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Autonomous Platoon Design Optimization Using SoS-Level Traffic Simulation-Based Analysis

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Chapter 1

Introduction

The ground shipping industry is very important for the United States economy, especially the trucking industry: more than 70% of the total freight tonnage is moved by trucks. This industry employs more than 3,5 million truck drivers and moves around 10,5 billion tons of freight every year using over 3,4 million heavy-duty class 8 trucks [1]. In order to move all these goods this industry uses over 144 billion of litres of Diesel fuel [1]. It's pretty clear that without trucks America stops. The ground industry has its own challenges:

1. Fuel price
2. Travel time
   (a) Accidents
   (b) Road construction
   (c) Traffic jam
   (d) Truck driver mandatory stops
3. Environmental footprint
4. Road safety

For example, the price of fuel is set by the free market so it is an uncertain cost, road accidents affect travel time but also road security, and environmental footprints affect people's health. These problems, in a way or another, affect the costs.

In figure 1.1 the costs of a single truck are reported.

As we can see, fuel and driver salary are the most expensive entries covering 64% of the total cost of a truck.

1.1 Fuel Price

Figure 1.2 shows the fuel price trend from November 2015 to May 2017 [3].

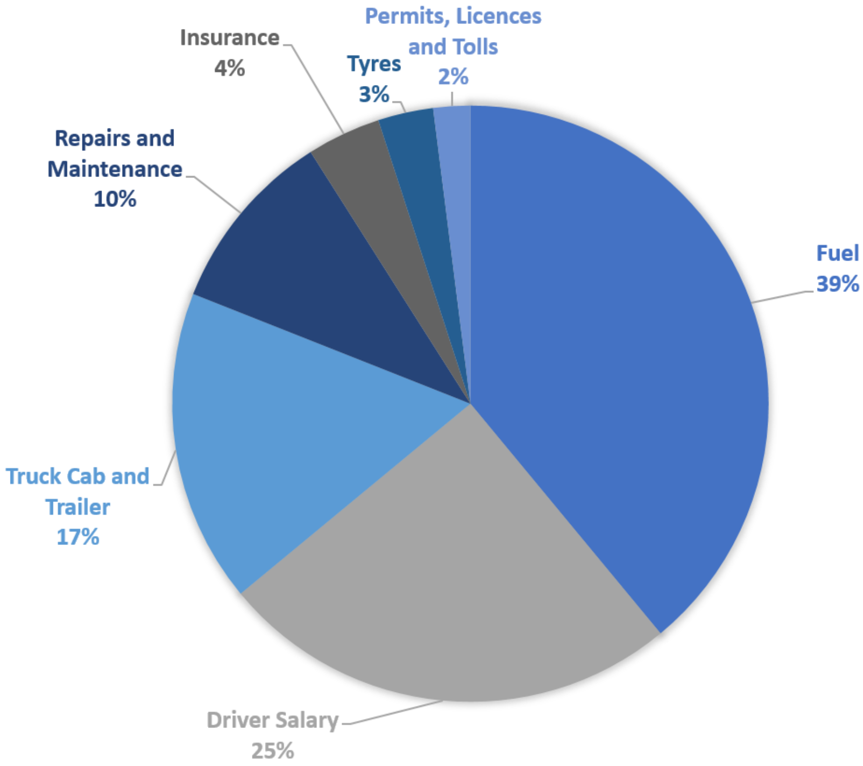


Figure 1.1: Costs referred to one truck [2]

Continuous fuel price variation is one of the causes of the different costs for the same trip, it would be a blessing for ground shipping companies to be able to rely on energy resources with a more stable price and lower cost, for example electricity.

1.2 Travel Time

Travel time is the most uncertain variable in a trip because there are many unforeseen events, like accidents, traffic jams, that could affect the trip duration.

1.2.1 Traffic Jam

Traffic jams in Highways and Urban Areas are one of the causes that affect travel time the most, and it is also one of the most unpredictable because of the individualistic way of choosing the route by each driver and the changeable flows of cars. It is estimated that every year Americans lose around 6.9 billion hours and 11.8 billion liters of fuel sitting in traffic jams [4].

1.2.2 Accidents

Accidents are bad, not only for the damage they cause: people can actually die (prayers and thoughts), but also because they generate traffic jams; for example, near Atlanta GA the I85 falls down because of a fire. There weren't fatalities but

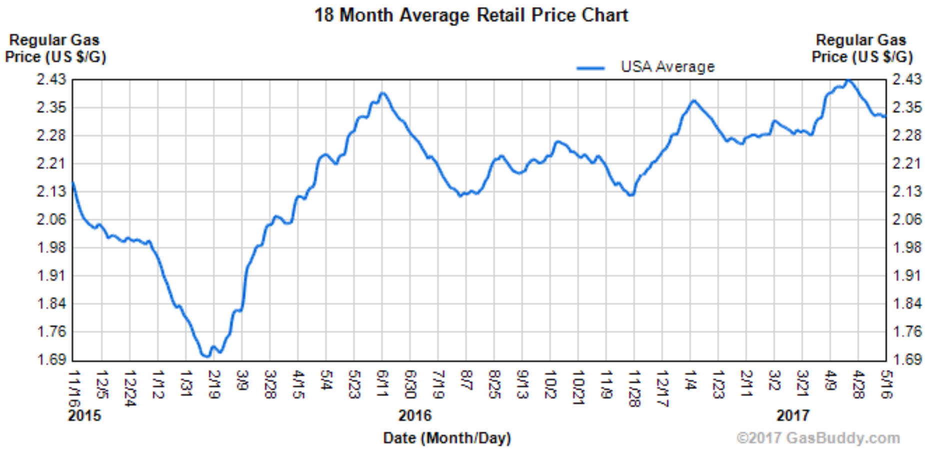


Figure 1.2: Fuel Price Trend [3]

the drivers were stuck in traffic for hours [5].

1.2.3 Road Construction

Work zones strongly affect freeway non recurring-delays: nearly 24 percent of delays could have been attributed to work zones, the equivalent of 888 million hours in 2014. In addition, 10% of overall congestion can be addressed to work zones, which means an annual loss of fuel around 1.2 billion litres in 2014 [4]

1.2.4 Truck Driver Mandatory Stops

In the US truck drivers have to follow hour of service regulations, the main rules are:

- 11-Hour Driving Limit: drivers may drive a maximum of 11 hours after 10 consecutive hours off duty
- 14-Hour Limit: drivers may not drive beyond 14th consecutive hours after coming on duty, following 10 consecutive hours off duty.
- 60/70-Hour Limit: drivers may not drive after 60/70 hours on duty in 7/8 consecutive days. A driver may restart a 7/8 consecutive day period after taking 34 or more consecutive hours off duty.

These rules affect truck drivers off time to ensure drivers are not tired [6].

The problems listed above could be mitigated by a centrally controlled guidance system: a computer that collects data from every vehicle in a large portion of road system in order to optimise the route for each vehicle based on a criterion (for example minimizing travel time).

1.3 Environmental Footprint

In the United States 12.8% of the fuel purchased is used by the trucking industry [7], currently accounting for 25% of road transport emissions, and predictions say that in the future road freight emissions will increase up to 2030 [8]. Trucks produce air pollution throughout their life, some of those are:

- Particulate matter (PM): poses the most serious threat to human health, as it can penetrate deep into the lungs
- Hydrocarbons (HC): at ground level this gas irritates the respiratory system
- Nitrogen oxides (NOx): these pollutants cause lung irritation and weaken the body's defenses against respiratory infections
- Carbon monoxide (CO): blocks oxygen from reaching brain, heart, and other vital organs
- Sulfur dioxide (SO2): can react in the atmosphere to form fine particles and poses the largest health risk to young children and asthmatics
- Hazardous air pollutants(toxics): have been related to birth defects, cancer, and other serious illnesses
- Greenhouse gases: such as CO2, that contribute to global warming

All these pollutants carry significant risks for human health and for the environment [9]. A way to reduce the air pollution could be switching from diesel powertrain to electric powertrain.

1.4 Road Safety

Every year trucks are involved in more than 5000 fatal accidents: where 84.7% of them happen in normal weather conditions; 18.8% of fatal accidents were on trips over 500 miles long;, and 22.6% of them were on local trip within 50 miles [10]; 32% of the fatal accidents involving trucks are caused by driver negligences like:

- Failure to stay in lane 10.9% [10]
- Inattentive driver 6.1% [10]
- High speed 4.8% [10]
- Failure to yield 4.0% [10]
- Involving alcohol 3.1% [10]
- Caused by drowsiness 1.6 % [10]

- Drug related 1.2% [10]
- Involving cellphone use 0.3% [10]

Most of these problems could be solved by using autonomous guidance systems on trucks, to help the driver prevent accidents.

1.5 Proposed Solution

A smart and integrated solution is needed to remove, or at least mitigate, all these problems, so that ground shipping companies could keep being competitive. In this thesis we analyse an integration of different technologies: truck platooning (2 or 3 trucks forming a convoy called "platoon"), autonomous guidance, electric powertrain, and centrally controlled guidance system.

Chapter 2

Truck Platooning Technology Overview

2.1 Truck Platooning

Truck platooning is a collection of vehicles led by a manually driven heavy lead vehicle. The vehicles behind (trucks and passenger cars) follow the lead vehicle automatically: both laterally and longitudinally [13].

This is the definition of the SARTRE project (SAfe Road TRain for the Environment) that includes the possibility to form road trains of heavy trucks and cars. In this work we consider platoons formed only by trucks because transportation is the core business of carriers, freight forwarders and logistics service provider. They use trucks more extensively than car-driving civilians therefore the assets needed to install the technology in their trucks will have a much shorter return of investment.

Truck platooning has an impact on the efficiency in fuel consumption because of the energy reduction due to a decreased drag coefficient. The fuel saved leads to a decreasing of the trip cost. Also, truck platooning has other benefits like increasing traffic volume capacity because of the shorter gaps among trucks, improving safety and comfort by removing the human input in the loop [14].

To better understand the benefits of truck platooning we must first talk about the basic aerodynamics principles around a moving vehicle and what changes with the platoon configuration. A vehicle in motion has to overcame two main resistance elements:

- Friction (internal and external)
- Air resistance

As we can see in figure 2.1 at low speed a moving vehicle uses the most of the engine power to overcame the internal friction and the contact friction between the

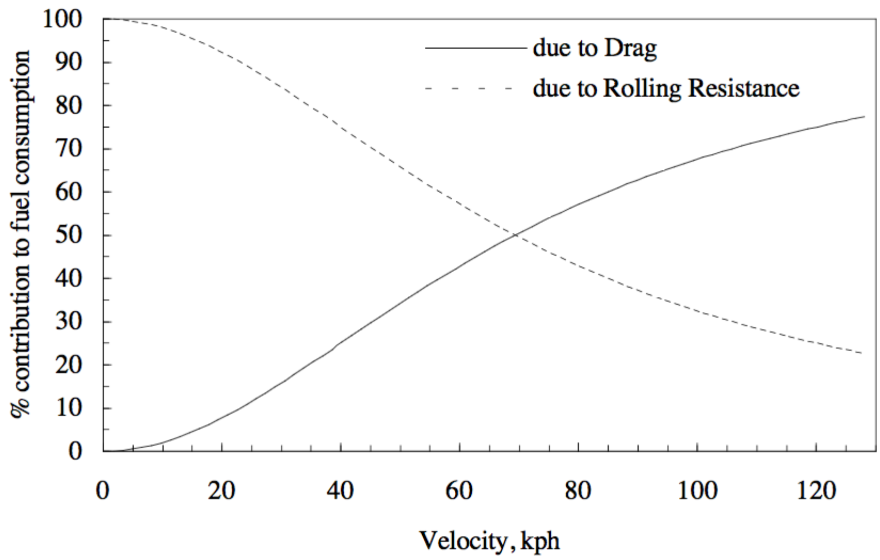


Figure 2.1: Percentage of total fuel consumption due to friction (rolling resistance) and drag force [15]

tyre and the ground [14]. When the vehicle reaches the speed of 70 km/h the engine power is used 50% for the rolling resistance and 50% for the drag resistance, at 90 km/h the percentage of power to overcome drag resistance is around 60%, when it reaches 110 km/h the engine power necessary to overcome drag resistance is 70%, at 130 km/h the percentage is 80%. We can say that over 70 km/h the drag resistance accounts for the most of the engine power [15].

Browand [16] states that the pressure difference between the front and the rear of a moving vehicle causes almost the 90% of the aerodynamic drag. A high pressure area is found at the front of the vehicle because of the impact of the car with the air. The air, following the lines of the vehicle, reduces some of its pressure. At the rear there is a low pressure area because of a turbulent wake flow generated by the air that passes through [14].

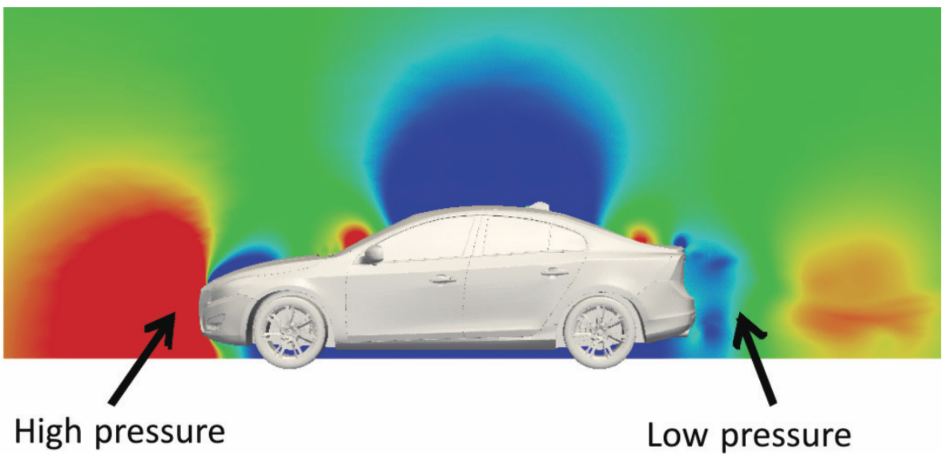


Figure 2.2: Pressures of a moving vehicle [14]

Platooning configuration affects the air behaviour around a vehicle, changing the pressure distribution. In fact, when two vehicles are platooning the following vehicle benefits from the lower pressure area at the rear of the first vehicle, and the second vehicle presence is doing a favor to the lead vehicle because it raises the pressure at the rear of the leading vehicle [14].

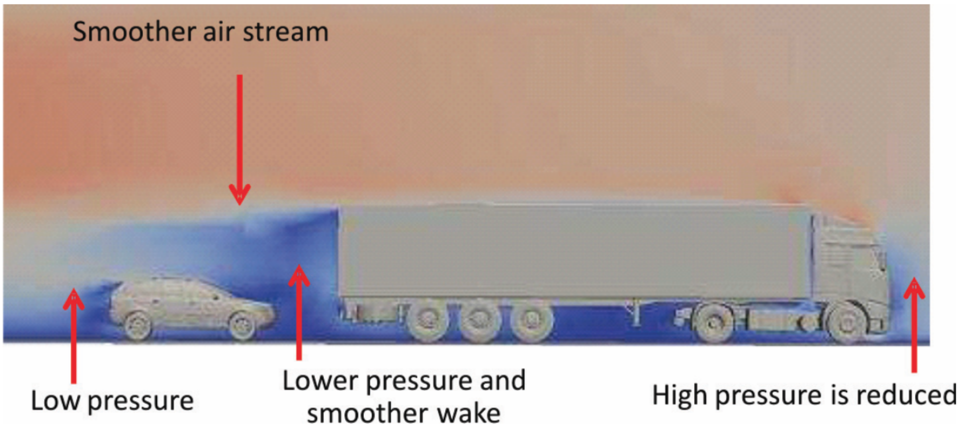


Figure 2.3: Platooning Effects [14]

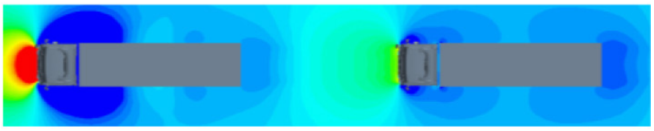
As we can see in figure 2.3, two vehicles platooning each have a pressure difference lower than if they were moving as single vehicles. The closer the distance between the vehicles the greater the platooning effect on the pressure distribution [14]. A structured road train can take advantage of the platooning effect because it transfers from vehicle to vehicle. The aerodynamics geometry of the vehicles and the distance (figure 2.4) between them affect the benefit of platooning [14].

However, truck platooning technology could be applied at different rates of automation, in reference [18] 5 level of automation were listed from no automation to full automation

In this work we decide to look into different configurations of automation in order to gain information on possible future scenarios. At first we recreate the actual scenario where every truck has a driver, a Diesel fuel powertrain, and they don't use truck platooning, then we consider every single combination till we end up with the most automated one: driverless trucks with electric powertrains that can move as a convoy.

Truck platooning is an aerodynamic approach to reduce pollution congestion [14]. The pollution reduction is achieved by reducing the quantity of fuel needed by vehicle via reducing aerodynamic drag coefficient [14]

(a) Static Pressure Distribution for a Single Truck



(b) Static Pressure Distribution for Two Trucks Platooning at 9.144 m (30 ft)

(c) Static Pressure Distribution for Two Trucks Platooning at 27.432 m (90 ft)

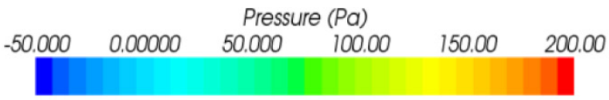


Figure 2.4: StaticPressure Distribution [17]

Level	Name	Narrative definition	Execution of steering and acceleration/ deceleration	Monitoring of driving environment	Fallback performance of *dynamic driving task*	System capability (*driving modes*)	BASt level	NHTSA level
***Human driver* monitors the driving environment**								
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a	Driver only	0
1	**Driver Assistance**	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes	Assisted	1
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes	Partially automated	2
***Automated driving system* ("system") monitors the driving environment**								
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task* with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes	Highly automated	3
4	**High Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes	Fully automated	3/4
5	**Full Automation**	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**	-	

Figure 2.5: Summary of Automation Level [18]

Chapter 3

Problem Definition

The goal of this work is to find the route for each truck that minimizes the total cost of the truck fleet for each combination of the design of experiment variables.

3.1 System of Systems Level

3.1.1 Simulation Environment

The open source traffic simulation package SUMO (Simulation of Urban MObility) was chosen as simulation environment. The SUMO package also includes a network import component and demand modeling component. SUMO is more than a traffic simulator, it is a suite of applications that helps you to perform a traffic simulation [19]. The main elements for a SUMO simulation are:

- Road networks
- Traffic demand

There are two ways to generate a road network, one by using the application "*netgen*" and the second one by using the application "*netconvert*". The latter application allows to read a road network from different formats like Shapefiles and Open Street Map; it also reads network files from other traffic simulators such as VISUM, Vissim or MATsim [19].

