Université Gustave Eiffel
LABORATOIRE GRETTIA
GÉNIE DES RÉSEAUX
DE TRANSPORT TERRESTRES
ET INFORMATIQUE AVANCÉE

Université Gustave Eiffel

LISER
LUXEMBOURG INSTITUTE OF
SOCIO-ECONOMIC RESEARCH

Séminaire Modélisation des réseaux de transport

RIDE-HAILING SYSTEM AUTONOMOUS FLEETS OF ELECTRIC VEHICLES

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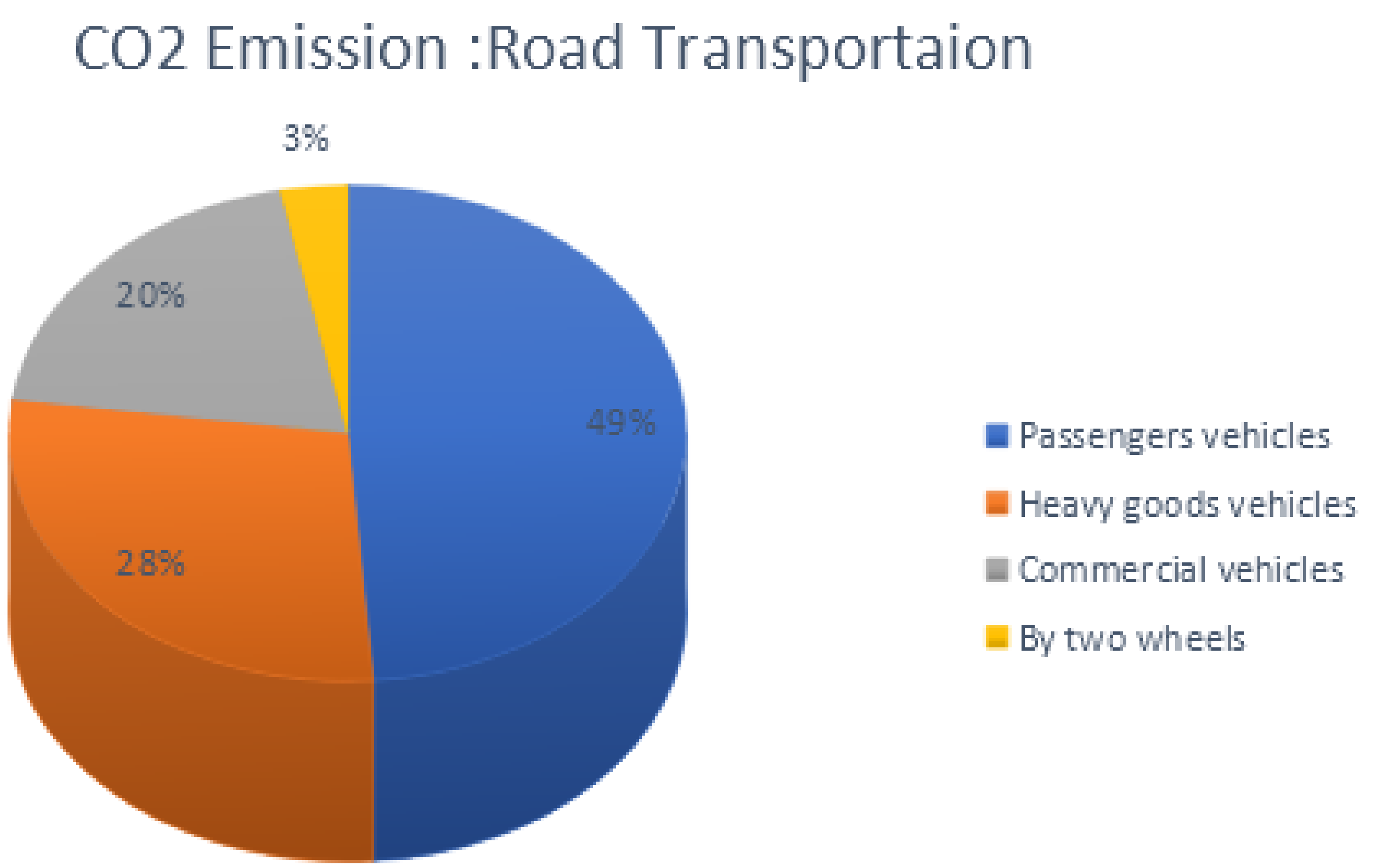
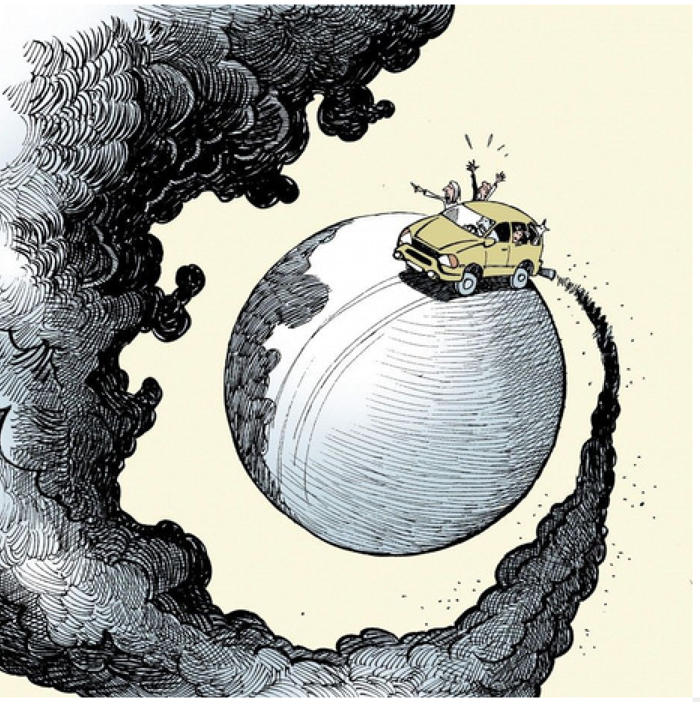
MOTIVATION





