements until 1300 veh/hour. Above that point, intersection becomes full very rapidly because of high traffic rate.

TABLE V
4-LANE ATT - DOI COMPARISON

Vehicle Count	Base AIM ATT(s)	PLO-AIM ATT(s)	Base AIM DOI(s)	PLO-AIM DOI(s)
600	18.8099	15.6904	5.31992	4.5614
800	30.7213	25.3996	17.2313	14.2706
1000	49.4704	42.9633	35.9804	31.8343
1200	67.0275	63.8058	53.5375	52.6768
1400	82.5357	82.1453	69.0457	71.0163
1600	93.2388	92.2236	79.7488	81.0946
1800	99.3265	100.4908	85.8365	89.3618
2000	104.5498	104.2902	91.0598	93.1612

Table 5 presents the comparison of 4-lane delay of intersection(DOI) and average travel time(ATT) data between AIM and PLO-AMI. PLO layer decreases the delay of intersection until the intersection is full and or until lanes have no advantage to each other. We can observe this effect of PLO layer until the traffic rate reaches to 1300 veh/hour. After that point, intersection gets full very rapidly. Therefore, PLO layer works in very short duration because of intersection crowdedness which is directly dependent on traffic rate. Because of that, average DOI does not decreases after 1300 veh/hour per lane which is very high.

Table 5 also shows us that, PLO layer decreases travel times. Because of lane organization, vehicles spend less time until they reach intersection. This decreases their travel time just like delay of intersection.

TABLE VI
6-LANE ATT - DOI COMPARISON

Vehicle Count	Base AIM ATT(s)	PLO-AIM ATT(s)	Base AIM DOI(s)	PLO-AIM DOI(s)
600	25.5685	21.1372	12.07856	10.0082
800	39.3960	35.579	25.90602	24.45
1000	59.7993	56.4695	46.30936	45.34050
1200	81.3401	76.8117	67.85012	65.6827
1400	94.0286	95.2200	80.53868	84.09101
1600	110.3578	107.5334	96.86738	97.40448
1800	116.0088	115.9122	102.51886	104.7832
2000	121.0703	124.573	107.58034	113.444

In the table 6, we also can observe the same PLO layer behavior for 6-lane scenario. Delay of intersection decreased until we reach 1300 veh/hour traffic level. We observed the simular effect of PLO layer when we compare the average travel times for each experiment.

Table 6 shows us that, PLO layer decreases travel times also for 6-lane scenario. Because of lane organization, vehicles spend less time until they reach intersection. This decreases their travel time just like delay of intersection. PLO layer effect can be seen also in 6-lane scenario. In the table 6, the decrease of average travel time is presented.

To sum up, PLO-AIM model outperformed base AIM model for traffic density rates less then 1300 veh/hour per lane which are denoted as acceptable traffic rates. Proposed PLO-AIM model reduced the average travel time reduced in between 0.2% - 17.3% and reduced average delay of intersection in between 1.6% - 17.1% for 4-lane and 6-lane scenarios.

D. Discussion

As we observed in our experiments, regulating the distribution of autonomous vehicles approaching the intersection on lanes made autonomous intersection crossing more efficient at acceptable traffic densities. In this study, we based on average intersection delay and average travel time criteria to evaluate the performance of autonomous intersections. With the vehicles using the potential approach to organize their own lanes, traffic flow has been managed in a more balanced form. Since the accumulations are balanced on the lanes, it has been observed that both the total travel time of the vehicles and the intersection delays have decreased.

As a result of the development and experiments we carried out in this study, we observed that lane management is a parameter that directly affects autonomous intersection management performance. The solution we offer has increased the performance of autonomous intersection management compared to the base AIM structure for acceptable traffic densities.