SUMO is a microscopic simulator: each vehicle is represented in SUMO simulation by at least an ID (name), a departure time and a route through the network. More vehicle's details can be added as physical properties, variables of the used movement model and graphic user interface [19].

One of SUMO tools is TraCI (Traffic Control Interface) that allows you to interact with a simulation online, to retrieve values of simulated objects and to manipulate their behaviour [19].

3.1.2 Truck Platoon Model

Figure 3.1 shows the type of truck we decided to investigate: a heavy duty class 8 truck.

Figure 3.1: Heavy Duty Class 8 Truck

In SUMO, truck platooning is modelled by using a single truck as long as the truck platoon itself. We decided to use this solution because it allows us to collect the most important data from SUMO simulation, that is the velocity trend during the whole trip. In this way we prevent some disadvantages as the control of the distance among the trucks in the platoon configuration, keeping the same lane, and changing lane while the trucks wait at traffic lights. After the simulation the velocity trend of a simulated truck is assigned to each truck in that platoon. In this manner the trucks in the same platoon have the same velocity trend, therefore they keep the imposed distance for the whole trip.

Energy Consumption Model

Once we get the velocity trends of all trucks, we compute the energy consumption using a simple model, starting from the energy rate required to keep the truck running at a speed v:

$$\dot{E}_{tot} = max(F_r v(t), \dot{E}_{idle}) \tag{3.1}$$

where:

- $\dot{E}_{idle}$ is the energy when the truck is not moving but it has the engine on
- F_r is the sum of all the on-road forces that occur on the truck (resistance force)
- $v(t)$ is the velocity at time t

In details:

$$F_r = F_I + F_{roll} + F_{climb} + F_{drag} \tag{3.2}$$

The components of the resistance force are:

- Inertia force
$$F_I = M\frac{dv}{dt} \tag{3.3}$$
where M is the mass of the trucks and $\frac{dv}{dt}$ is the acceleration

- Rolling resistance force
$$F_{roll} = \mu M g \tag{3.4}$$
where μ is the rolling resistance coefficient and g is the gravity acceleration

- Climbing force
$$F_{climb} = M g \theta \tag{3.5}$$
where θ is the road grade due to varying terrain altitude

- Aerodynamic drag force
$$F_{drag} = \frac{1}{2}\rho c_d v^2 A \tag{3.6}$$
where:
  - ρ is the air density
  - v is the truck velocity
  - A is the frontal area of the truck
  - c_d is the drag coefficient

The truck platooning benefits come in the drag force. In fact, due to the shrunk distance among the trucks, each truck has a platoon drag coefficient $c_{d,platoon}$ lower than the single truck drag coefficient $c_{d,single}$. The drag coefficient formula can be derived from the drag force formula 3.6:

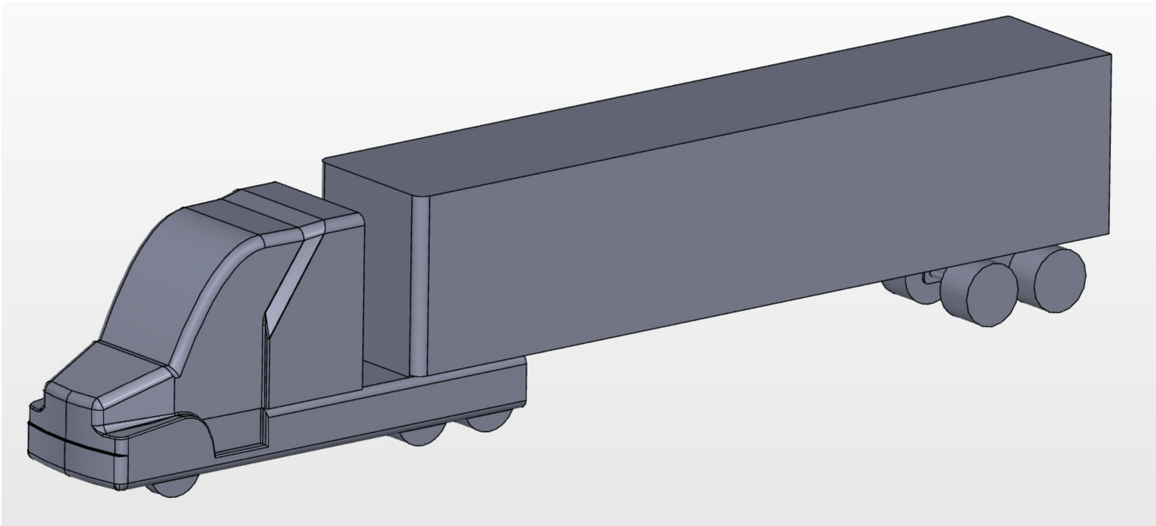
$$c_d = \frac{2F_{drag}}{\rho A v^2} \tag{3.7}$$

This way the energy consumption will be different between the single truck and the platoon configuration

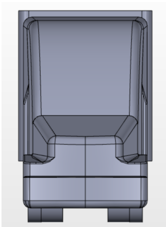
Platooning Drag Coefficient - Surrogate Model

Drag coefficient is relatively independent from the size because it is normalized by a characteristic area, for ground vehicle is the frontal area. Also, it is not so dependent from the speed as we can see from figure 3.3. For these reasons is used by aerodynamicists as a comparison quantity rather than the drag force itself [15].

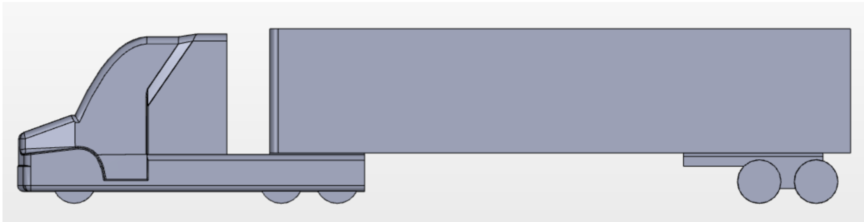
At the beginning, the approach was to calculate the drag coefficient with a Computational Fluid Dynamics (CFD) simulation of the drag coefficient for each truck in a platoon and for each platooning configuration. We decided to use the commercial program STAR CCM+ by Siemens, because of its simple GUI, ASDL availability and



(a) GCM Model



(b) GCM front view



(c) GCM lateral view

(d) GCM top view

Figure 3.2: General Conventional Model

the ASDL experts who could help me set up the cases. The Generic Conventional Model (Figure 3.2) was selected as the simulation model because it's suitable for the American market and the model was available in the literature, together with data for the validation [20].

In the paper [20], Pointer tried to match the experimental data collected in [21] to evaluate commercial CFD prediction on heavy duty trucks drag coefficient. The experimental model was 1/8th scale with the approximate dimensions:

- GCM length $L = 2.46$ m (97 in)
- GCM width $W = 0.33$ m (13 in)
- GCM height $H = 0.53$ m (21 in)

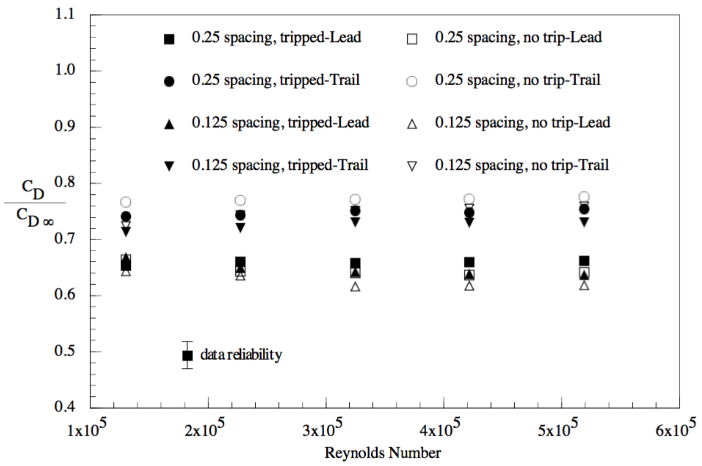


Figure 3.3: Effect of Reynolds Number on Drag Coefficient [15]

GCM model size in Star CCM+ were scaled to 1:1 therefore the GCM dimensions are:

- GCM length is around $L = 19$ m (748 in)
- GCM width is around $W = 2.64$ m (104 in)
- GCM height is around $H = 4.24$ m (167 in)

A yaw angle = 0 was chosen for the CFD simulation. In this case we can use half of the model for the simulation because of the model symmetry and the boundary condition. The fluid domain is a block with these dimensions [17]:

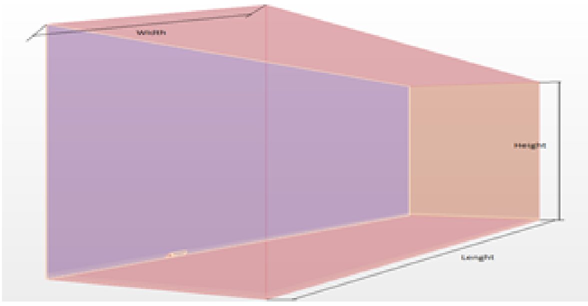
- Fluid domain lenght: $L = 500$ m
- Fluid domain width: $2W = 250$ m (we simulate half truck so the fluid domain width is $W = 125$ m)
- Fluid domain height: $H = 200$ m

In figure 3.4 we can see the different surface that wrap the half truck model.

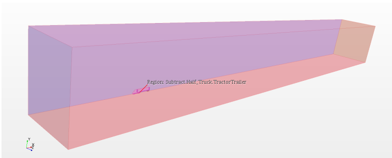
We decided to use a hexaedron unstructured mesh. Unstructured mesh was chosen because the simulation is 3D with complicate shape and building a structured one is almost impossible. Hexaedron type of cell was selected because it is more accurate and easy to use.

An automatic wake refinement based on the turbulent kinetic (TKe) energy was used in the CFD simulation. The size of the cell were brought to a certain value in the region were the TKe was higher than 1000. In figure 3.6 we can see the refinement at the back of the truck.

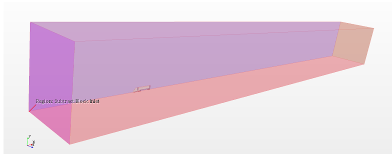
In paper [20] were evaluated some turbulent models using the GCM model. We used this data for the CFD validation. Pointer [20] compares a several turbulent models keeping the configuration constant:



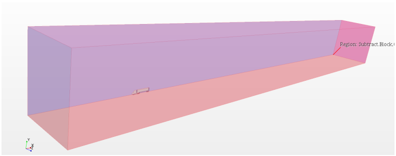
(a) Fluid Domain



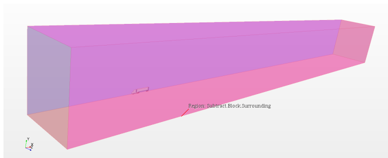
(b) Half Truck Fluid Domain



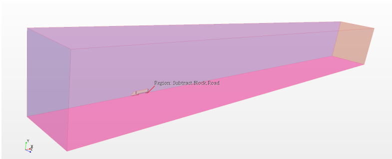
(c) Inlet Fluid Domain



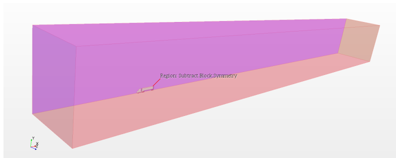
(d) Outlet Fluid Domain



(e) Surrounding Fluid Domain



(f) Road Fluid Domain



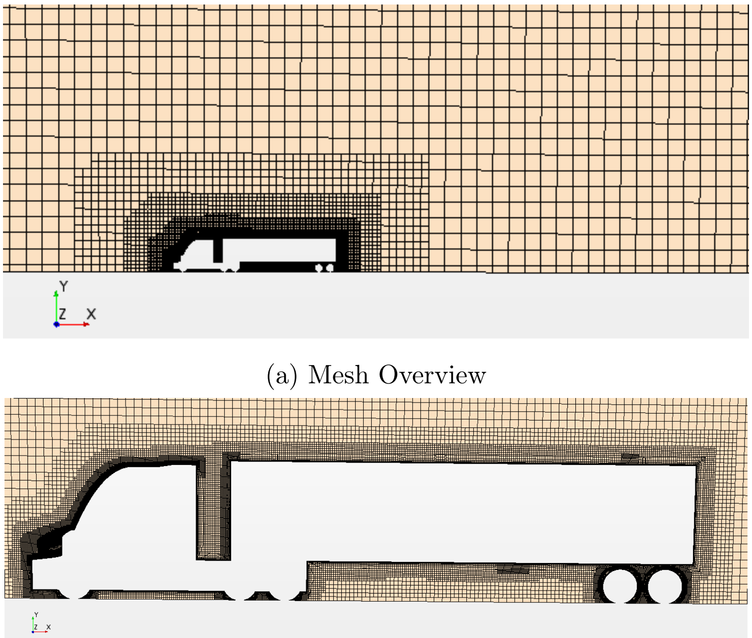
(g) Symmetry Fluid Domain

Figure 3.4: Fluid Domain

- A vehicle width-based Reynolds number = 1.1 million
- Mach number 0.15
- Yaw angle = 0
- Inlet boundary condition: uniform velocity $v = 51.45$ m/s
- Output boundary condition: zero gradient condition
- Symmetry boundary condition

In table 3.1 there are Pointer's results [20], $k - \omega$ SST model was chosen as turbulent model because it is the one with the lowest percent of error.

Boundary conditions were applied to the surfaces in figures 3.4. We decided to use a velocity inlet boundary condition for the inlet surface, the same used in [20].



(a) Mesh Overview

(b) Prism Layer Mesh

Figure 3.5: Hexaedron Unstructured Mesh

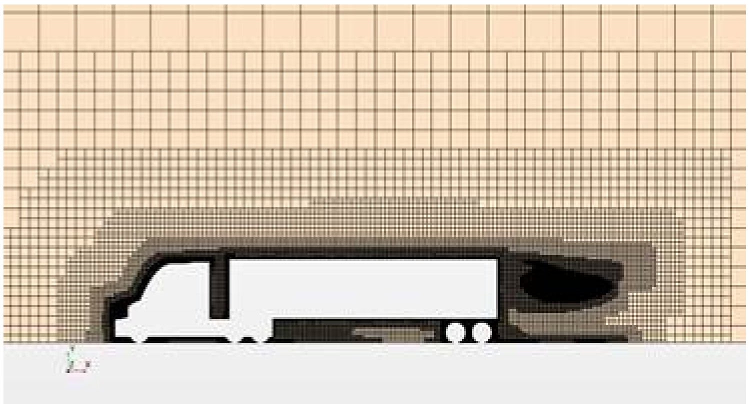


Figure 3.6: Wake Refinement

A velocity inlet boundary condition was also applied to the road and surrounding surfaces (figures 3.4c, 3.4f, 3.4e). The only difference between the inlet surface and the others is the direction of velocity: on the inlet the velocity direction is normal to surface, for the surrounding and road is normal to the inlet surface (and parallel to the two considered surfaces). The velocity inlet boundary condition was chosen for the surrounding and road surfaces in order to simulate the truck moving on the road at velocity v. This trick supposes the implicit hypotesis that in the reality the air is not moving. Actually the truck is moving at velocity v and the air is not moving. In this simulation the truck is not moving and the air is moving with a velocity $-v$ (opposite direction). A pressure outlet boundary condition was used for the outlet surface (figure 3.4d), that is the same boundary condition used in [20]. A symmetry boundary condition was applied to the symmetry surface (figure 3.4g), and finally a

	Experiment	$k - \varepsilon$ Model	$k - \omega$ SST Model	RNG Model	Chen's Model	Quadratic Model
Predicted Drag	0.398	0.402	0.401	0.389	0.3919	0.3815
Percent of Error in Prediction	-	1.0	0.8	2.3	1.61	4.32

Table 3.1: Turbulence model comparison [20]

CFD simulation configuration		
$d_{trucks} = 6$ m, $N^{\circ}_{trucks} = 2$	$d_{trucks} = 14$ m, $N^{\circ}_{trucks} = 2$	$d_{trucks} = 27$ m, $N^{\circ}_{trucks} = 2$
$d_{trucks} = 6$ m, $N^{\circ}_{trucks} = 3$	$d_{trucks} = 14$ m, $N^{\circ}_{trucks} = 3$	$d_{trucks} = 27$ m, $N^{\circ}_{trucks} = 3$

Table 3.2: CFD simulation configuration

wall boundary condition was used for the half truck model (figure 3.4b).

The main purpose was to simulate different configurations of truck platooning:

- Number of trucks in the platoon (N°_{trucks}): 2 or 3
- Distance between the trucks (d_{trucks}): 6 m, 14 m, 27 m

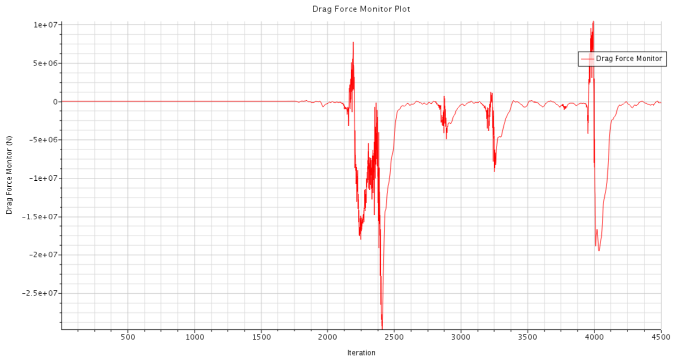
the combination of all these variables generate all truck platooning CFD simulations configuration

Unfortunately, after several attempts with different settings of values for the mesh generation and for the relaxation factors the CFD simulations didn't converge, as we can see in figure 3.7). The reasons why the CFD simulation didn't converge could be:

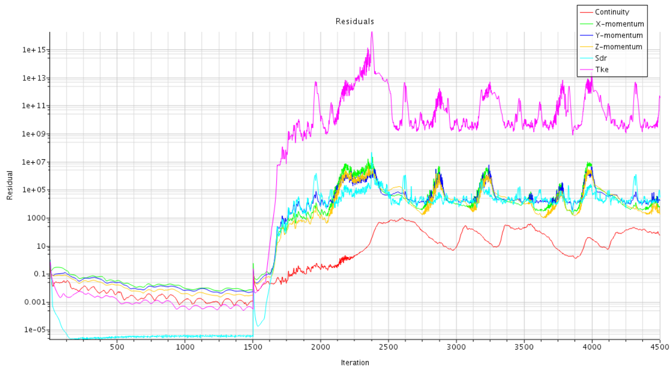
- Coarse mesh
- Complexity of truck shape (too many details)
- Steady simulation

A solution to the first issue could be to increase the mesh number of elements, the second one could be worked out by a less detailed truck model, and the third problem could be solved by a Large Eddy Simulation(LES). A LES is an unsteady simulation that could catch time variant phenomena. In the rear region there is a turbulent flow due to the separation of the boundary layer. this turbulent phenomena could create periodic vortexes that impede the simulation converge.