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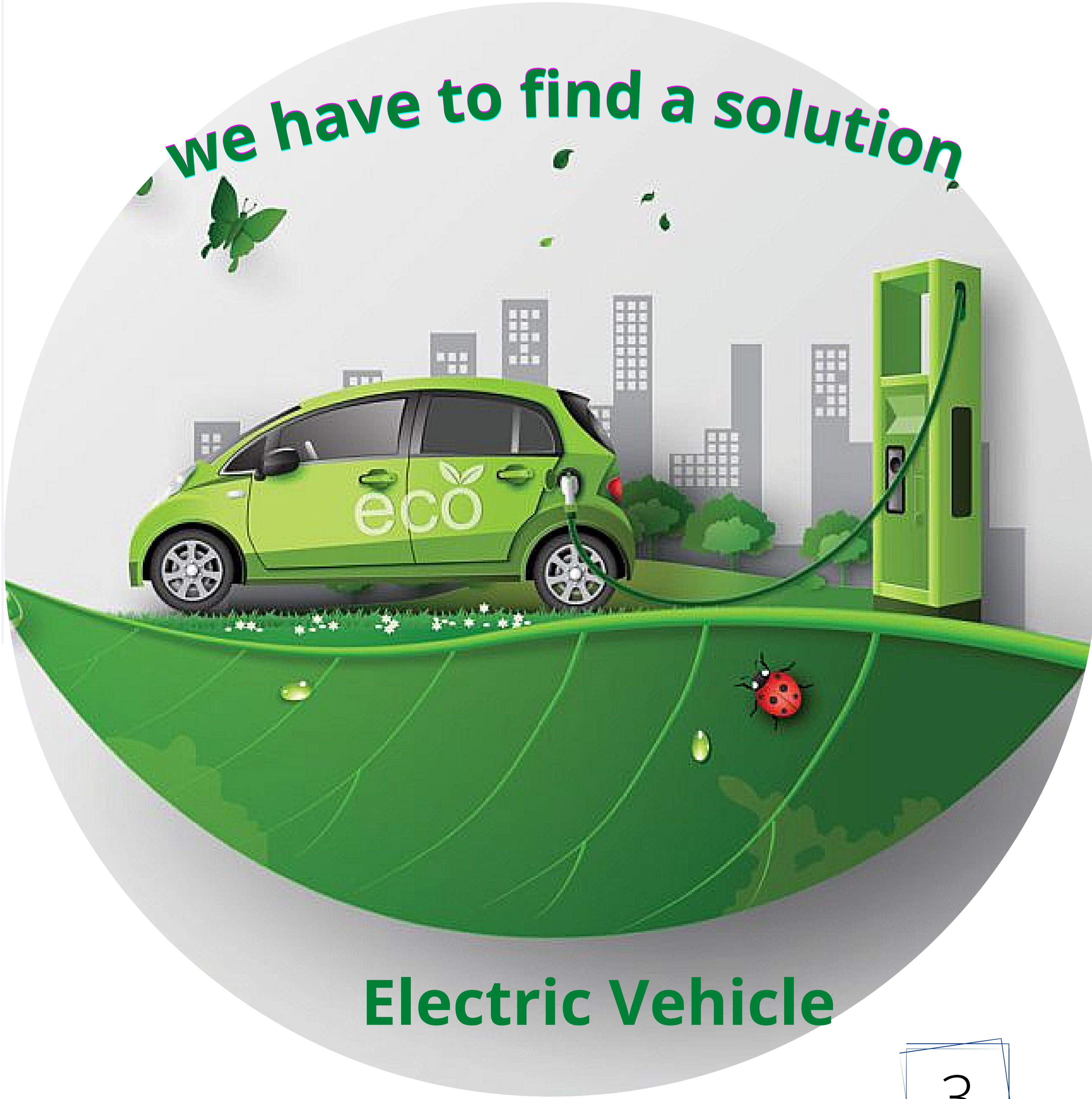
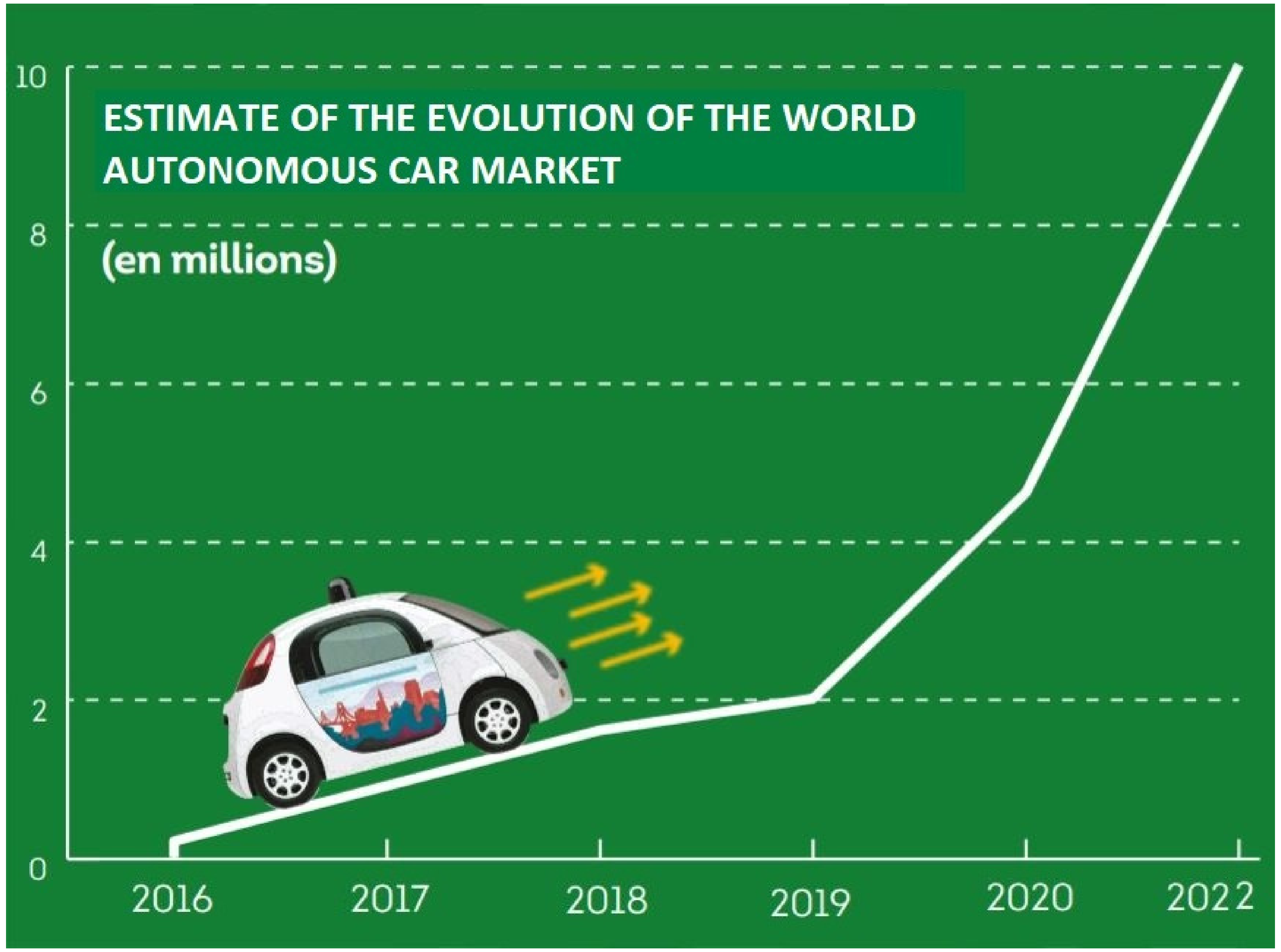