Additionally, we observed that at high traffic densities, the effect of the potential based lane arrangement layer gradually diminished. However, this is not a problem with the potential approach. Since the intersection reaches its maximum capacity very quickly at high traffic rates, no lane has an advantage over other lanes. For this reason, there is no benefit in changing lanes. Therefore, the effect of a lane management and potential based lane changes can only be observed in a short time until the intersection is full. Since this time is too short, the effect of the PLO layer is not be observed at high traffic densities.

In future studies, we plan to use this approach not only to reorganize the lanes, but also to plan all the routes of autonomous vehicles with potential-based intuitive choices. With this approach, we aim to create a potential-based autonomous vehicle management strategy different from the existing methods in the literature. The scope of decisions taken by autonomous vehicles can be expanded by adding additional parameters that will express the different intentions and preferences of the vehicles or passengers to the potential calculation we use in this study. With this concept, real-life intuitive driving will be modeled more accurately by autonomous vehicles.

V. CONCLUSION

In conclusion, autonomous intersection management is one of the popular subjects about autonomous vehicles. Also, these two areas trigger each other to expand. Developments in intelligent vehicles feeds the developments in management of intelligent vehicles. As the vehicles are getting smarter, the management systems are also getting smarter. Because of that different solutions from multiple disciplines can be applied for this topic.

This study presents the effects of lane organization by using potential approach in order to improve performance of autonomous intersection management. In light of the results we have achieved, we have seen that managing the lanes of vehicles entering intersections has a significant impact on determining autonomous intersection management performance. By managing the lanes, we have managed to decrease intersection delay and travel times of vehicles for specified traffic rates. We showed that we increased the intersection performance with this decrease in our performance criteria.

We also managed this lane management not by a central moderator, but as the vehicles switched the most advantageous lane for themselves as a result of potential-based decisions.

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REFERENCES

[1] K. Dresner and P. Stone, “Multiagent traffic management: An improved intersection control mechanism,” in *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems*, 2005, pp. 471–477.

[2] C. Yu, W. Sun, H. X. Liu, and X. Yang, “Managing connected and automated vehicles at isolated intersections: From reservation-to optimization-based methods,” *Transportation research part B: methodological*, vol. 122, pp. 416–435, 2019.

[3] M. Khayatian, M. Mehrabian, and A. Shrivastava, “Rim: Robust intersection management for connected autonomous vehicles,” in *2018 IEEE Real-Time Systems Symposium (RTSS)*. IEEE, 2018, pp. 35–44.

[4] B. Liu, Q. Shi, Z. Song, and A. El Kamel, “Trajectory planning for autonomous intersection management of connected vehicles,” *Simulation Modelling Practice and Theory*, vol. 90, pp. 16–30, 2019.

[5] R. Chen, J. Hu, M. W. Levin, and D. Rey, “Stability-based analysis of autonomous intersection management with pedestrians,” *Transportation Research Part C: Emerging Technologies*, vol. 114, pp. 463–483, 2020.

[6] Y. Wu, H. Chen, and F. Zhu, “Dcl-aim: Decentralized coordination learning of autonomous intersection management for connected and automated vehicles,” *Transportation Research Part C: Emerging Technologies*, vol. 103, pp. 246–260, 2019.

[7] M. Hausknecht, T.-C. Au, and P. Stone, “Autonomous intersection management: Multi-intersection optimization,” in *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2011, pp. 4581–4586.

[8] C. Y. Ozcan and M. Haciomeroglu, “A path-based multi-agent navigation model,” *The Visual Computer*, vol. 31, no. 6-8, pp. 863–872, 2015.

[9] J. Van Den Berg, S. J. Guy, M. Lin, and D. Manocha, “Reciprocal nbody collision avoidance,” in *Robotics research*. Springer, 2011, pp. 3–19.

[10] C. Y. Ozcan, E. Akcapinar Sezer, and M. Haciomeroglu, “A timebased global path planning strategy for crowd navigation,” *Computer Animation and Virtual Worlds*, vol. 30, no. 2, p. e1864, 2019.