Unfortunately, the time was running as the simulation didn't converge and we couldn't implement these options. To solve this problem we decided to use data



(a) Drag Force Trend



(b) Residuals Trend

Figure 3.7: Non Converged Example of Drag Force and Residuals Graphs

available in the literature. In the paper [15] the authors studied the effect of platooning on cars. The model car they used was 1991 GM Lumina APV that is a monovolume (see figure 3.10).

The authors of [15] quantified the behaviour of vehicle drag coefficient as a function of vehicle spacing for different sizes of platoons. In figure 3.8 we can see the normalized drag coefficient as a function of vehicle spacing of a 2 vehicle platoon, and in figure 3.9 the one for a 3 vehicle platoon.

In both graphs the y-axis represents the ratio between the space among vehicles in the platoon and the vehicle length, the spacing is measured on centerline from the rear bumper of the leader model to the front bumper of the follower. The x-axis represents the C_D *ratio* between the drag coefficient of each platoon member and the C_D of the same model in isolation. The C_D *ratio* represents the change in drag that occur for the unique aerodynamics of the platoon [15].

The graph 3.8 can be split in 2 parts: the part before spacing ratio = 1, called *strong interaction*, and the part over spacing ratio = 1 called *weak interaction*. In the strong interaction part, both the lead and trail drag coefficients decrease. There is a point around spacing ratio = 0.35 where the C_D ratio is the same for both vehicles, and below spacing ratio = 0.35 the drag coefficients ratio of the trail vechicle is higher than the drag ratio of the leading vehicle [15]. In the weak interaction part

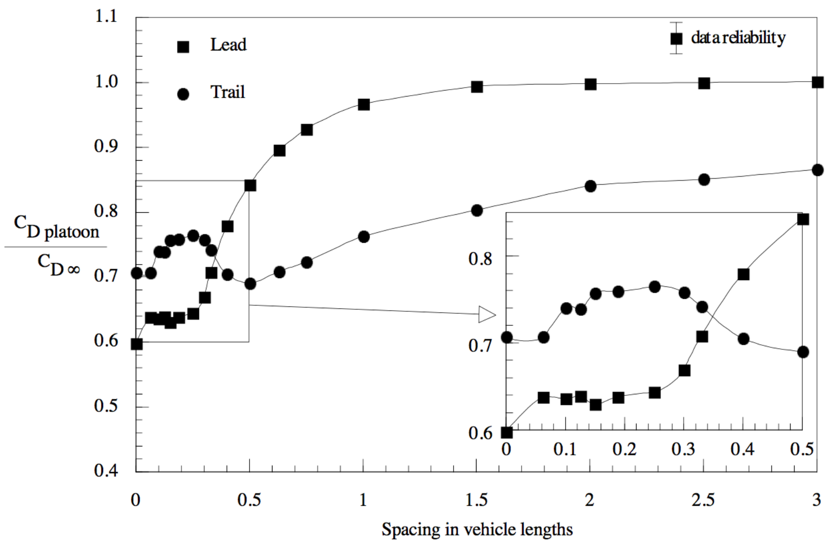


Figure 3.8: Results for a two vehicles platoon [15]

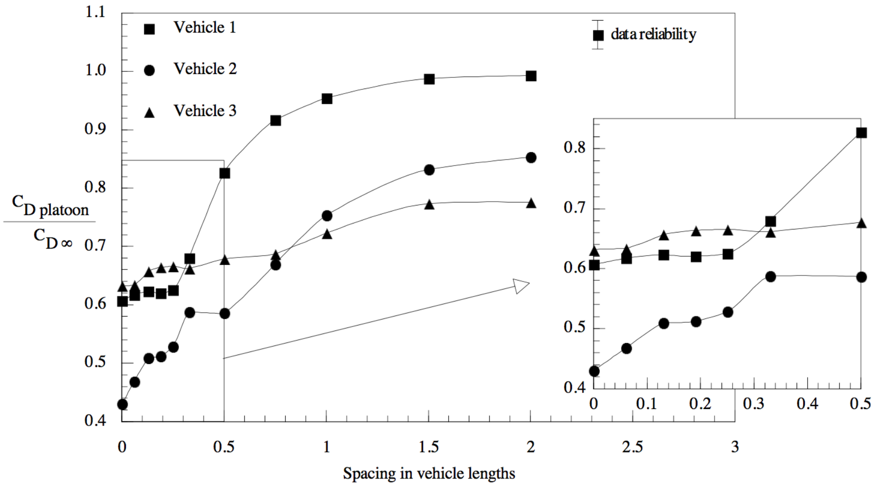


Figure 3.9: Results for a three vehicles platoon [15]

the leading vehicle drag coefficient doesn't get any benefits from platooning, but the trail vehicle drag coefficient decrease because the vehicle is contained in wake of the lead one [15].

The graph 3.9 can also be split in 2 parts: the *strong interaction* one, below spacing ratio = 1, and the *weak interaction*. In the strong interaction part there are 2 crossover points: one around spacing ratio = 0.85 between the vehicle 2 and vehicle 3, and the other one around spacing ratio = 0.3 between vehicle 1 and vehicle 3. Also, there is much variation at a short spacing ratio. The authors of [15] think that these drag ratio behaviours reflect the physical changes taking place in flow field at a short spacing ratio. In the weak interaction part they expected that vehicle 2 trend had the lower drag ratio trend, but it isn't: vehicle 3 has the lowest trend after the crossover point at spacing ratio = 0.85.

Figure 3.10: 1991 GM Lumina APV

	Number of Trucks: $N^{\circ}_{trucks} = 2$		
	$d_{trucks} = 6$	$d_{trucks} = 14$	$d_{trucks} = 27$
$c_{d,Leader}$	0.2753	0.3712	0.3982
$c_{d,Follower1}$	0.3005	0.2896	0.3203

Table 3.3: Drag coefficient truck platoon composed by 3 trucks

We decided to use this data for two main reasons:

- The thesis main goal is to present a method to calculate the routes for a fleet of trucks in order to minimize the total cost of the fleet, so the drag coefficient trend is a module that could be changed with a more sophisticated one and the method will still work.

- In this study we are not comparing different shapes of trucks, but only one shape, so we can imagine that in the whole world there is a truck that has this drag trend in function of the truck spacing.

This graphs 3.8, 3.9 gives a reasonable drag coefficient behaviour as a function of the vehicle spacing because the rough GCM model and the GM Lumina shapes are similar. Both shapes could be approximated by a box for the nose and a higher box for the rest of the vehicle.

The spacing ratio for the chosen distances are: $\frac{d_{trucks}}{L_{truck}} = 0.3158$, $\frac{d_{trucks}}{L_{truck}} = 0.7368$, and $\frac{d_{trucks}}{L_{truck}} = 1.4211$.

So the drag coefficients used in this design of experiment are shown in tables 3.3 3.4

As we can see the different distances catch all the possible combinations and they are well distributed among the two parts: *strong interaction* and *weak interaction*.

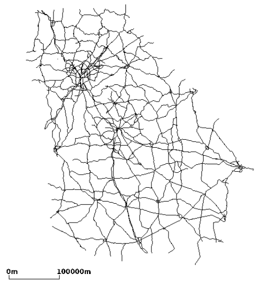
	Number of Trucks: $N^{\circ}_{trucks} = 3$		
	$d_{trucks} = 6$	$d_{trucks} = 14$	$d_{trucks} = 27$
$c_{d,Leader}$	0.2668	0.3665	0.3943
$c_{d,Follower1}$	0.2316	0.2657	0.3303
$c_{d,Follower2}$	0.2653	0.2752	0.3081

Table 3.4: Drag coefficient truck platoon composed by 3 trucks

3.1.3 Transportation System

The transportation system where the trucks drive the most is the highway, also the average highway speed is around 110 km/h (68.35 mph). As we can see in figure 2.1 at this speed 70% of the engine power is used to overcame the drag force, so in the highway the truck platooning benefits would be greater than in a urban scenario.

(a) SUMO Map: State of Georgia, US



(b) State of Georgia Map

Figure 3.11: Highway's Network of Georgia, US

For these reasons we decided to simulate only the highway system. At the beginning the portion of the US road system that we wanted to consider was the Georgia road system, so the first proposed map was the Georgia state highway network 3.11. This network 3.11 was complete, it had all the highways, the main road, and the immission lanes, but for the purpose of this thesis testing this method; was too much especially computationally speaking.

After that first try we decided to simplify the network, but we also decided to enlarge the evaluated map. In figure 3.12 it's shown the new considered map. We decide to simulate the flows of goods among these cities:

- Atlanta
- Montgomery
- Savannah
- Chattanooga
- Greenville

Figure 3.12: Enlarged Considered Map

So in the following next maps each city were placed on a single edge, because we are ignoring the urban part of the map and focusing only on the highway system. The trucks would drive from one of the cities edge to another one. Each city edge were chosen on the simplified map to reflect the city position in the real map.

The second map 3.13 that was suggest was a simpler one, it was a grid map where all the edges were highway roads with 3 lanes for each direction. Each cross was controlled by a traffic light in order to permit vehicle left turn even in simulation with high traffic. This network 3.13 was discarded because the possible routes between a point A and a point B weren't so different. Also, it was so large it required a lot of cars to simulate a high density traffic scenario: computationally speaking this map wasn't a good trade off.

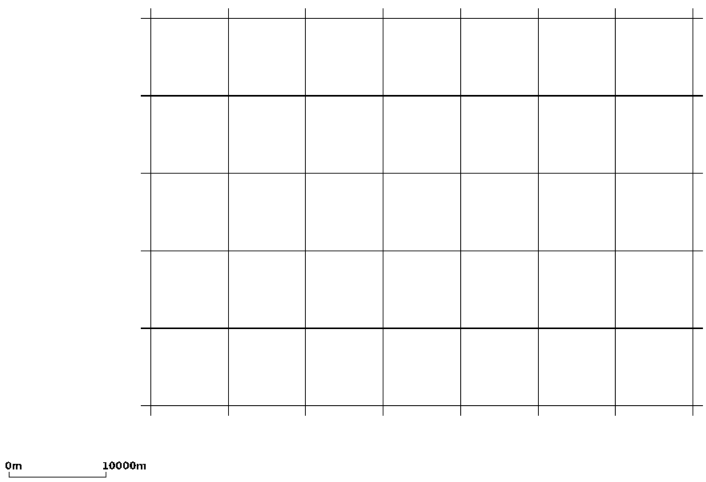


Figure 3.13: SUMO Map: Grid Network

The last type of map suggested is a "spider map". This network 3.14 has 11 arms and it has no center. We decided to remove the center because it would have been a 11 road cross that is quite unusual. Also, this geometry made the possible routes between two point, A and B, much different in shape and traffic. Indeed the

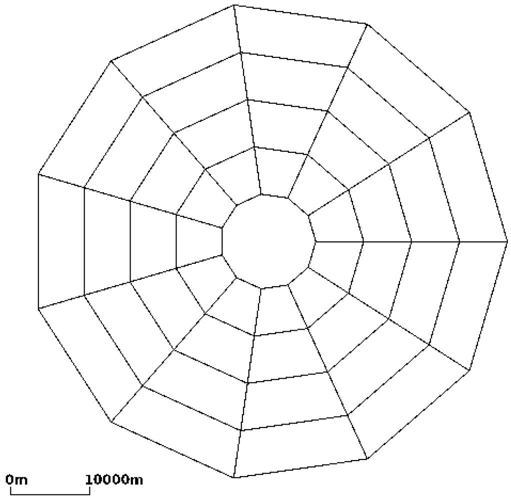


Figure 3.14: SUMO Map: "Spider" Network

smallest circle that connects all the 11 arms would be the one with higher traffic because, starting from a point A, it's always included in the shortest path to reach the opposite side of the map. Even in the spider network 3.14 all the edges were highways (3 lanes for each direction and the average US highway speed limit of 113 km/h (70 mph)) and each cross was regulated by a traffic light.

Both the grid map 3.13 and the spider map 3.14 were generated using "netgenerate", a program in the SUMO package to generate maps.

This is the command used to generate the spider map:

```
netgenerate
    -s true
    --spider.arm-number=11
    --spider.circle-number=5
    --spider.space-radius=6000
    --spider.omit-center=true
    --output-prefix=spider_map_name
    -o path\to\save\folder\.net.xml
    --default.lanenumber=3
    --default.speed=31.5
    --default-junction-type=traffic_light
```

For more information about the meaning of the single commands see [22].

The model of all maps has been done using the graph theory: where roads are represented as edges and the junctions as nodes. The map is a .xml file where there are all the information about edges, junctions, traffic lights, and complementary edges.

All the previous reasons convinced us to choose the spider map 3.14, among all the options, as the final test map for the simulation.

3.1.4 Trucks

The 18 wheel trucks are used for the longest trip and they are the main users of the highway system. In figure 3.1 there is the real shape of a heavy duty class 8 truck, but in the simulation we don't need so much realism. In figure 3.15 we can see how SUMO represent trucks.

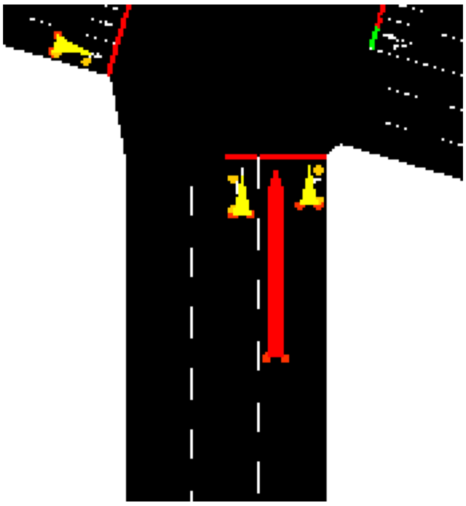


Figure 3.15: Truck Representation in SUMO

Moving and controlling trucks in a convoy formation was really complicated because of the SUMO changing lane model and the SUMO following model. Some of the main problems that we came up with, were:

- Maintain the distance between trucks in a convoy
- Keeping all the trucks of a platoon in the same lane.

The distance between the trucks is a DOE variable, so it is fixed, the distance is not a variable that we collect from the SUMO simulation. Moreover, the purpose of this thesis work is not to investigate how the traffic affects the truck platooning distance, but it is to find out how traffic affects the trucks velocity (because the energy model depends on the velocity, see 3.1). After these well-placed questions we came up to the conclusion that truck platooning control system is not necessary for the purpose of this work. So we decided to simulate the trucks convoy in SUMO as a single truck, as long as the platoon itself.

For example, in figure 3.16 we can see a platoon of 3 trucks (truck length = 19 m) at the distance of 14 meters would be approximate by a single truck with a length of $3 \times 19 + 2 \times 14 = 85$ m. This solution is called "one truck to rule a platoon" (OTRuP). The OTRuP let us collect the trend velocity of one truck, and when we calculate the cost of each truck in a platoon we will use the same velocity trend (because two objects maintain the same distance when they have the same velocity). This solution solves the previous problems of truck platooning control, and also maintains

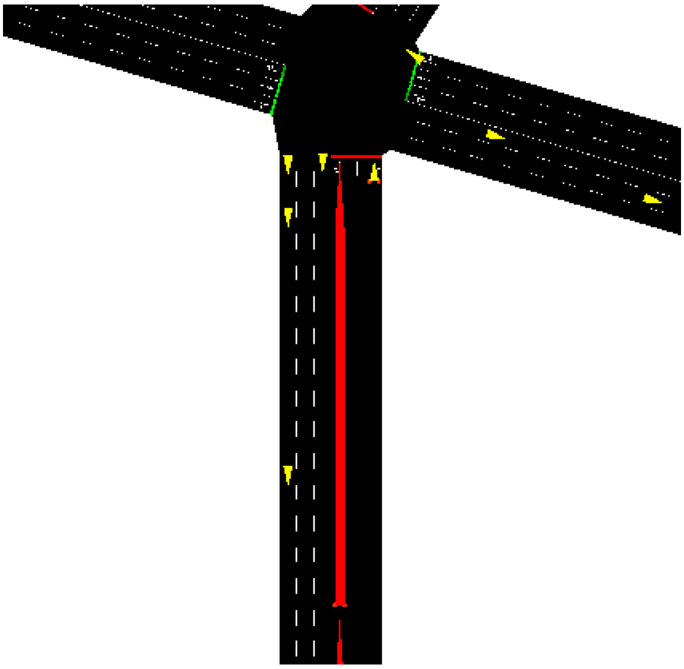


Figure 3.16: SUMO truck convoy with the platoon distance = 14 m

	Truck Platooning Road Usage		
	$d_{platoon} = 6$ m	$d_{platoon} = 14$ m	$d_{platoon} = 27$ m
$N^{\circ}_{trucks} = 2$	44 m	52 m	65 m
$N^{\circ}_{trucks} = 3$	69 m	85 m	111 m

Table 3.5: Platooning Road Usage

the platoon road usage (length of the road occupied by trucks in the platoon and the distance between them). Unfortunately the OTRuP solution has a setback: when the convoy is not moving the trucks keep the platoon distance (in the example 14 meters).

The OTRuP solution could be used under the hypothesis that the trucks in a convoy always keep the platoon distance even when they are not moving. In table 3.5 are listed all the possible platooning configurations and their road usage.

In the simulation we decided to use 60 trucks, because it's a representative number of trucks of a fleet owner, and in a future scenario, where a third part company's business is forming truck platoons between different carriers [23]. Also, the chosen number of trucks is divisible by 2 and 3 (the considered numbers of trucks in a platoon).

3.1.5 Demand

The demand is a flow chart with information about each truck trip such as origin, destination, departure time, and arrival time. We can see an example in table 3.6 the truck's demand chart can be used to generate the truck's flow chart 3.7 and the

ID	truck0	truck1	...	truck58	truck59
Origin	Atlanta	Atlanta	...	Greenville	Greenville
Destination	Montgomery	Montgomery	...	Chattaanooga	Chattaanooga
Departure Time	7:00 am	7:00 am	...	7:05 am	7:05 am
Arrival Time	9:23 am	9:23 am	...	11:14 am	11:14 am

Table 3.6: Demand Chart

		Destination				
		Atlanta	Montgomery	Chattanooga	Savannah	Greenville
Origin	Atlanta	0	6	6	6	0
	Montgomery	0	0	0	0	6
	Chattanooga	18	0	0	0	0
	Savannah	6	0	0	0	0
	Greenville	6	0	6	0	0

Table 3.7: Truck's Flow Chart

maximum travel time chart 3.8. In table 3.7 there is the flow chart of the number of trucks between each starting and end point. Table 3.8 shows the maximum travel time for each possible trip. The travel time table is symmetric and the values are generated by open street maps approximation.

Demand Generation

The demand weren't available in the literature, so it was generated using population city based criteria to assign the probability of a city to be chosen as origin or destination of a trip. The information cities are listed in table 3.9.