MOTIVATION



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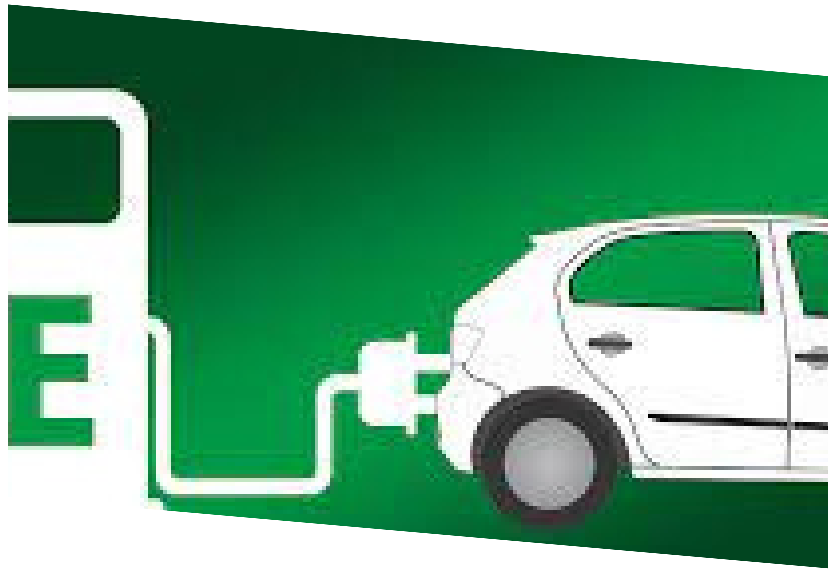
Challenges

-Electric vehicle



-Autonomous vehicle

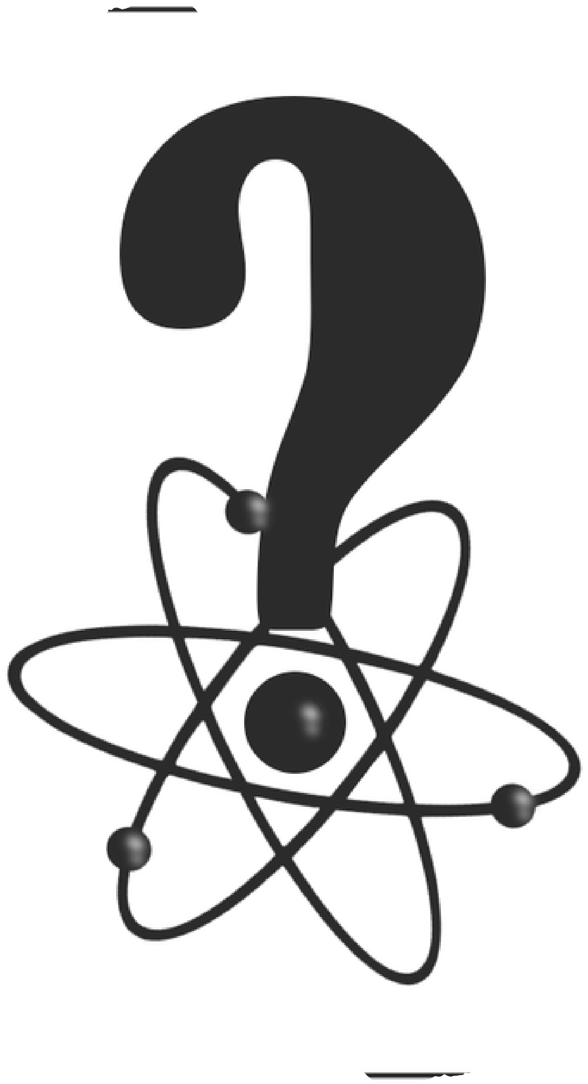
-They are multiple services : Ride hailing / Ride sharing …

Research a Scoop

-Provide mobility services
- Need to manage the charging plan and service plan all together

Scientific Question

How do we formulate and solve the problem of fleet management and charging plan for the fleet of AEV including the profit of driveres and system?