Using a set of $N_{tot,truck}/6$ (in this case 60/6) pairs, random numbers were chosen: each pair corresponds to the origin city and the destination city, and 6 trucks were assigned to that trip.

3.1.6 Routing Algorithm

There are several different options for the routing algorithm:

- Conventional GPS:
- Connected GPS
- Smatphone routing app
- Centralized cloud guidance

		Ending Pont				
	udm: [s]	Atlanta	Montgomery	Chattanooga	Savannah	Greenville
Starting Point	Atlanta	0	8568 ($2h23min$)	6588 ($1h50min$)	13248 ($3h41min$)	8352 ($2h19min$)
	Montgomery	8568 ($2h22min$)	0	12348 ($3h26min$)	18792 ($5h13min$)	16560 ($4h36min$)
	Chattanooga	6588 ($1h50min$)	12348 ($3h26min$)	0	19548 ($5h26min$)	14940 ($4h9min$)
	Savannah	13248 ($3h41min$)	18792 ($5h13min$)	19548 ($5h26min$)	0	13968 ($3h53min$)
	Greenville	8352 ($2h19min$)	16560 ($4h36min$)	14940 ($4h9min$)	13968 ($3h53min$)	0

Table 3.8: Travel Time Chart

	Atlanta	Montgomery	Chattaanooga	Savannah	Greenville
Population	472522	200022	177561	146763	67453
Probability	0.444	0.188	0.167	0.138	0.063
% Probability	44.4%	18.8%	16.7%	13.8%	6.3%
Interval	$[0 - 0.444[$	$[0.444 - 0.632[$	$[0.632 - 0.799[$	$[0.799 - 0.937[$	$[0.937 - 1.0]$

Table 3.9: Cities Information

The conventional GPS use the Dijstra's algorithm which is the basic routing algorithm that calculate the shortest path without any additional information regarding traffic. The connected GPS use the one shot routing algorithm which also calculate the shortest route algorithm, but considering the traffic level at the departure time. The smartphone routing app use a Multiple shot routing algorithm which it calculates the shortest route, but considering traffic level at departure time and updating the path throughout the trip. The centralized cloud guidance use DUA-Gawron algorithm which it approaches the routing problem in a global prospective: the target becomes the global optimization. Therefore the set of output routes for the trucks accounts for interaction of the truck routes itself, it means that is not an individualistic approach, minimizing the energy consumption of a single truck, but it is a global approach that tries minimizing the energy consumption of each truck taking in consideration the others trucks energy consumption. plus the centralized cloud guidance is the only one that allow us to perform truck platooning, because of its global approach can organize convoys.

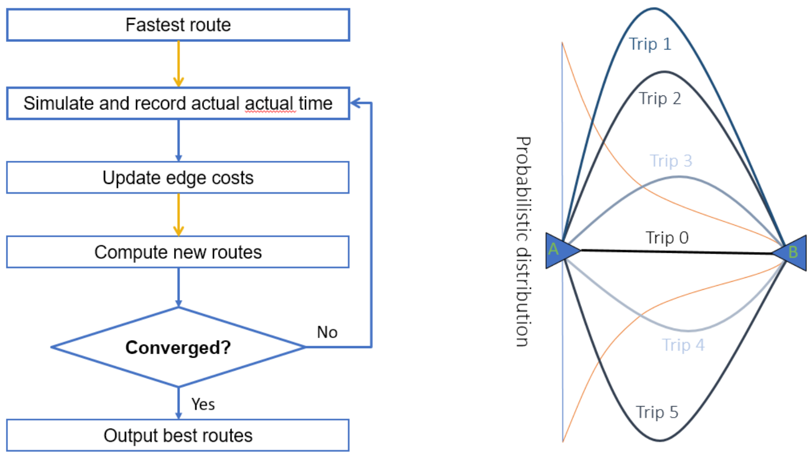


Figure 3.17: DUA Gawron algorithm diagram

We decided to use the centralized cloud guidance for our porpuse of studying truck platooning. Reason why we use Dynamic User Assignment algorithms 3.17, used in [24], [25] for a similar porpuse.

The DUA-Gawron algorithm is also available in SUMO. In figure 3.18 we can see the algorithm used to evaluate the DOE cases.

The first step in fig. 3.18 is using the DUA-Gawron algorithm to decide the routes of the trucks in the network. At the first iteration the DUA algorithm use the Dijkstra's algorithm to set the routes for the trucks The SUMO program is used to simulate the scenario, during the simulation TraCI collected the following information every time step for every truck in the network:

- Truck ID: name of the truck

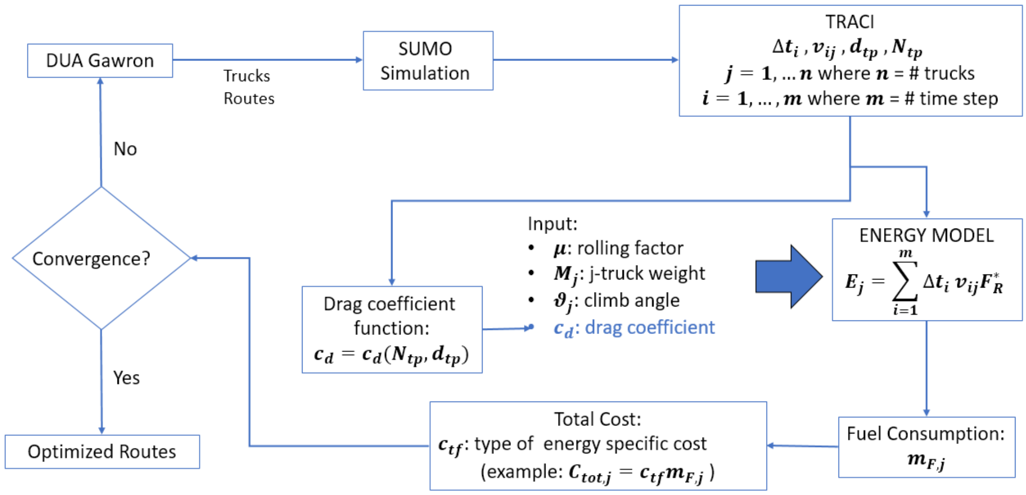


Figure 3.18: Cases DOE algorithm

- Truck Velocity: v_{ij}
- Truck Edge: edge name where the truck is at the time t
- Time Step: Δt_i

All these informations were stored, and then used to calculate the total energy (using the model presented in section 3.1.2) for each truck. The fuel consumption calculation depends on the type of powertrain:

if it's Diesel fuel we calculate the total mass of fuel consumed using this formula

$$m_{F,j} = \frac{E_j}{H_u \eta_{DieselEngine}} \tag{3.8}$$

where:

- E_j: is the total energy consumed during the whole trip
- $H_u = 43000$ [kJ/kg]: is the lower heating value [12]
- $\eta_{DieselEngine} = 0.33$: is the Diesel engine efficiency [12]; the theoretical efficiency of Diesel engine is 0.45 for trucks, but it is an optimistic value based on laboratory test, we decided to use a lower value to better reflect the reality.

If it's an electric powertrain the total energy is only divided by the electric engine efficiency $\eta_{ElectricEngine}$:

$$m_{F,j} = \frac{E_j}{\eta_{ElectricEngine}} \tag{3.9}$$

$\eta_{ElectricEngine} = 0.98$ is the value chosen because of the high performance of electric engine.

After finding the fuel consumption we calculated the total cost for each truck using this formula:

$$C_{tot} = c_f m_{F,j} \tag{3.10}$$

where c_f is the specific cost of the energy type

- For Diesel fuel $c_f = 0.621$ [$/liter] Average value in Atlanta [26]
- For electricity $c_f = 0.1$ [$/kWh] Average value in Georgia [27]

After the total cost calculation we can update the edge costs. Then we check the convergence and if it converged we found the optimized route, else we go back to the routing algorithm. Starting from the second iteration the DUA-Gawron method uses a probabilistic distributions together with route cost and recording past iterations to choose new routes for the trucks. This approach avoids moving congestions back and forth between two areas of the network.

3.2 Design of Experiment Variables

At a system level we have all the design of experiment variables, they are divided in:

- System of Systems level DOE variables (SoS level)
- System level DOE variables

SoS level variables are the ones that controlled the environment where the trucks (Systems) are moving. In this case there is only one SoS level variable, that is:

- Traffic Density: represents the cars traffic level
  - No traffic: Zero cars in the network. It's part of baseline scenario
  - Low density: 7500 cars in the network that enters in 750 s
  - Medium density: 15000 cars in the network that enters in 1500 s
  - High density: 30000 cars in the network that enters in 3000 s

System level variables affect the trucks configuration and they are controllable by the user, in this case the carrier. These variables are:

- Number of truck forming a platoon:
  - No truck platooning: they move as a single convoy: it's part of baseline scenarios
  - Platoon of 2 trucks: to catch the intermediate behaviour
  - Platoon of 3 trucks: maximum number of trucks considered because of the highway's wall of trucks problem [23]

- Distance among trucks: we chose this value because we need to address the regulation on the safe distance between the trucks, and for different weather conditions. Also we want to investigate relent distance case for all the truck involved in the platoon.
  - No Distance: when trucks are moving alone
  - 6 meters: minimum distance to get benefit from truck platooning for all trucks [14]
  - 14 meters: medium distance to catch an intermediate behaviour
  - 27 meters: maximum distance to get some benefit from truck platooning for all trucks [17].
- Powertrain:
  - Diesel: internal combustion engine that represents the standard technology for trucks
  - Electric: several truck industries are presenting their electric truck option, in the future electric trucks will increase their number.
- Driver: different driver configuration are investigate because of the enhancement of the autonomous guidance technology:
  - All human drivers: human drivers in all trucks
  - Human lead and autonomous following (Intermediate autonomous): driver in the leading vehicle and autonomous trucking in the following ones
  - No human drivers: autonomous trucks:

In the end we have 5 variables, but not all the variables where used in all combinations. We have to distinguish between the DOE cases with $N^{\circ}_{truck} = 1$ and the DOE cases with $N^{\circ}_{truck} \neq 1$

3.2.1 DOE cases with $N^{\circ}_{truck} = 1$

This group of cases is a bit different from the others because not all the variables are used to generate the combination.

The variables are:

- Traffic Density = [No Traffic, Low Density, Medium Density, High Density]
- $N^{\circ}_{truck} = 1$
- Distance = No Distance
- Powertrain = [Combustion, Electric]

Case Label	Traffic Density	N°_{truck}	Distance	Powertrain	Driver
Case 1	No Traffic	1	No Distance	Combustion	All Humans
Case 2	No Traffic	1	No Distance	Combustion	Autonomous
Case 3	No Traffic	1	No Distance	Electric	All Humans
Case 4	No Traffic	1	No Distance	Electric	Autonomous
Case 5	Low Density	1	No Distance	Combustion	All Humans
Case 6	Low Density	1	No Distance	Combustion	Autonomous
Case 7	Low Density	1	No Distance	Electric	All Humans
Case 8	Low Density	1	No Distance	Electric	Autonomous
Case 9	Medium Density	1	No Distance	Combustion	All Humans
Case 10	Medium Density	1	No Distance	Combustion	Autonomous
Case 11	Medium Density	1	No Distance	Electric	All Humans
Case 12	Medium Density	1	No Distance	Electric	Autonomous
Case 13	High Density	1	No Distance	Combustion	All Humans
Case 14	High Density	1	No Distance	Combustion	Autonomous
Case 15	High Density	1	No Distance	Electric	All Humans
Case 16	High Density	1	No Distance	Electric	Autonomous

Table 3.10: DOE cases with $N^{\circ}_{truck} = 1$

- Driver = [All Humans, Autonomous]

The total number of cases with $N^{\circ}_{truck} = 1$ is: $4 \times 2 \times 2 = 16$.
In table 3.10 the DOE cases combination are listed:

3.2.2 DOE cases with $N^{\circ}_{truck} \neq 1$

These are the rest of the DOE cases:

- Traffic Density = [No Traffic, Low Density, Medium Density, High Density]
- $N^{\circ}_{truck} = [2, 3]$
- Distance = [6, 14, 27]
- Powertrain = [Combustion, Electric]
- Driver = [All Humans, Intermediate Autonomous, Autonomous]

The total number of cases with $N^{\circ}_{truck} \neq 1$ is: $4 \times 2 \times 3 \times 2 \times 3 = 144$.
We split the 144 DOE cases according to the traffic density in order to make them more readble.
In tables 3.11, 3.12, 3.13, 3.14 the DOE cases combination associated with traffic density equal to "No traffic", "Low Density", "Medium Density" and "High Density".

The total number of cases simulated is: $16 + 144 = 160$.

Case Label	Traffic Density	N°_{truck}	Distance [m]	Powertrain	Driver
Case 17	No Traffic	2	6	Combustion	All Humans
Case 18	No Traffic	2	6	Combustion	Intermediate Autonomous
Case 19	No Traffic	2	6	Combustion	Autonomous
Case 20	No Traffic	2	6	Electric	All Humans
Case 21	No Traffic	2	6	Electric	Intermediate Autonomous
Case 22	No Traffic	2	6	Electric	Autonomous
Case 23	No Traffic	2	14	Combustion	All Humans
Case 24	No Traffic	2	14	Combustion	Intermediate Autonomous
Case 25	No Traffic	2	14	Combustion	Autonomous
Case 26	No Traffic	2	14	Electric	All Humans
Case 27	No Traffic	2	14	Electric	Intermediate Autonomous
Case 28	No Traffic	2	14	Electric	Autonomous
Case 29	No Traffic	2	27	Combustion	All Humans
Case 30	No Traffic	2	27	Combustion	Intermediate Autonomous
Case 31	No Traffic	2	27	Combustion	Autonomous
Case 32	No Traffic	2	27	Electric	All Humans
Case 33	No Traffic	2	27	Electric	Intermediate Autonomous
Case 34	No Traffic	2	27	Electric	Autonomous
Case 35	No Traffic	3	6	Combustion	All Humans
Case 36	No Traffic	3	6	Combustion	Intermediate Autonomous
Case 37	No Traffic	3	6	Combustion	Autonomous
Case 38	No Traffic	3	6	Electric	All Humans
Case 39	No Traffic	3	6	Electric	Intermediate Autonomous
Case 40	No Traffic	3	6	Electric	Autonomous
Case 41	No Traffic	3	14	Combustion	All Humans
Case 42	No Traffic	3	14	Combustion	Intermediate Autonomous
Case 43	No Traffic	3	14	Combustion	Autonomous
Case 44	No Traffic	3	14	Electric	All Humans
Case 45	No Traffic	3	14	Electric	Intermediate Autonomous
Case 46	No Traffic	3	14	Electric	Autonomous
Case 47	No Traffic	3	27	Combustion	All Humans
Case 48	No Traffic	3	27	Combustion	Intermediate Autonomous
Case 49	No Traffic	3	27	Combustion	Autonomous
Case 50	No Traffic	3	27	Electric	All Humans
Case 51	No Traffic	3	27	Electric	Intermediate Autonomous
Case 52	No Traffic	3	27	Electric	Autonomous

Table 3.11: DOE cases with traffic density = "No Traffic"

Case Label	Traffic Density	N°_{truck}	Distance [m]	Powertrain	Driver
Case 53	Low Density	2	6	Combustion	All Humans
Case 54	Low Density	2	6	Combustion	Intermediate Autonomous
Case 55	Low Density	2	6	Combustion	Autonomous
Case 56	Low Density	2	6	Electric	All Humans
Case 57	Low Density	2	6	Electric	Intermediate Autonomous
Case 58	Low Density	2	6	Electric	Autonomous
Case 59	Low Density	2	14	Combustion	All Humans
Case 60	Low Density	2	14	Combustion	Intermediate Autonomous
Case 61	Low Density	2	14	Combustion	Autonomous
Case 62	Low Density	2	14	Electric	All Humans
Case 63	Low Density	2	14	Electric	Intermediate Autonomous
Case 64	Low Density	2	14	Electric	Autonomous
Case 65	Low Density	2	27	Combustion	All Humans
Case 66	Low Density	2	27	Combustion	Intermediate Autonomous
Case 67	Low Density	2	27	Combustion	Autonomous
Case 68	Low Density	2	27	Electric	All Humans
Case 69	Low Density	2	27	Electric	Intermediate Autonomous
Case 70	Low Density	2	27	Electric	Autonomous
Case 71	Low Density	3	6	Combustion	All Humans
Case 72	Low Density	3	6	Combustion	Intermediate Autonomous
Case 73	Low Density	3	6	Combustion	Autonomous
Case 74	Low Density	3	6	Electric	All Humans
Case 75	Low Density	3	6	Electric	Intermediate Autonomous
Case 76	Low Density	3	6	Electric	Autonomous
Case 77	Low Density	3	14	Combustion	All Humans
Case 78	Low Density	3	14	Combustion	Intermediate Autonomous
Case 79	Low Density	3	14	Combustion	Autonomous
Case 80	Low Density	3	14	Electric	All Humans
Case 81	Low Density	3	14	Electric	Intermediate Autonomous
Case 82	Low Density	3	14	Electric	Autonomous
Case 83	Low Density	3	27	Combustion	All Humans
Case 84	Low Density	3	27	Combustion	Intermediate Autonomous
Case 85	Low Density	3	27	Combustion	Autonomous
Case 86	Low Density	3	27	Electric	All Humans
Case 87	Low Density	3	27	Electric	Intermediate Autonomous
Case 88	Low Density	3	27	Electric	Autonomous

Table 3.12: DOE cases with traffic density = "Low Density"

Case Label	Traffic Density	N°_{truck}	Distance [m]	Powertrain	Driver
Case 89	Medium Density	2	6	Combustion	All Humans
Case 90	Medium Density	2	6	Combustion	Intermediate Autonomous
Case 91	Medium Density	2	6	Combustion	Autonomous
Case 92	Medium Density	2	6	Electric	All Humans
Case 93	Medium Density	2	6	Electric	Intermediate Autonomous
Case 94	Medium Density	2	6	Electric	Autonomous
Case 95	Medium Density	2	14	Combustion	All Humans
Case 96	Medium Density	2	14	Combustion	Intermediate Autonomous
Case 97	Medium Density	2	14	Combustion	Autonomous
Case 98	Medium Density	2	14	Electric	All Humans
Case 99	Medium Density	2	14	Electric	Intermediate Autonomous
Case 100	Medium Density	2	14	Electric	Autonomous
Case 101	Medium Density	2	27	Combustion	All Humans
Case 102	Medium Density	2	27	Combustion	Intermediate Autonomous
Case 103	Medium Density	2	27	Combustion	Autonomous
Case 104	Medium Density	2	27	Electric	All Humans
Case 105	Medium Density	2	27	Electric	Intermediate Autonomous
Case 106	Medium Density	2	27	Electric	Autonomous
Case 107	Medium Density	3	6	Combustion	All Humans
Case 108	Medium Density	3	6	Combustion	Intermediate Autonomous
Case 109	Medium Density	3	6	Combustion	Autonomous
Case 110	Medium Density	3	6	Electric	All Humans
Case 111	Medium Density	3	6	Electric	Intermediate Autonomous
Case 112	Medium Density	3	6	Electric	Autonomous
Case 113	Medium Density	3	14	Combustion	All Humans
Case 114	Medium Density	3	14	Combustion	Intermediate Autonomous
Case 115	Medium Density	3	14	Combustion	Autonomous
Case 116	Medium Density	3	14	Electric	All Humans
Case 117	Medium Density	3	14	Electric	Intermediate Autonomous
Case 118	Medium Density	3	14	Electric	Autonomous
Case 119	Medium Density	3	27	Combustion	All Humans
Case 120	Medium Density	3	27	Combustion	Intermediate Autonomous
Case 121	Medium Density	3	27	Combustion	Autonomous
Case 122	Medium Density	3	27	Electric	All Humans
Case 123	Medium Density	3	27	Electric	Intermediate Autonomous
Case 124	Medium Density	3	27	Electric	Autonomous

Table 3.13: DOE cases with traffic density = "Medium Density"

Case Label	Traffic Density	N°_{truck}	Distance [m]	Powertrain	Driver
Case 125	High Density	2	6	Combustion	All Humans
Case 126	High Density	2	6	Combustion	Intermediate Autonomous
Case 127	High Density	2	6	Combustion	Autonomous
Case 128	High Density	2	6	Electric	All Humans
Case 129	High Density	2	6	Electric	Intermediate Autonomous
Case 130	High Density	2	6	Electric	Autonomous
Case 131	High Density	2	14	Combustion	All Humans
Case 132	High Density	2	14	Combustion	Intermediate Autonomous
Case 133	High Density	2	14	Combustion	Autonomous
Case 134	High Density	2	14	Electric	All Humans
Case 135	High Density	2	14	Electric	Intermediate Autonomous
Case 136	High Density	2	14	Electric	Autonomous
Case 137	High Density	2	27	Combustion	All Humans
Case 138	High Density	2	27	Combustion	Intermediate Autonomous
Case 139	High Density	2	27	Combustion	Autonomous
Case 140	High Density	2	27	Electric	All Humans
Case 141	High Density	2	27	Electric	Intermediate Autonomous
Case 142	High Density	2	27	Electric	Autonomous
Case 143	High Density	3	6	Combustion	All Humans
Case 144	High Density	3	6	Combustion	Intermediate Autonomous
Case 145	High Density	3	6	Combustion	Autonomous
Case 146	High Density	3	6	Electric	All Humans
Case 147	High Density	3	6	Electric	Intermediate Autonomous
Case 148	High Density	3	6	Electric	Autonomous
Case 149	High Density	3	14	Combustion	All Humans
Case 150	High Density	3	14	Combustion	Intermediate Autonomous
Case 151	High Density	3	14	Combustion	Autonomous
Case 152	High Density	3	14	Electric	All Humans
Case 153	High Density	3	14	Electric	Intermediate Autonomous
Case 154	High Density	3	14	Electric	Autonomous
Case 155	High Density	3	27	Combustion	All Humans
Case 156	High Density	3	27	Combustion	Intermediate Autonomous
Case 157	High Density	3	27	Combustion	Autonomous
Case 158	High Density	3	27	Electric	All Humans
Case 159	High Density	3	27	Electric	Intermediate Autonomous
Case 160	High Density	3	27	Electric	Autonomous

Table 3.14: DOE cases with traffic density = "High Density"

Chapter 4

Results

The simulation results presented in this chapter would be only the low density and medium density and high density because they are the more relevant.

The baseline scenario is the case number 6: it represent the most common solution used by the ground shipping industry, the single truck with Diesel powertrain a driver for each truck. Some contraction were used to present the DoE variables: "None" instead of "No Distance" (between trucks), "C" and "E" instead of "Combustion" and "Electric", and "lead human" instead of "Intermediate Autonomous".

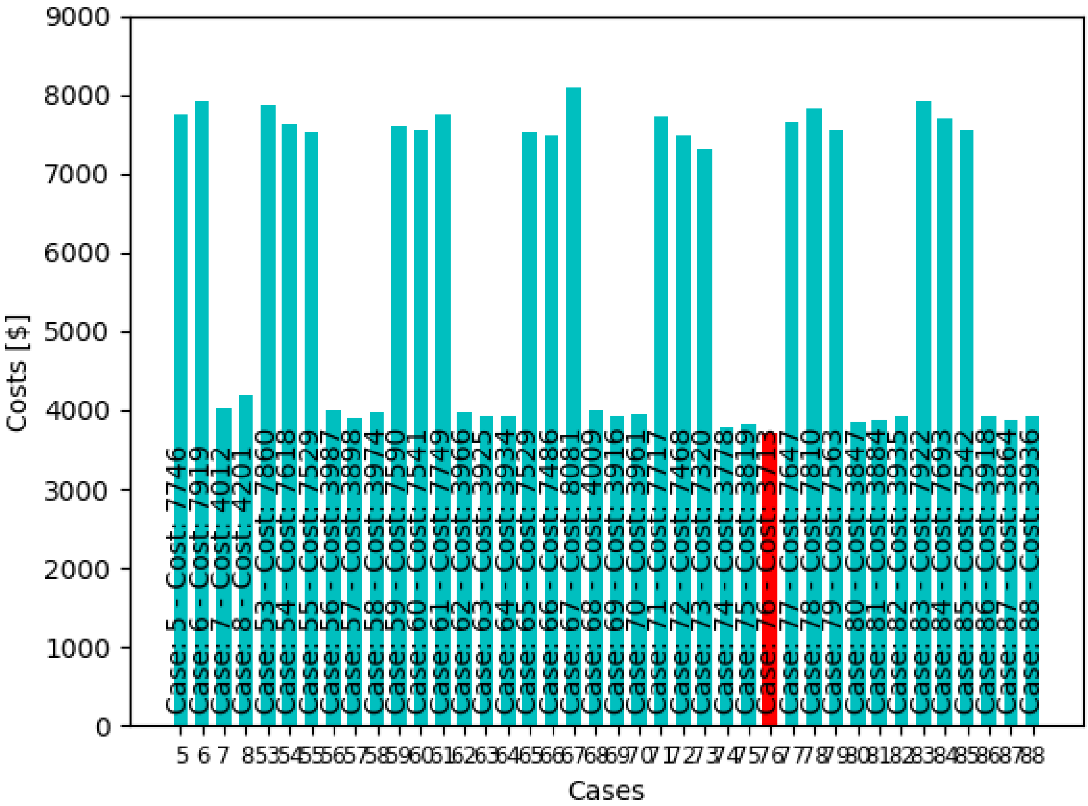


Figure 4.1: Costs of Low Density Cases Graph

4.1 Low Traffic Density Results

The results of the simulations with low traffic density cases are shown in figure 4.1 with a bar chart. For each case we did 16 iterations, and in the bar charts we present the optimal iteration. We chose that number of iteration because it is a trade off between the computational effort and exploration of the feasible region. The DoE variables of all cases are listed in table 4.1.

The baseline scenario for low density traffic is case number 6: it represents the most common solution used by the ground shipping industry: single trucks with Diesel powertrain, a driver for each truck.

The fleet of trucks reached the minimum cost in case number 76, highlighted in table 4.1 and figure 4.1, the configuration is: platoons of 3 trucks at a distance of 6 meters with electric powertrain and a driver on each truck. It is surprising that the optimum configuration is the one with a driver for each truck. The same configuration should reach even better results without drivers. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration. Also we can see that configurations with platoons of 3 trucks at a distance of 6 meters with electric powertrain are less expensive solutions.

4.1.1 No Truck Platooning Scenarios

The results of simulations with low traffic density and no platooning are shown in figure 4.2 with a bar chart. The DoE variables of all cases are listed in table 4.2.

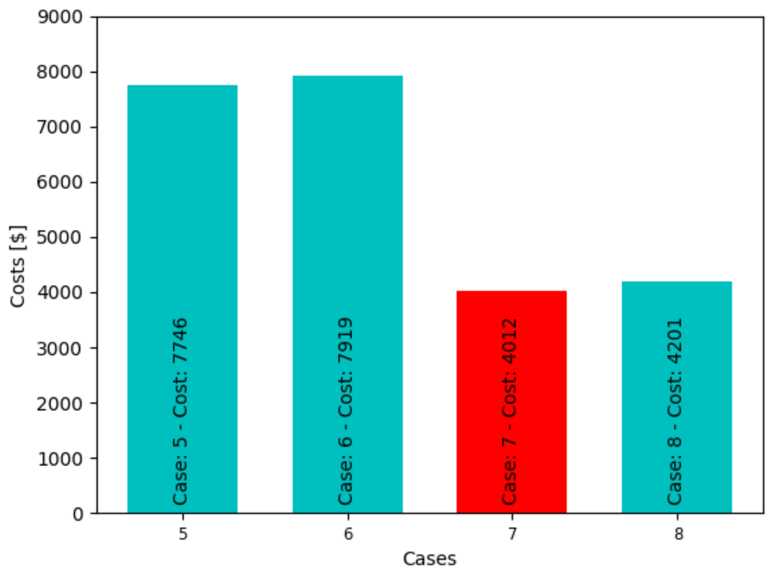


Figure 4.2: Costs of Low Density Cases for a NO Truck Platooning scenario

We can see in figure 4.2 that the best configuration is number 7: single truck with electric pow-

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
5	low density	1	None	C	autonomous	7746.52657285
6	low density	1	None	C	all humans	7919.14164631
7	low density	1	None	E	autonomous	4012.932751
8	low density	1	None	E	all humans	4201.29768791
53	low density	2	6	C	autonomous	7860.711058
54	low density	2	6	C	lead human	7618.81305297
55	low density	2	6	C	all humans	7529.60215494
56	low density	2	6	E	autonomous	3987.54669628
57	low density	2	6	E	lead human	3898.86362117
58	low density	2	6	E	all humans	3974.74226226
59	low density	2	14	C	autonomous	7590.91485479
60	low density	2	14	C	lead human	7541.99095916
61	low density	2	14	C	all humans	7749.6411358
62	low density	2	14	E	autonomous	3966.2897303
63	low density	2	14	E	lead human	3925.76548553
64	low density	2	14	E	all humans	3934.19269309
65	low density	2	27	C	autonomous	7529.20588059
66	low density	2	27	C	lead human	7486.78777986
67	low density	2	27	C	all humans	8081.66737566
68	low density	2	27	E	autonomous	4009.74432967
69	low density	2	27	E	lead human	3916.01624847
70	low density	2	27	E	all humans	3961.35989152
71	low density	3	6	C	autonomous	7717.188618
72	low density	3	6	C	lead human	7468.43903834
73	low density	3	6	C	all humans	7320.33270501
74	low density	3	6	E	autonomous	3778.15672943
75	low density	3	6	E	lead human	3819.01422054
76	**low density**	**3**	**6**	**E**	**all humans**	**3713.05501956**
77	low density	3	14	C	autonomous	7647.19780808
78	low density	3	14	C	lead human	7810.24484538
79	low density	3	14	C	all humans	7563.53685178
80	low density	3	14	E	autonomous	3847.78172155
81	low density	3	14	E	lead human	3884.37928371
82	low density	3	14	E	all humans	3935.54238689
83	low density	3	27	C	autonomous	7922.41297321
84	low density	3	27	C	lead human	7693.36015407
85	low density	3	27	C	all humans	7542.50327065
86	low density	3	27	E	autonomous	3918.57750716
87	low density	3	27	E	lead human	3864.52662902
88	low density	3	27	E	all humans	3936.55588608

Table 4.1: DOE Variables for the cases in figure 4.1

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
5	low density	1	None	C	autonomous	7746.52657285
6	low density	1	None	C	all humans	7919.14164631
7	**low density**	**1**	**None**	**E**	**autonomous**	**4012.932751**
8	low density	1	None	E	all humans	4201.29768791

Table 4.2: DOE Variable for the cases in the figure 4.2

ertrain and driverless. The worst solution is the configuration number 6: single truck with Diesel powertrain and a driver. The latter configuration is the most common right now, so we can see that all the other solutions are better than the baseline scenario. The higher cost reduction, 47%, is achieved when we change powertrain from Diesel to electric.

4.1.2 Truck Platooning Scenarios

Platoon of 2 Trucks

The results of the simulations with low traffic density and 2 trucks platoon cases are shown in figure 4.3 with a bar chart. The DoE variables of all cases are listed in table 4.3.

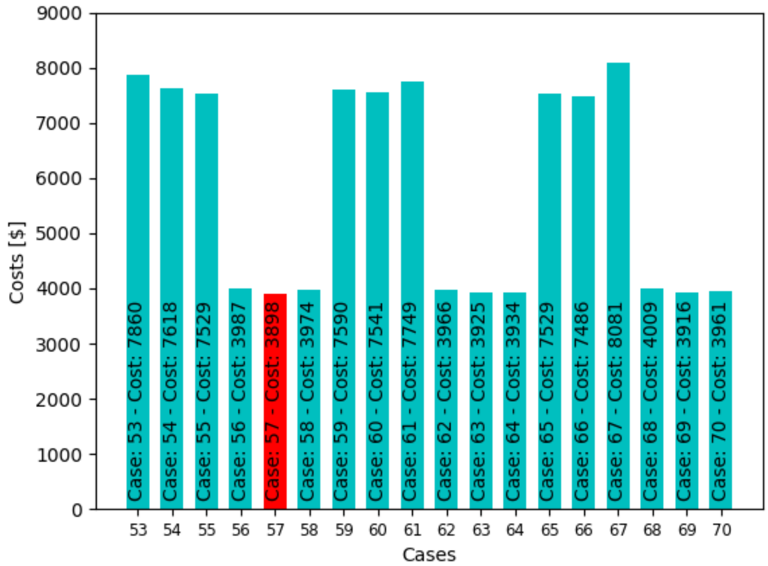


Figure 4.3: Costs of Low Density Cases for a 2 Trucks Platoon scenario

The configuration with the lowest cost is number 57: 2 truck platoon with a 6 meter distance, electric powertrain and the driver only in the leading truck of a platoon. The optimal solution involves a driver for each truck platoon; as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The percentage of cost reduction between the optimal case (number 57) and the baseline scenario (case 6) is around 51% ($= |7919 - 3898|/7919$).

We can notice that electric configuration are always better than the Diesel ones, and also the cost of electric configurations doesn't change too much over the distance (in this case max 2.8%) compared to the Diesel ones (max cost increment 7.3%).

Platoon of 3 Trucks

The results of the simulations with low traffic density and 3 trucks platoon cases are shown in figure 4.4 with a bar chart. The DoE variables of all cases are listed in table 4.4.

The configuration with the lowest cost is number 57: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each truck. The optimal solution involves a driver for each truck;

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
53	low density	2	6	C	autonomous	7860.711058
54	low density	2	6	C	lead human	7618.81305297
55	low density	2	6	C	all humans	7529.60215494
56	low density	2	6	E	autonomous	3987.54669628
57	**low density**	**2**	**6**	**E**	**lead human**	**3898.86362117**
58	low density	2	6	E	all humans	3974.74226226
59	low density	2	14	C	autonomous	7590.91485479
60	low density	2	14	C	lead human	7541.99095916
61	low density	2	14	C	all humans	7749.6411358
62	low density	2	14	E	autonomous	3966.2897303
63	low density	2	14	E	lead human	3925.76548553
64	low density	2	14	E	all humans	3934.19269309
65	low density	2	27	C	autonomous	7529.20588059
66	low density	2	27	C	lead human	7486.78777986
67	low density	2	27	C	all humans	8081.66737566
68	low density	2	27	E	autonomous	4009.74432967
69	low density	2	27	E	lead human	3916.01624847
70	low density	2	27	E	all humans	3961.35989152

Table 4.3: Doe Variables foer the cases in figure 4.3

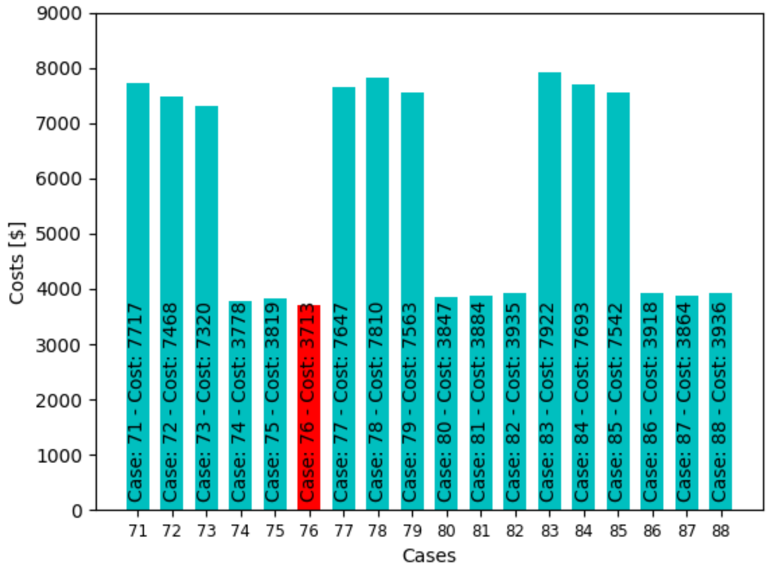


Figure 4.4: Costs of Low Density Cases for a 3 Trucks Platoon scenario

as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The percentage of cost reduction between the optimal case (number 57) and the baseline scenario (case 6) is around 53% ($= |7919 - 3713|/7919$).

Even in this group of cases the electric configuration are always better than the Diesel ones and the electric solutions are less variable over the distance.

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
71	low density	3	6	C	autonomous	7717.188618
72	low density	3	6	C	lead human	7468.43903834
73	low density	3	6	C	all humans	7320.33270501
74	low density	3	6	E	autonomous	3778.15672943
75	low density	3	6	E	lead human	3819.01422054
76	**low density**	**3**	**6**	**E**	**all humans**	**3713.05501956**
77	low density	3	14	C	autonomous	7647.19780808
78	low density	3	14	C	lead human	7810.24484538
79	low density	3	14	C	all humans	7563.53685178
80	low density	3	14	E	autonomous	3847.78172155
81	low density	3	14	E	lead human	3884.37928371
82	low density	3	14	E	all humans	3935.54238689
83	low density	3	27	C	autonomous	7922.41297321
84	low density	3	27	C	lead human	7693.36015407
85	low density	3	27	C	all humans	7542.50327065
86	low density	3	27	E	autonomous	3918.57750716
87	low density	3	27	E	lead human	3864.52662902
88	low density	3	27	E	all humans	3936.55588608

Table 4.4: Doe Variables of the cases in figure 4.4

4.1.3 Same Powertrain

Diesel Fuel Powertrain

The results of the simulations with low traffic density and Diesel powertrain cases are shown in figure 4.5 with a bar chart. The DoE variables of all cases are listed in table 4.5.