1:Liteerature Review
2: Mathematical formulation
3: Agent Based Simulation
4: Flowchart

Litterature Review

Fleet Management

(Maoet al. 2020) : A dynamic taxi ride-hailing

(Lacobucci2021):A ride sharing Autonomous Electric Vehicle system interacting with passengers

(Maciejewski 2016):Ride-hailing the assignment of passengers to vehicles, as traffic dynamics can alter the closer vehicle.

Charging Plan

(Zhang et al2020) : A charging framework for EV for a transport by studing the parameters like battery capacity , rate power , system cost ..

(Shi al . 2014): analyzed 3 electric vehicle charging modes

(Tai-Yu-Ma 2021) : An online charging sheduling model

Reinforcement Learning

(Kullman et al2020) : An operatoe AEV using the DQN algorithm

(Hu et al2017) :Used Deep Reinforcement Learning to learn the objective coefficients in a math program

(Verma2017) Used reinforcement learning to develop a system that helps the driver to predict the location of coming requests

These 3 issues are not adressed all together with a good level of detail in each part

Literature review

Type of mobility services :
Car pooling
Ride-hailing
Ride-sharing

Assignment manage used :
Fleet management
Charging process

Mathematical formulation:
Linear
Non-Linear
Mixed Integer Programming

Cost Function:
Driver
Passenger

Methodology:
Optimization
RL method

Simulation Configuration

Solution Algorithm

Research	Problem setting					Mobility service			Assignment models							Mathematical formulation				Time-dependency	
	Supply			Demand		Car pooling	Ride-sharing	Ride-hailing	Fleet managment		Chamging process			Repositioning						
	EV	AV	AEV	Fixed	On-demand				Predictive	Reactive	Time	Price	Heterogeneity		Linear	Non-linear	MIP	Model-free	Static	Dynamic
Alshamsi, al (2009)		x			x															x
Galland et al. (2014)		x			x	x									x					x
Chen,et al(2016)			x		x		x		x		x							x		x
Wang et al. (2018c)		x			x		x												x	
Lacobucci et al(2018)			x		x		x		x		x	x			x		x		x	
Oda ,Tachibana (2018)		x			x			x										x		x
Chaoui et al. (2018)	x				x											x				x
Nezafat (2019)		x			x			x												x
Yu et al.(2019)			x		x															x
Yang et al.(2019)			x																x	
Loeb et al. (2019)			x	x			x		x		x							x		x
You et al (2019)		x		x			x											x		x
Tan et al.(2019)	x				x			x	x							x				x
Bacchiani et al.(2019)					x															x
Wu et al.(2019a)	x			x														x		x
Miao et al.(2019)			x		x		x		x		x							x		x
Webb et al (2019)			x		x		x		x			x						x	x	
Qi et al. (2019)	x			x											x				x	
Balaji et al. (2019)		x			x															x
Bacchiani et al.(2019)		x													x					
Al-Kanj et al.(2020)			x	x				x				x		x	x					x
Zhang et al. (2020)			x					x	x									x		x
Wu et al.(2020)			x		x			x	x		x	x						x		x
Nishitani et al.(2020)		x														x				x
Wang , Sun (2020)		x			x			x							x					x
Kullman, Cousineau (2020)			x		x			x		x	x			x	x		x			x
Chao Mao et al. (2020)		x			x		x	x	x					x				x		x
Smart et al (2021)			x		x			x	x			x		x		x				x
Pan et al (2021)			x		x			x	x		x							x		x
Tai-Yu Ma (2021)	x				x					x	x	x	x		x					
Mohamed Alhusin (2022)		x			x											x				x
This work			x		x			x		x	x	x	x	x	x		x			x