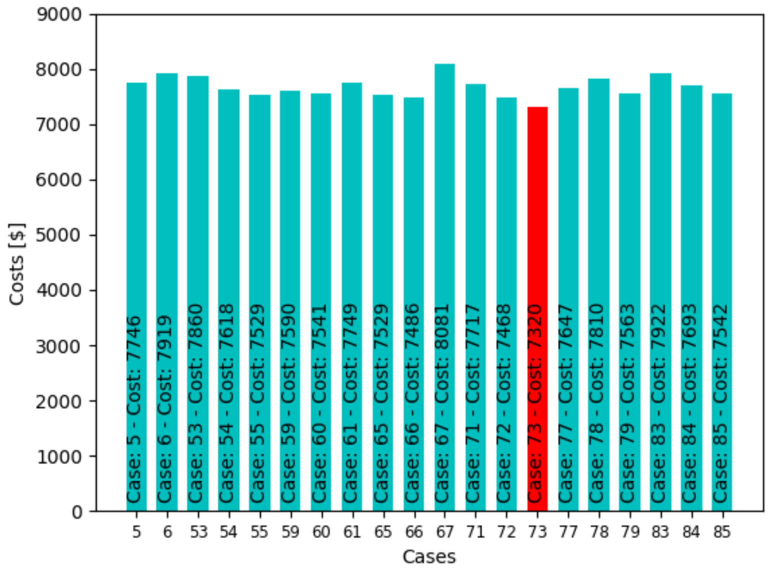


Figure 4.5: Costs of Low Density Cases where trucks use Diesel Engine

The configuration with the lowest cost is number 73: 3 truck platoon with a 6 meter distance, Diesel powertrain and a driver in each truck. The optimal solution involves a driver for each truck; as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The maximum saving is around 9.4% $(= (|8081 - 7320|)/8081)$ and it is between case 67 and case 73. Case 67 is the one with: with platoons of 2 trucks with a distance of 27 meter ,a Diesel powertrain and a driver for each trucks.

The cost saving between baseline scenario (case 6) and the best (case 73) is around 7.5% $(= (|7919 - 7320|)/7919)$.

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
5	low density	1	None	C	autonomous	7746.52657285
6	low density	1	None	C	all humans	7919.14164631
53	low density	2	6	C	autonomous	7860.711058
54	low density	2	6	C	lead human	7618.81305297
55	low density	2	6	C	all humans	7529.60215494
59	low density	2	14	C	autonomous	7590.91485479
60	low density	2	14	C	lead human	7541.99095916
61	low density	2	14	C	all humans	7749.6411358
65	low density	2	27	C	autonomous	7529.20588059
66	low density	2	27	C	lead human	7486.78777986
67	low density	2	27	C	all humans	8081.66737566
71	low density	3	6	C	autonomous	7717.188618
72	low density	3	6	C	lead human	7468.43903834
73	**low density**	**3**	**6**	**C**	**all humans**	**7320.33270501**
77	low density	3	14	C	autonomous	7647.19780808
78	low density	3	14	C	lead human	7810.24484538
79	low density	3	14	C	all humans	7563.53685178
83	low density	3	27	C	autonomous	7922.41297321
84	low density	3	27	C	lead human	7693.36015407
85	low density	3	27	C	all humans	7542.50327065

Table 4.5: Doe Variables of the cases in figure 4.5

Electric Powertrain

The results of the simulations with low traffic density and electric powertrain cases are shown in figure 4.6 with a bar chart. The DoE variables of all cases are listed in table 4.6.

The configuration with the lowest cost is number 76: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each truck. The optimal solution involves a driver for each truck; as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The maximum difference of 53% $(= (|7919 - 3713|)/7919)$ is between the cases 76 (the optimal one) and 6 (baseline, the worst one).

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
7	low density	1	None	E	autonomous	4012.932751
8	low density	1	None	E	all humans	4201.29768791
56	low density	2	6	E	autonomous	3987.54669628
57	low density	2	6	E	lead human	3898.86362117
58	low density	2	6	E	all humans	3974.74226226
62	low density	2	14	E	autonomous	3966.2897303
63	low density	2	14	E	lead human	3925.76548553
64	low density	2	14	E	all humans	3934.19269309
68	low density	2	27	E	autonomous	4009.74432967
69	low density	2	27	E	lead human	3916.01624847
70	low density	2	27	E	all humans	3961.35989152
74	low density	3	6	E	autonomous	3778.15672943
75	low density	3	6	E	lead human	3819.01422054
76	**low density**	**3**	**6**	**E**	**all humans**	**3713.05501956**
80	low density	3	14	E	autonomous	3847.78172155
81	low density	3	14	E	lead human	3884.37928371
82	low density	3	14	E	all humans	3935.54238689
86	low density	3	27	E	autonomous	3918.57750716
87	low density	3	27	E	lead human	3864.52662902
88	low density	3	27	E	all humans	3936.55588608

Table 4.6: Doe Variables of the cases in figure 4.6

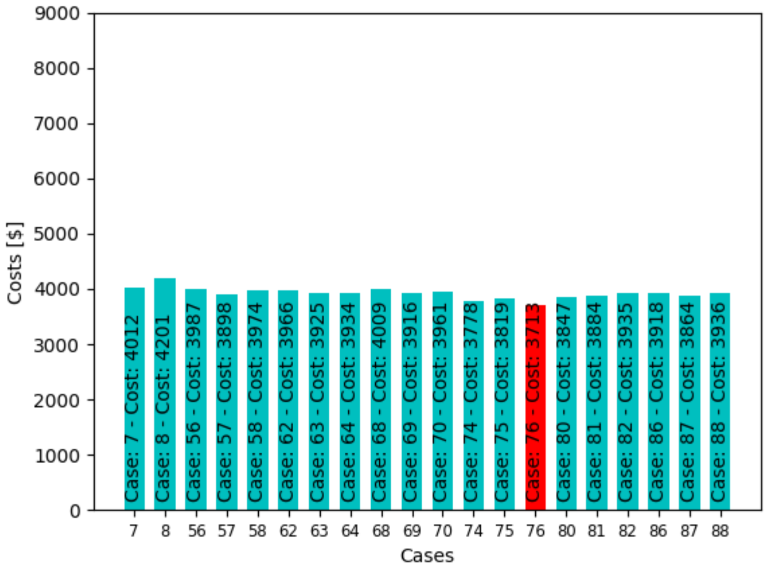


Figure 4.6: Costs of Low Density Cases where trucks use electric powertrain

4.1.4 Driver

All Trucks With a Driver

In figure 4.7 are presented, in a bar chart, the results of the simulations with low traffic density and a driver for each trucks are shown in figure 4.8 with a bar chart. The DoE variables of all cases are listed in table 4.7.

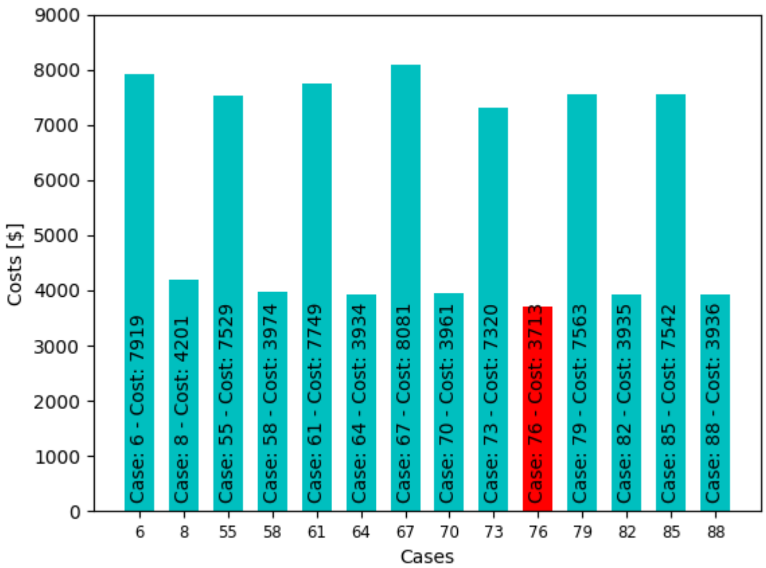


Figure 4.7: Costs of Low Density Cases where all trucks have a driver

The configuration with the lowest cost is number 76: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each truck. As we expect the optimum solution is the one with

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
6	low density	1	None	C	all humans	7919.14164631
8	low density	1	None	E	all humans	4201.29768791
55	low density	2	6	C	all humans	7529.60215494
58	low density	2	6	E	all humans	3974.74226226
61	low density	2	14	C	all humans	7749.6411358
64	low density	2	14	E	all humans	3934.19269309
67	low density	2	27	C	all humans	8081.66737566
70	low density	2	27	E	all humans	3961.35989152
73	low density	3	6	C	all humans	7320.33270501
76	**low density**	**3**	**6**	**E**	**all humans**	**3713.05501956**
79	low density	3	14	C	all humans	7563.53685178
82	low density	3	14	E	all humans	3935.54238689
85	low density	3	27	C	all humans	7542.50327065
88	low density	3	27	E	all humans	3936.55588608

Table 4.7: Doe Variables of the cases in figure 4.7

shortest distance, the highest number of trucks and electric powertrain.

The percentage of cost reduction between the optimal solution (case 76) and the worst (the baseline, case 6) is around 53% $((|7919 - 3713|)/7919)$.

Driver Only in the Leading Truck

The results of the simulations with low traffic density and a driver only or the leading truck of a platoon are shown in figure 4.8 with a bar chart. The DoE variables of all cases are listed in table 4.8.

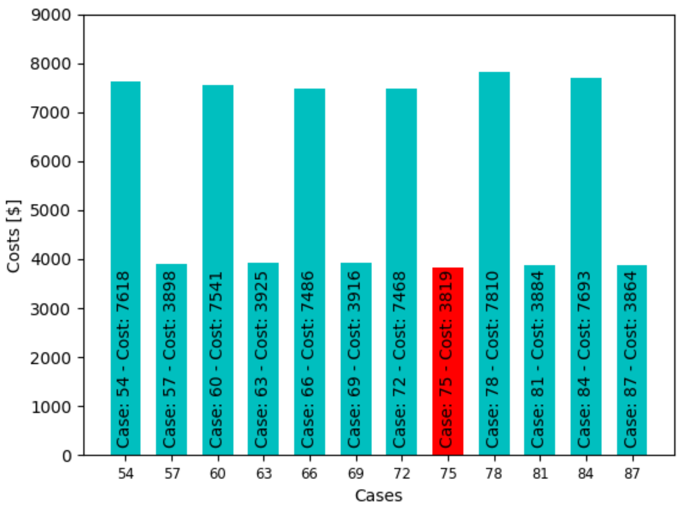


Figure 4.8: Costs of Low Density Cases where only the leading truck of a platoon has a driver

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
54	low density	2	6	C	lead human	7618.81305297
57	low density	2	6	E	lead human	3898.86362117
60	low density	2	14	C	lead human	7541.99095916
63	low density	2	14	E	lead human	3925.76548553
66	low density	2	27	C	lead human	7486.78777986
69	low density	2	27	E	lead human	3916.01624847
72	low density	3	6	C	lead human	7468.43903834
75	**low density**	**3**	**6**	**E**	**lead human**	**3819.01422054**
78	low density	3	14	C	lead human	7810.24484538
81	low density	3	14	E	lead human	3884.37928371
84	low density	3	27	C	lead human	7693.36015407
87	low density	3	27	E	lead human	3864.52662902

Table 4.8: Doe Variables of the cases in figure 4.8

In figure 4.8 we can see the highlighted optimal configuration(case 75): 3 truck platoon with a 6 meter distance, electric powertrain and a driver for each leader truck in a platoon. As we expected the optimal solution is the one with the shortest distance, highest number of trucks and electric powertrain.

The percentage of cost reduction between the optimal solution (case 75) and the worst (the baseline, case 6) is around 52% $(= (|7919 - 3819|)/7919)$.

The worst result is scored by the configuration in case number 78: 3 truck platoon with 14 meter distance, Diesel powertrain and a driver for each leading truck in a platoon.

The percentage of cost reduction between the optimal solution (case 75) and the worst (case 78) is around 51% $(= (|7810 - 3819|)/7810)$.

Driverless - Autonomous Trucks

The results of the simulations with low traffic density and autonomous truck are shown in figure 4.9 with a bar chart. The DoE variables of all cases are listed in table 4.9.

The configuration with the lowest cost is number 74: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each truck.

The percentage of cost reduction between the optimal solution (case 74) and the worst (the baseline, case 6) is around 52% $(= (|7919 - 3778|)/7919)$.

The worst case is number 83 with the configuration of 3 truck platoon at a distance of 27 meter, Diesel powertrain and autonomous trucks.

The percentage of cost reduction between the optimal solution (case 74) and the worst (case 83) is around 51% $((|7922 - 3778|)/7922)$.

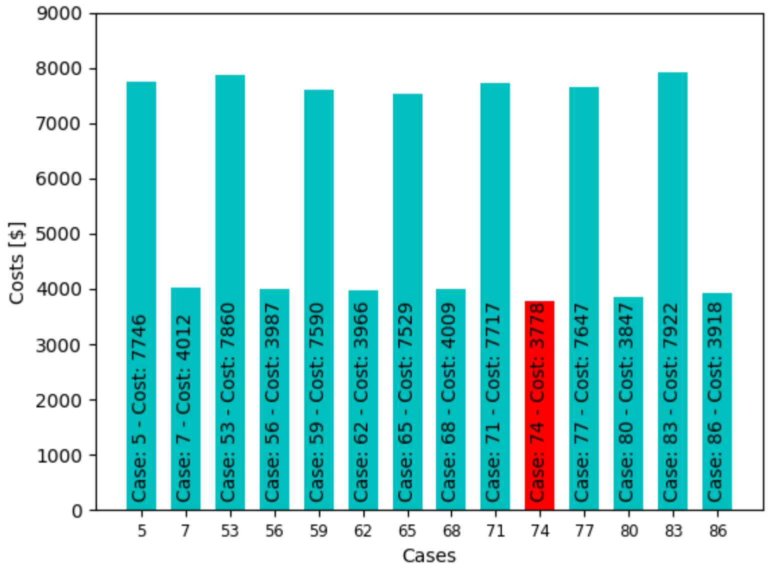


Figure 4.9: Costs of Low Density Cases where all the trucks are autonomous (No Driver)

4.2 Medium Traffic Density Results

The results of the simulations with medium traffic density are shown in figure 4.10 with a bar chart. We showed the results of the optimal solution found for each case. The DoE variables of all cases are listed in table 4.10.

The baseline scenario for medium density traffic is the case number 10: it represents the most common solution used by the ground shipping industry: single trucks with Diesel powertrain, a driver for each truck.

The configuration with the lowest cost is number 111: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each leading truck in a platoon. The optimal solution involves a driver for each truck platoon; as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The worst case is number 96 with the higher cost. The configuration of this case is: 2 truck platoon at a distance of 14 meter with Diesel powertrain and a driver for each truck platoon. We expected that the worst situation should be the baseline scenario, because it doesn't benefit of the drag reduction, electric powertrain and autonomous guidance. This different outcome is due to the interaction of the traffic with the truck platoons, as we said before, but also it could be the different configuration of the platoon that could affect the car traffic (for example different value of road usage; see table 3.5)

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
5	low density	1	None	C	autonomous	7746.52657285
7	low density	1	None	E	autonomous	4012.932751
53	low density	2	6	C	autonomous	7860.711058
56	low density	2	6	E	autonomous	3987.54669628
59	low density	2	14	C	autonomous	7590.91485479
62	low density	2	14	E	autonomous	3966.2897303
65	low density	2	27	C	autonomous	7529.20588059
68	low density	2	27	E	autonomous	4009.74432967
71	low density	3	6	C	autonomous	7717.188618
74	**low density**	**3**	**6**	**E**	**autonomous**	**3778.15672943**
77	low density	3	14	C	autonomous	7647.19780808
80	low density	3	14	E	autonomous	3847.78172155
83	low density	3	27	C	autonomous	7922.41297321
86	low density	3	27	E	autonomous	3918.57750716

Table 4.9: Doe Variables of the cases in figure 4.9

4.2.1 No Truck Platooning Scenarios

The results of the simulations with medium traffic density and no platooning cases are shown in figure 4.11 with a bar chart. We showed the results of the optimal solution found for each case. The DoE variables of all cases are listed in table 4.11.

We can see in figure 4.2 that the best configuration is number 11: single truck with electric powertrain and driverless. The worst solution is the configuration number 10: single truck with Diesel powertrain and a driver. The latter configuration is the most common right now, so we can see that all the other solutions are better than the baseline scenario. The higher cost reduction, 45%, is achieved when we change powertrain from Diesel to electric.