Research	cost function				Methodology		Simulation configuration		Solution algorithm
	Driver		Passenger		Optimization	ML method (RL)	Multi agent	traffic model	
	Service cost	Fuel cost/time	Service cost	Waiting time					
Alshamsi, al (2009)	x			x			x		Self-organization
Galland et al. (2014)	x		x	x			x		Route matching algorithm
Chen,et al(2016)	x	x		x	x				Multinomial logit mode
Wang et al. (2018c)	x					x			DQN
Lacobucci et al(2018)		x		x	x			x	Optimization algorithm
Oda ,Tachibana (2018)	x			x		x		x	DQN
Chaoui et al. (2018)		x				x			DQN
Nezafat (2019)	x		x			x		x	A3C
Yu et al.(2019)		x	x			x			A3C
Yang et al.(2019)						x			DDPG
Loeb et al. (2019)	x	x			x				Logit choice model
You et al (2019)	x		x			x	x		DNN
Tan et al.(2019)	x		x			x		x	DDPG
Bacchiani et al.(2019)						x			A3C
Wu et al.(2019a)		x	x			x			DDPG
Miao et al.(2019)		x	x	x	x			x	Multi-objective optimization model
Webb et al (2019)	x	x	x	x	x				Multinomial Logit choice model
Qi et al. (2019)		x				x		x	DDQN
Balaji et al. (2019)	x			x		x			PPO
Bacchiani et al.(2019)						x	x		A3C
Al-Kanj et al.(2020)	x				x				Dynamic programming
Zhang et al. (2020)				x	x		x		K-means clustering
Wu et al.(2020)		x	x		x			x	Logit choice model
Nishitani et al.(2020)	x					x		x	Double dueling
Wang , Sun (2020)	x		x	x		x	x		PPO
Kullman, Cousineau (2020)	x					x			DQN,DDQN,D3QN
Chao Mao et al. (2020)	x		x	x		x	x		Actor-critic
Smart et al (2021)	x		x			x		x	DQN
Pan et al (2021)	x		x		x			x	Model predictive control
Tai-Yu Ma (2021)	x				x			x	Langrangian algorithm
Mohamed Alhusin (2022)	x					x	x		DQN
This work	**x**	**x**	**x**	**x**		**x**	**x**		**DQN**

This work

Problem Setting Autonomous Electric vehicle	**Mobility Service** Ride Hailing	**Time Dependency** Dynamic	**Assignment Models** Charging Process & Repositioning
Mathematical formulation MILP	**Cost Function** Driver service Cost & Fuel cost Passanger service Cost & waiting time	**Methodology** RL Method DQN Algorithms	**Simulation Configuration** Multi-Agnet

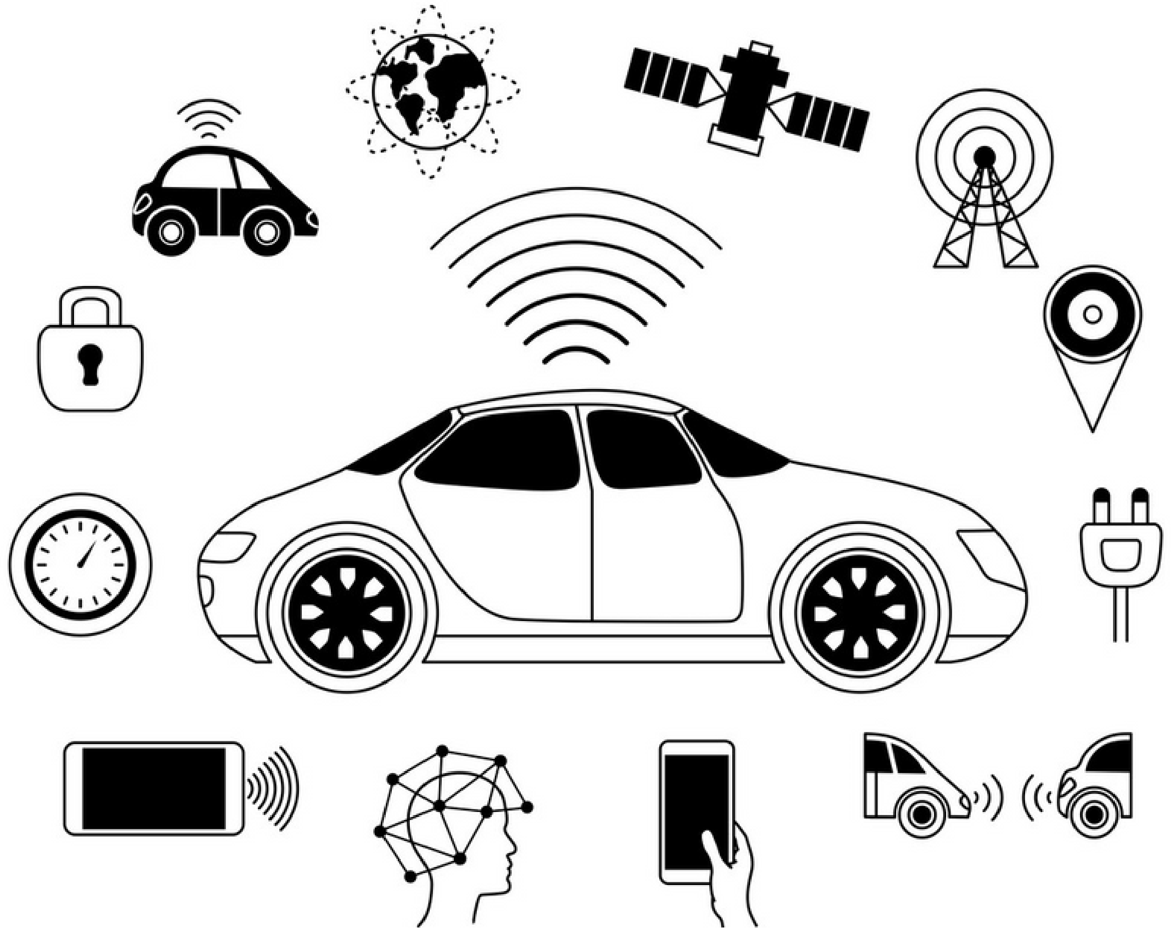
METHODOLOGY

Problem Statement

Recharging

Repositionning

Serving demand



METHODOLOGY

Mathematical Formulation

$$B = \sum_{t \in T} \max R(s,a) \quad (1)$$

→ **OBJECTIVE FUNCTION**

$$R(s,a) = \sum_{t}^{T} C + \sum_{t}^{T} A + \sum_{t}^{T} R\ r \quad (2)$$

→ **REWARD FUNCTION**

I

II

III

Inspired by Tai-Yu-Ma Two-stage battery recharge scheduling and vehicle-charger assignment policy for dynamic electric dial-a-ride services -plosone -1-27(2021)

Part I

C 'represents the overall assignement status of charging sation in the system

$$c = \min [\sum_{\theta \in O} \sum_{k \in K} \gamma f + \sum_{\theta \in O} \sum_{k \in K} \alpha' + \sum_{\theta \in O} \sum_{k \in K} N_1 V_{\theta k}] + \min \sum_{t}^{T} \rho_e q_c \quad (3)$$

C' : to minimize the total charging , the waiting time and the travel time until arriving at charging station

C'' : To minimize the total cost of the vehicle

Part I

$$C' = \min\left[\sum_{\theta\in O}\sum_{k\in K}\gamma f + \sum_{\theta\in O}\sum_{k\in K}\alpha' + \sum_{\theta\in O}\sum_{k\in K}N_1 V_{\theta k}\right] \quad (4)$$

Factor representing the relationship between the amount of energy that the charger needs and the charging rates of the charger , and the time of recharging

The waiting time of vehicle “O” at charge “K”

Travel time from the location of vehicle “o” to the charge “K”

Part I

C" : To minimize the total cost of the vehicle

(5)

C" = $\min \sum_{t}^{T} \rho_e q_c$ → Energie Price (euro/KWH) , Amount of energy charged

$\sum_{k \in K} V_{\theta k} = 1 \quad ; \quad \forall \theta \in O$ (6) → Contraints 6 : that each vehicle is assigned to one charger station

Part I

$0 \leq q_t \leq q_{\max} \quad ; \quad t \in [1,T]$ (7) → The amount of energy

$e_{t+1} = e_t + q_t - \lambda t$ (8) → The transition state : evaluate the energy level

$e_t + q_t > = \lambda_t + e_{\min}$ (9) → Level of energy and the quantity of energy to be no less than the energy demand plus a minimum reserve energy emin.

$e_{\min} \leq e_t \leq e_{\max}$ (10) → Energy level limits states the upper and lower bounds of the energy level at the beginning of each epoch

$e_L = e_{\max}$ (11) → The initial energy levelto start the 1st vehicle mission on the day

$\theta \geq K$ (12) → The number of vehicles and the charging stations

Part II

A represents the service plane: the assignment of vehicle to passenger and

minimize the waiting time of the whole period

$$A = \sum_{\theta \in O} \sum_{m \in M} N_2 V_{OM} + \min \sum_{\theta \in O} \sum_{m \in M} \alpha \qquad \textbf{(13)}$$

Travel time from the location of vehicle “o” to the client “c”

The waiting time of the client to have a vehicle

Part II

$V_{OM} \in [0,1]$ (14)

Contraints 14 : that each vehicle is assigned to customer

$$M_t^p = D_t + M_{t-1}^p - R_{t-1} \quad (15)$$

The state function describing the evolution using a demand generator to know the number of users should answer