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
9	medium density	1	None	C	autonomous	7466.51019803
10	medium density	1	None	C	all humans	7499.48486323
11	medium density	1	None	E	autonomous	3891.85530467
12	medium density	1	None	E	all humans	4091.93679818
89	medium density	2	6	C	autonomous	7397.52697126
90	medium density	2	6	C	lead human	7611.42943376
91	medium density	2	6	C	all humans	7605.35773713
92	medium density	2	6	E	autonomous	3914.56577132
93	medium density	2	6	E	lead human	3896.81372935
94	medium density	2	6	E	all humans	3835.38730921
95	medium density	2	14	C	autonomous	7388.54835207
96	medium density	2	14	C	lead human	7778.61489765
97	medium density	2	14	C	all humans	7352.19197174
98	medium density	2	14	E	autonomous	3908.8793718
99	medium density	2	14	E	lead human	3875.13769135
100	medium density	2	14	E	all humans	3878.61605228
101	medium density	2	27	C	autonomous	7604.98106839
102	medium density	2	27	C	lead human	7448.14205848
103	medium density	2	27	C	all humans	7519.68220594
104	medium density	2	27	E	autonomous	3998.17427851
105	medium density	2	27	E	lead human	3911.32452858
106	medium density	2	27	E	all humans	3935.02439945
107	medium density	3	6	C	autonomous	7503.69662159
108	medium density	3	6	C	lead human	7630.83526716
109	medium density	3	6	C	all humans	6991.88219957
110	medium density	3	6	E	autonomous	3749.88938101
111	**medium density**	**3**	**6**	**E**	**lead human**	**3659.77799466**
112	medium density	3	6	E	all humans	3884.06312375
113	medium density	3	14	C	autonomous	7237.40138475
114	medium density	3	14	C	lead human	7579.39539807
115	medium density	3	14	C	all humans	7458.241382
116	medium density	3	14	E	autonomous	3813.37983774
117	medium density	3	14	E	lead human	3729.33682158
118	medium density	3	14	E	all humans	3932.70572766
119	medium density	3	27	C	autonomous	7660.12636787
120	medium density	3	27	C	lead human	7360.4531699
121	medium density	3	27	C	all humans	7281.90098359
122	medium density	3	27	E	autonomous	3837.61509137
123	medium density	3	27	E	lead human	3901.97945436
124	medium density	3	27	E	all humans	3900.9298646

Table 4.10: Doe Variables of the cases in figure 4.10

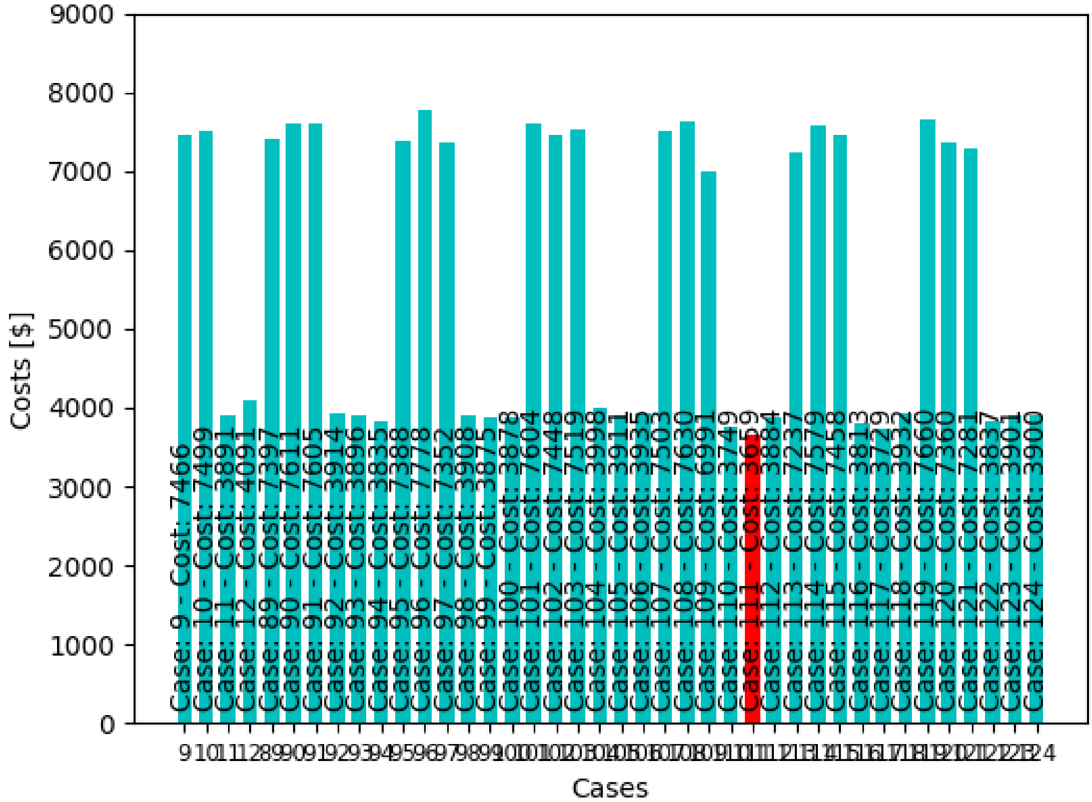


Figure 4.10: Costs of Medium Density Cases Graph

4.2.2 Truck Platooning Scenarios

Platoon of 2 Trucks

The results of the simulations with medium traffic density and 2 trucks platoon cases are shown in figure 4.12 with a bar chart. The DoE variables of all cases are listed in table 4.12.

The configuration with the lowest cost is number 94: 2 truck platoon with a 6 meter distance, electric powertrain and a driver for each truck. The optimal solution involves a driver for each truck; as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
9	medium density	1	None	C	autonomous	7466.51019803
10	medium density	1	None	C	all humans	7499.48486323
11	**medium density**	**1**	**None**	**E**	**autonomous**	**3891.85530467**
12	medium density	1	None	E	all humans	4091.93679818

Table 4.11: Doe Variables of the cases in figure 4.11

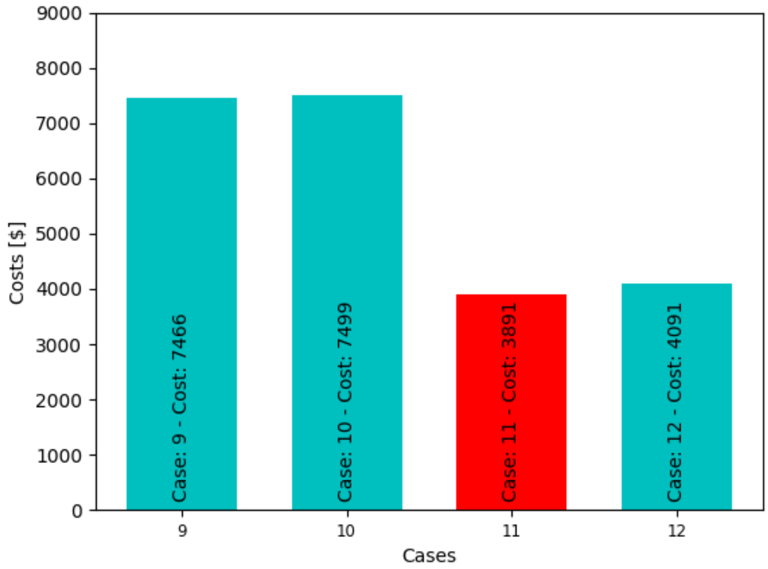


Figure 4.11: Costs of Medium Density Cases for a NO Truck Platooning scenario

an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The percentage of cost reduction between the optimal solution (case 94) and the baseline scenario (case 10) is around 49% (= $(|7499 - 3835|)/7499$).

The worst case is number 96 with the configuration of 2 truck platoon at a distance of 14 meter, Diesel powertrain and a driver for each leading truck in a platoon.

The percentage of cost reduction between optimal solution (case 94) and the worst (case 96) is around 51% ($((|7778 - 3835|)/7778$).

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
89	medium density	2	6	C	autonomous	7397.52697126
90	medium density	2	6	C	lead human	7611.42943376
91	medium density	2	6	C	all humans	7605.35773713
92	medium density	2	6	E	autonomous	3914.56577132
93	medium density	2	6	E	lead human	3896.81372935
94	**medium density**	**2**	**6**	**E**	**all humans**	**3835.38730921**
95	medium density	2	14	C	autonomous	7388.54835207
96	medium density	2	14	C	lead human	7778.61489765
97	medium density	2	14	C	all humans	7352.19197174
98	medium density	2	14	E	autonomous	3908.8793718
99	medium density	2	14	E	lead human	3875.13769135
100	medium density	2	14	E	all humans	3878.61605228
101	medium density	2	27	C	autonomous	7604.98106839
102	medium density	2	27	C	lead human	7448.14205848
103	medium density	2	27	C	all humans	7519.68220594
104	medium density	2	27	E	autonomous	3998.17427851
105	medium density	2	27	E	lead human	3911.32452858
106	medium density	2	27	E	all humans	3935.02439945

Table 4.12: Doe Variables of the cases in figure 4.12

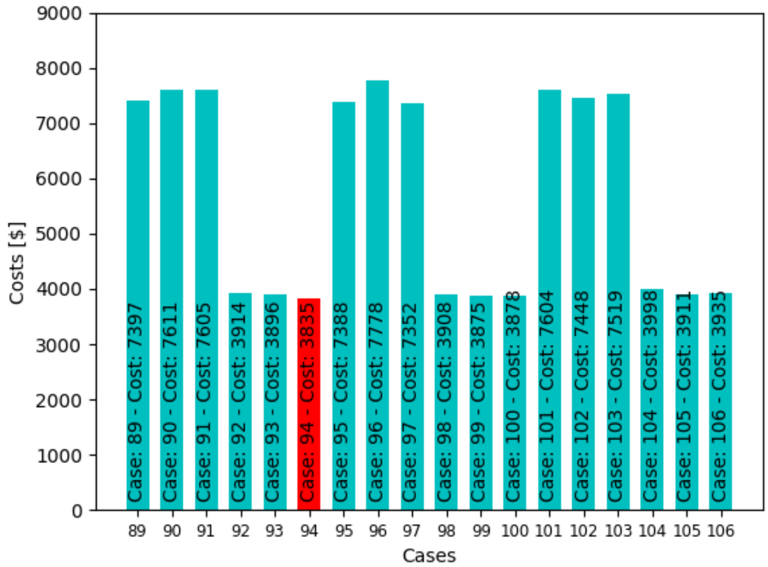


Figure 4.12: Costs of Medium Density Cases for a 2 Trucks Platoon scenario

Platoon of 3 Trucks

The results of the simulations with medium traffic density and 3 trucks platoon cases are shown in figure 4.13 with a bar chart. The DoE variables of all cases are listed in table 4.13.

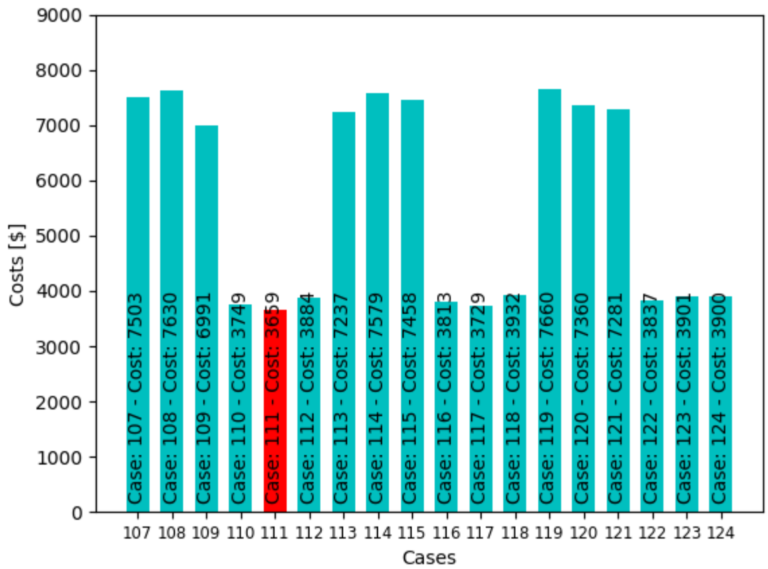


Figure 4.13: Costs of Medium Density Cases for a 3 Trucks Platoon scenario

The configuration with the lowest cost is the number 111: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each leading truck in a platoon. It's the same case treated in section 4.2.

The percentage of cost reduction between the optimal solution (case 111) and the worst (case 10)

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
107	medium density	3	6	C	autonomous	7503.69662159
108	medium density	3	6	C	lead human	7630.83526716
109	medium density	3	6	C	all humans	6991.88219957
110	medium density	3	6	E	autonomous	3749.88938101
111	**medium density**	**3**	**6**	**E**	**lead human**	**3659.77799466**
112	medium density	3	6	E	all humans	3884.06312375
113	medium density	3	14	C	autonomous	7237.40138475
114	medium density	3	14	C	lead human	7579.39539807
115	medium density	3	14	C	all humans	7458.241382
116	medium density	3	14	E	autonomous	3813.37983774
117	medium density	3	14	E	lead human	3729.33682158
118	medium density	3	14	E	all humans	3932.70572766
119	medium density	3	27	C	autonomous	7660.12636787
120	medium density	3	27	C	lead human	7360.4531699
121	medium density	3	27	C	all humans	7281.90098359
122	medium density	3	27	E	autonomous	3837.61509137
123	medium density	3	27	E	lead human	3901.97945436
124	medium density	3	27	E	all humans	3900.9298646

Table 4.13: Doe Variables of the cases in figure 4.13

is around 51% ($= (|7499 - 3659|)/7499$).

The worst case is number 119, with the higher cost; the case configuration is: 3 truck platoon at a distance of 27 meter with Diesel powertrain and autonomous trucks.

The maximum difference between cases 111 (optimal one) and 119 (the worst) is around 52%($= (|7660 - 3659|)/7660$).

4.2.3 Same Powertrain

Diesel Fuel Powertrain

The results of the simulations with medium traffic density and Diesel powertrain cases are shown in figure 4.14 with a bar chart. The DoE variables of all cases are listed in table 4.14

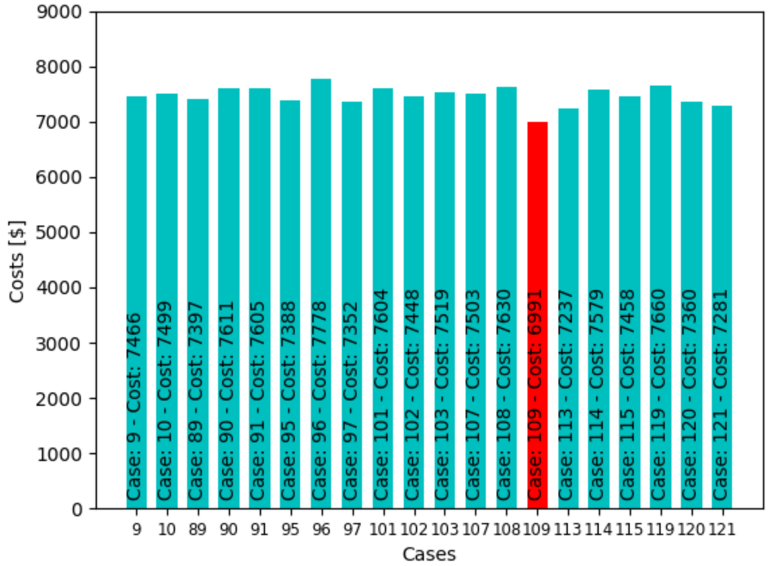


Figure 4.14: Costs of Medium Density Cases when trucks use Diesel Engine

We can see in figure 4.14 that the best configuration is the number 109: 3 trucks in a platoon at the distance of 6 meters with Diesel powertrain and a driver in each truck The optimal solution involves a driver for each truck; as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The percentage of cost reduction between the optimal solution (case 109) and the worst (case 10) is around 7% $(= (|7499 - 6991|)/7499)$.

In this sample the worst case is number 96, with the higher cost: the configuration of this case is: 2 truck platoon at a distance of 14 meters with Diesel powertrain and a driver for each leading track in a platoon.

The percentage of cost reduction between the optimum solution (case 109) and the worst case (case 96) is around 10% $((|7778 - 6991|)/7778)$.

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
9	medium density	1	None	C	autonomous	7466.51019803
10	medium density	1	None	C	all humans	7499.48486323
89	medium density	2	6	C	autonomous	7397.52697126
90	medium density	2	6	C	lead human	7611.42943376
91	medium density	2	6	C	all humans	7605.35773713
95	medium density	2	14	C	autonomous	7388.54835207
96	medium density	2	14	C	lead human	7778.61489765
97	medium density	2	14	C	all humans	7352.19197174
101	medium density	2	27	C	autonomous	7604.98106839
102	medium density	2	27	C	lead human	7448.14205848
103	medium density	2	27	C	all humans	7519.68220594
107	medium density	3	6	C	autonomous	7503.69662159
108	medium density	3	6	C	lead human	7630.83526716
109	**medium density**	**3**	**6**	**C**	**all humans**	**6991.88219957**
113	medium density	3	14	C	autonomous	7237.40138475
114	medium density	3	14	C	lead human	7579.39539807
115	medium density	3	14	C	all humans	7458.241382
119	medium density	3	27	C	autonomous	7660.12636787
120	medium density	3	27	C	lead human	7360.4531699
121	medium density	3	27	C	all humans	7281.90098359

Table 4.14: Doe Variables of the cases in figure 4.13

Electric Powertrain

The results of the simulations with medium traffic density and electric powertrain cases are shown in figure 4.15 with a bar chart. The DoE variables of all cases are listed in table 4.15.

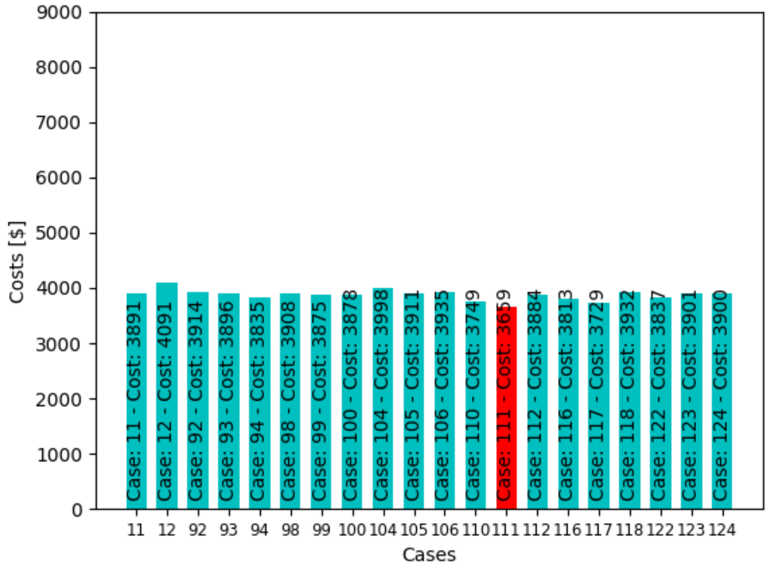


Figure 4.15: Costs of Medium Density Cases when trucks use Electric Engine

The configuration with the lowest cost is number 111: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each leading truck in a platoon. As we said in section 4.2 this configuration is the best of all the medium density traffic simulation cases.

The percentage of cost reduction between the optimal solution (case 111) and the worst (case 10) is around 51% (= (|7499 − 3659|)/7499).

In this sample the worst case is number 12, with the higher cost. The configuration of this case is: single truck with electric powertrain and a driver for each truck.

The percentage of cost reduction between the optimal solution (case 109) and the worst (case 96) is around 10% ((|4091 − 3659|)/4091).

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
11	medium density	1	None	E	autonomous	3891.85530467
12	medium density	1	None	E	all humans	4091.93679818
92	medium density	2	6	E	autonomous	3914.56577132
93	medium density	2	6	E	lead human	3896.81372935
94	medium density	2	6	E	all humans	3835.38730921
98	medium density	2	14	E	autonomous	3908.8793718
99	medium density	2	14	E	lead human	3875.13769135
100	medium density	2	14	E	all humans	3878.61605228
104	medium density	2	27	E	autonomous	3998.17427851
105	medium density	2	27	E	lead human	3911.32452858
106	medium density	2	27	E	all humans	3935.02439945
110	medium density	3	6	E	autonomous	3749.88938101
111	**medium density**	**3**	**6**	**E**	**lead human**	**3659.77799466**
112	medium density	3	6	E	all humans	3884.06312375
116	medium density	3	14	E	autonomous	3813.37983774
117	medium density	3	14	E	lead human	3729.33682158
118	medium density	3	14	E	all humans	3932.70572766
122	medium density	3	27	E	autonomous	3837.61509137
123	medium density	3	27	E	lead human	3901.97945436
124	medium density	3	27	E	all humans	3900.9298646

Table 4.15: Doe Variables of the cases in figure 4.15

4.2.4 Driver

All Trucks With a Driver

The results of the simulations with low traffic density and a driver for each trucks are shown in figure 4.16 with a bar chart. The DoE variables of all cases are listed in table 4.16

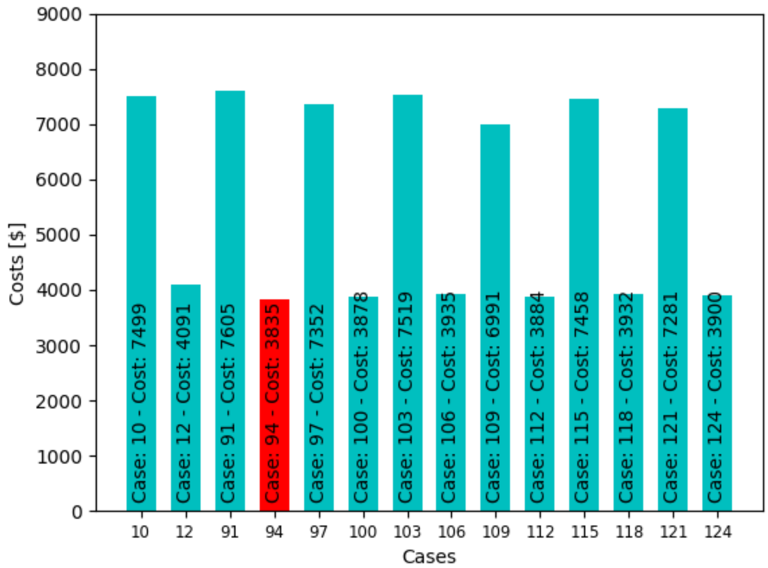


Figure 4.16: Costs of Medium Density Cases when all trucks have a driver

The configuration with the lowest cost is number 94: 2 trucks in a platoon with a 6 meter distance, electric powertrain and a driver in each truck. The optimal solution involves a driver for each truck platoon; as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The percentage of cost reduction between the optimum solution (case 94) and the worst case (case 10) is around 49% $(= (|7499 - 3835|)/7499)$.

The worst case is number 91, with the highest cost; the configuration of this case is: 2 truck platoons at a distance of 6 meters with Diesel powertrain and a driver for each truck.

The maximum difference between cases 94 (optimal one) and 91 (the worst) is around 50% $(= (|7605 - 3835|)/7605)$.

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
10	medium density	1	None	C	all humans	7499.48486323
12	medium density	1	None	E	all humans	4091.93679818
91	medium density	2	6	C	all humans	7605.35773713
94	**medium density**	**2**	**6**	**E**	**all humans**	**3835.38730921**
97	medium density	2	14	C	all humans	7352.19197174
100	medium density	2	14	E	all humans	3878.61605228
103	medium density	2	27	C	all humans	7519.68220594
106	medium density	2	27	E	all humans	3935.02439945
109	medium density	3	6	C	all humans	6991.88219957
112	medium density	3	6	E	all humans	3884.06312375
115	medium density	3	14	C	all humans	7458.241382
118	medium density	3	14	E	all humans	3932.70572766
121	medium density	3	27	C	all humans	7281.90098359
124	medium density	3	27	E	all humans	3900.9298646

Table 4.16: Doe Variables of the cases in figure 4.16

Driver Only in the Lead Truck

the results of the simulations with low traffic density and a driver only in the leading truck of a platoon are shown in figure 4.17 with in a bar chart. The DoE variables of all cases are listed In table 4.17.

The configuration with the lowest cost is the number 111: 3 trucks in a platoon with a 6 meter distance, electric powertrain and a driver in the leading truck of a platoon. The optimal solution involves a driver for each truck platoon; as we said in section 4.1 a configuration without drivers should lead to better results. The relative small number of iterations could be the reason why the algorithm didn't catch this solution in the more promising configuration. Also, the stochastic component of the simulation system could be an important factor, because the routes of all the cars are the same but small events could change the position and velocity of them, and the chain effect could have brought the system to a different configuration.

The percentage of cost reduction between the optimal solution (case 111) and the worst (case 10) is around 51% ($= (|7499 - 3659|)/7499$).

In this sample the worst case is number 96 with the higher cost. The configuration of this case is: 2 truck platoon at a distance of 14 meters with Diesel powertrain and a driver for each leading truck in a platoon.

The percentage of cost reduction between the optimal solution (case 111) and the worst (case 96) is around 53% ($(|7778 - 3659|)/7778$).

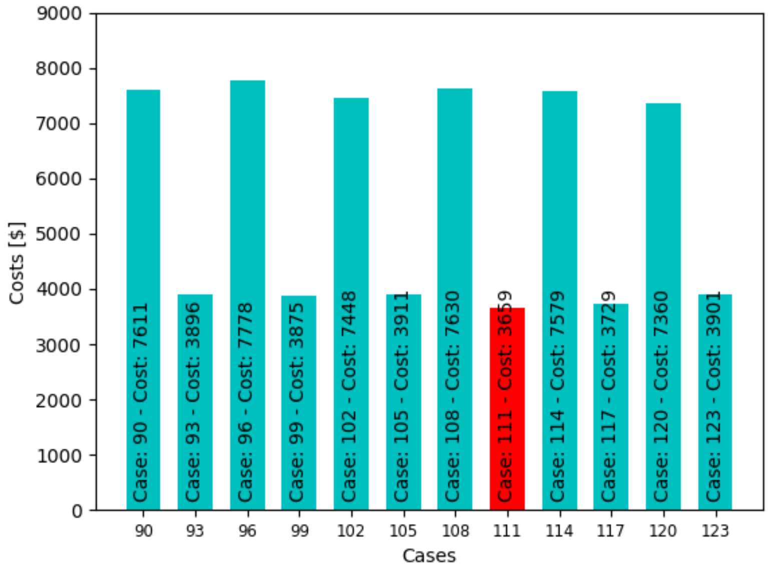


Figure 4.17: Costs of Medium Density Cases when only the leader truck has a driver

Driverless - Autonomous Trucks

The results of the simulations with low traffic density and autonomous trucks are shown in figure 4.18 with a bar chart The DoE variables of all considered cases are listed in table 4.18

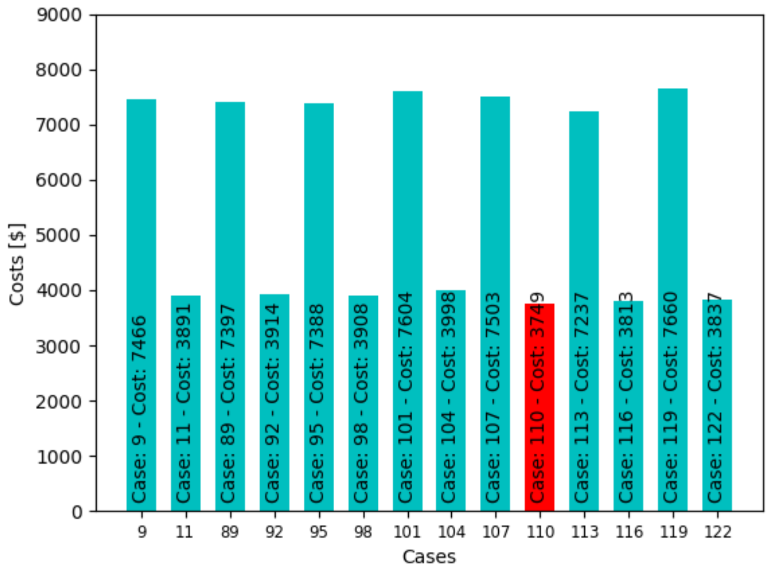


Figure 4.18: Costs of Medium Density Cases where all the trucks are autonomous (No Drivers)

The configuration with lowest cost is number 110: 3 trucks in a platoon with a 6 meter distance, electric powertrain and autonomous trucks.

The percentage of cost reduction between the optimum solution (case 110) and the worst case (case 10) is around 50% (= $(|7499 - 3749|)/7499$).

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
90	medium density	2	6	C	lead human	7611.42943376
93	medium density	2	6	E	lead human	3896.81372935
96	medium density	2	14	C	lead human	7778.61489765
99	medium density	2	14	E	lead human	3875.13769135
102	medium density	2	27	C	lead human	7448.14205848
105	medium density	2	27	E	lead human	3911.32452858
108	medium density	3	6	C	lead human	7630.83526716
111	**medium density**	**3**	**6**	**E**	**lead human**	**3659.77799466**
114	medium density	3	14	C	lead human	7579.39539807
117	medium density	3	14	E	lead human	3729.33682158
120	medium density	3	27	C	lead human	7360.4531699
123	medium density	3	27	E	lead human	3901.97945436

Table 4.17: Doe Variables of the cases in figure 4.17

In this sample the worst case is the number 119 with the higher cost. The configuration of this case is: 3 truck platoon at a distance of 27 meters with Diesel powertrain and autonomous truck.

The maximum percentage of cost reduction between the optimum solution (case 110) and the worst case (case 119) is around 51% $((|7660 - 3749|)/7660)$.

Case ID	Traffic Density	N°_{trucks}	Distance [m]	Powertrain	Driver	Cost [$]
9	medium density	1	None	C	autonomous	7466.51019803
11	medium density	1	None	E	autonomous	3891.85530467
89	medium density	2	6	C	autonomous	7397.52697126
92	medium density	2	6	E	autonomous	3914.56577132
95	medium density	2	14	C	autonomous	7388.54835207
98	medium density	2	14	E	autonomous	3908.8793718
101	medium density	2	27	C	autonomous	7604.98106839
104	medium density	2	27	E	autonomous	3998.17427851
107	medium density	3	6	C	autonomous	7503.69662159
110	**medium density**	**3**	**6**	**E**	**autonomous**	**3749.88938101**
113	medium density	3	14	C	autonomous	7237.40138475
116	medium density	3	14	E	autonomous	3813.37983774
119	medium density	3	27	C	autonomous	7660.12636787
122	medium density	3	27	E	autonomous	3837.61509137

Table 4.18: Doe Variables of the cases in figure 4.18

Chapter 5

Conclusions

In this work was presented a method to find the optimum routes for a fleet of trucks moving in a simulated traffic environment, also a design of experiment was done to evaluate the effects of an emerging technology (truck platooning, see section 3.1.2) on main decision variable for a truck fleet owner: *cost*

The method uses the open source Simulation of Urban MObility (SUMO) package (see section 3.1.1), a customized routing algorithm (based on DUA-Gawron algorithm, see section 3.1.6) with inputs: a road map (see section 3.1.3), and a demand chart (see section 3.1.5).

After all the simulations were done ,the data were divided and analyzed in different condition; the main division were done among car traffic density (see chapter 4). The other design of experiment variables were: density of the car traffic, number of trucks in a platoon, distance between trucks, powertrain, and truck drivers.

In each of the main groups of simulations higher cost reductions, around 50%, were always reached with platoon configurations of 3 trucks at a 6 meter distance with an electric powertrain. A few more words should be spent for the driver variable: the highest cost reduction is reached in configurations with a driver for each lead truck in a platoon (called *lead driver* configuration). During the simulations the driver variable has been accounted only as a cost, therefore we could say that the solution found for a *lead driver* simulation should score an even better cost with a configuration that uses autonomous trucks. Unfortunately, for time constraints, and simulations time needed, it wasn't possible to investigate this problem.

In the low density group of cases we looked into different subsets (for example: subset low density and Diesel powertrain). These subsets and optimum solutions were:

- No truck platooning: single truck with electric powertrain and driverless; with a 47% cost reduction compared to the baseline scenario
- Platoon of 2 trucks: 2 truck platoon with a 6 meter distance, electric powertrain and a driver only in the leader truck; with a cost reduction compared to the

baseline scenario is around 51%

- Platoon of 3 trucks: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each truck; with a cost reduction compared to the baseline scenario is around 53%
- Diesel powertrain: 3 truck platoon with a 6 meter distance, Diesel powertrain and a driver in each truck; the cost reduction achieved between the latter case and the baseline scenario is around 7.5%
- Electric powertrain: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each truck; the cost reduction compared to the baseline scenario is around 53%.

In the medium density group of cases we looked into different subsets (for example: subset medium density and electric powertrain). These subsets and optimum solutions were:

- No truck platooning: single truck with electric powertrain and driverless; gives a 45% cost reduction compared to the baseline scenario
- Platoon of 2 trucks: 2 truck platoon with a 6 meter distance, electric powertrain and a driver only in the leader truck; where a cost reduction compared to the baseline scenario is around 49%
- Platoon of 3 trucks: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each truck; where a cost reduction compare to the baseline scenario is around 51%
- Diesel powertrain: 3 truck platoon with a 6 meter distance, Diesel powertrain and a driver in each truck; the cost reduction achieved between the latter case and the baseline scenario is around 7%
- Electric powertrain: 3 truck platoon with a 6 meter distance, electric powertrain and a driver in each truck; the cost reduction compared to the baseline scenario is around 51%

In conclusion, we can say that in all traffic conditions truck platooning technology gives some benefits in decreasing cost at least by a percentage of 7%. The main cost reduction is achieved by switching from Diesel powertrain to electric: we prove that the cost reduction is around 50%

This work is only the beginning, there are a lot of possibilities for future work like: looking into the driver problem simulations; to investigate higher level of density traffic; to enhance the drag coefficient model with a specific one for the type of truck; implementing a truck platooning formation algorithm; to investigate a wider number of cases (more than 3 trucks in a platoon) testing the method with a real case scenario;

Bibliography

[1] American Trucking Associations. Reports, trend and statistics. Accessed: June 02, 2017. URL: http://www.trucking.org/News_and_Information_Reports.aspx.

[2] Truckers Report. The real cost of trucking - per mile operating cost of a commercial truck. Accessed: June 02, 2017. URL: https://www.thetruckersreport.com/infographics/cost-of-trucking/.

[3] GasBuddy. 18 month average retail price chart. Accessed: May 16, 2017. URL: https://www.gasbuddy.com/Charts.

[4] Federal Highway Administration U.S. Department of Transportation. Facts and statistics - work zone mobility. Accessed: June 04, 2017. URL: https://ops.fhwa.dot.gov/wz/resources/facts_stats/mobility.htm.

[5] Amanda Jackson Chris Boyette Dave Alsup Martin Savidge and Jamiel Lynch. I-85 fire: Section of atlanta highway collapses. Accessed: June 04, 2017. URL: http://www.cnn.com/2017/03/30/us/atlanta-i-85-fire/index.html.

[6] Federal Motor Carrier Safety Administration. Summary of hours of service regulations. Accessed: June 04, 2017. URL: https://www.fmcsa.dot.gov/regulations/hours-service/summary-hours-service-regulations.

[7] TruckInfo.net. Trucking statistics. Accessed: June 04, 2017. URL: https://www.truckinfo.net/trucking/stats.htm.

[8] Transport and Environment. Trucks and co2. Accessed: June 04, 2017. URL: https://www.transportenvironment.org/what-we-do/smarter-lorries/lorries-co2.

[9] Union of Concerned Scientists science for healthy planet and safer world. Cars, trucks, and air pollution. Accessed: June 04, 2017. URL: http://www.ucsusa.org/clean-vehicles/vehicles-air-pollution-and-human-health/cars-trucks-air-pollution.

[10] HEALTHINFOGRAPHICS. Truck accidents. Accessed: June 04, 2017. URL: `https://healthinfographics.wordpress.com/2012/12/24/truck-accidents/`.

[11] Henk Kaarle Versteeg and Weeratunge Malalasekera. *An introduction to computational fluid dynamics: the finite volume method.* Pearson Education, 2007.

[12] Wikipedia. Wikipedia. Accessed: November 29, 2017. URL: `https://en.wikipedia.org/wiki/Main_Page`.

[13] Carl Bergenhem, Steven Shladover, Erik Coelingh, Christoffer Englund, and Sadayuki Tsugawa. Overview of platooning systems. In *Proceedings of the 19th ITS World Congress, Oct 22-26, Vienna, Austria (2012)*, 2012.

[14] Arturo Davila, Eduardo del Pozo, Enric Aramburu, and Alex Freixas. Environmental benefits of vehicle platooning. Technical report, SAE Technical Paper, 2013.

[15] Michael Zabat, Nick Stabile, Stefano Farascaroli, and Frederick Browand. The aerodynamic performance of platoons: A final report. *California Partners for Advanced Transit and Highways (PATH)*, 1995.

[16] Fred Browand. Reducing aerodynamic drag and fuel consumption. In *Advanced Transportation Workshop, October*, pages 10–11, 2005.

[17] Prasad Vegendla, Tanju Sofu, Rohit Saha, Mahesh Madurai Kumar, and Long-Kung Hwang. Investigation of aerodynamic influence on truck platooning. Technical report, SAE Technical Paper, 2015.

[18] BW Smith. Summary of levels of driving automation for on-road vehicles. *Center for Internet and Society, Stanford Law School*, 2013.

[19] Michael Behrisch, Laura Bieker, Jakob Erdmann, and Daniel Krajzewicz. Sumo–simulation of urban mobility: an overview. In *Proceedings of SIMUL 2011, The Third International Conference on Advances in System Simulation.* ThinkMind, 2011.

[20] David Pointer. Evaluation of commercial cfd code capabilities for prediction of heavy vehicle drag coefficients. *AIAA Paper*, 2254:2004, 2004.

[21] Dale Satran. An experimental study of the generic conventional model (gcm) in the nasa ames 7-by-10-foot wind tunnel. In *The Aerodynamics of Heavy Vehicles: Trucks, Buses, and Trains*, pages 171–171. Springer, 2004.

[22] Behrisch. Netgenerate. Accessed: November 29, 2017. URL: `http://sumo.dlr.de/w/index.php?title=NETGENERATE&oldid=10045`.

[23] Robbert Janssen, Han Zwijnenberg, Iris Blankers, and Janiek de Kruijff. Truck platooning: Driving the future of transportation. 2015.

[24] George Bucsan, Alex Goupilleau, Pierre Frene, Manish Pokhrel, Michael Balchanos, Dimitri Mavris, Masanori Ishigaki, Atsushi Iwai, and Jae Seung Lee. Mobility analysis of electric autonomous vehicle networks driven by energy-efficient rerouting, 06 2017.

[25] John Robinson, Michael Balchanos, and Dimitri Mavris. Exploration and trade-off of advanced sensor fusion architectures in designing for reduced congestion using advanced traffic management techniques, 07 2017.

[26] Gas Price Watch. Atlanta, ga lowest diesel gas prices. Accessed: September 14, 2017. URL: `http://www.gaspricewatch.com/GA-georgia/Atlanta/diesel-gas-prices/page-1/2.htm`.

[27] Electricity Local. Residential electricity rates & consumption in georgia. Accessed: September 14, 2017. URL: `https://www.electricitylocal.com/states/georgia/`.

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