Demand of number of customer of new request of each epoch t

number of users should answer at (t-1)

The total number of users answered at(t-1)

Rr: about the repositionning of the vehicle waiting future requests :

each vehicle can be assigned to its place

$$Rr = \sum_{\theta \in O} \sum_{p \in P} d^{v}{}_{op} \quad (17)$$

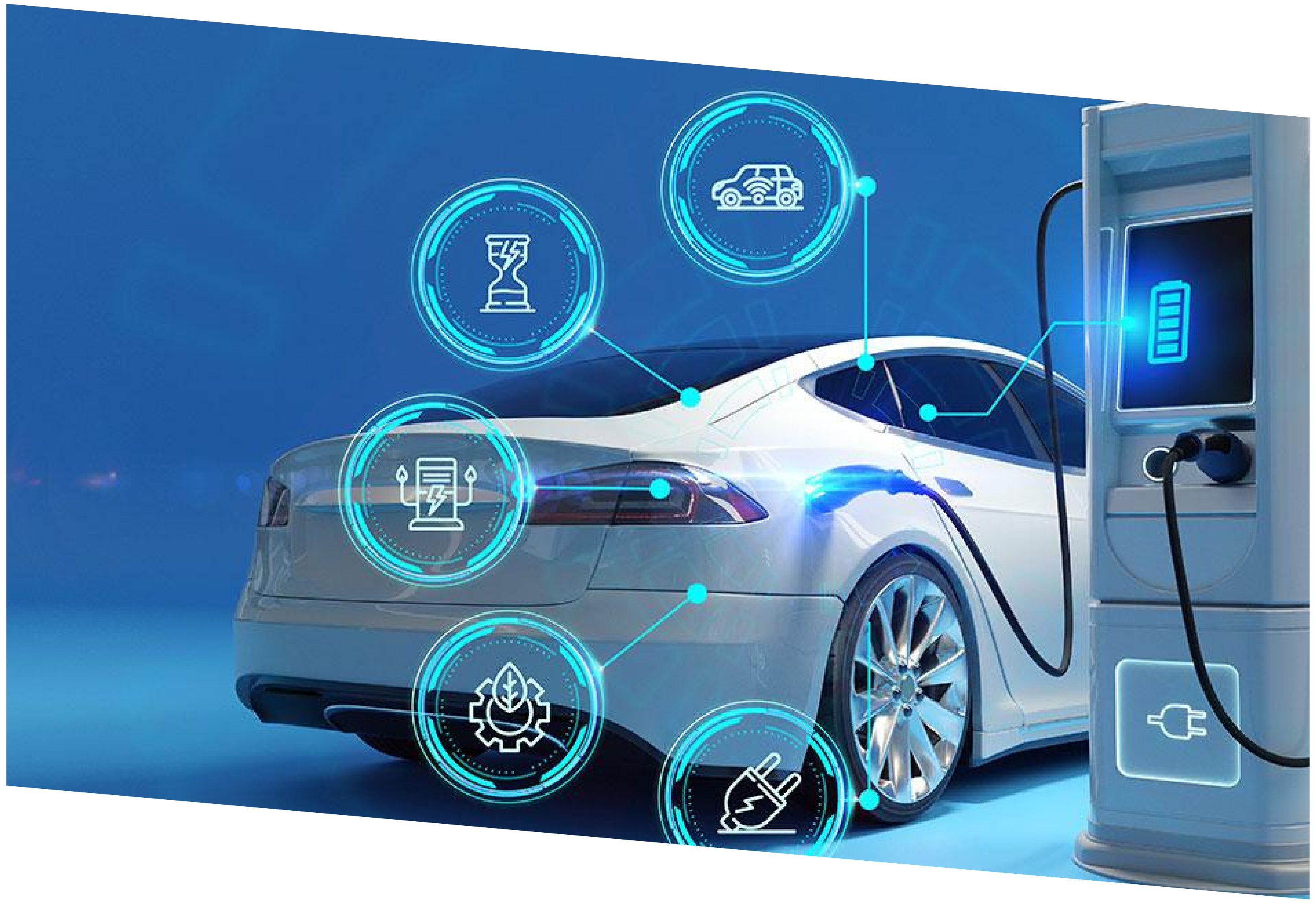
Travel distance from the location of vehicle "o" to the point "p"

$$\sum_{p \in P} V_{\theta P} = 1 \quad ; \quad \forall \theta \in O \quad (18)$$

To make sure that each vehicle can be assigned to one point

METHODOLOGY

Agent Based Approach

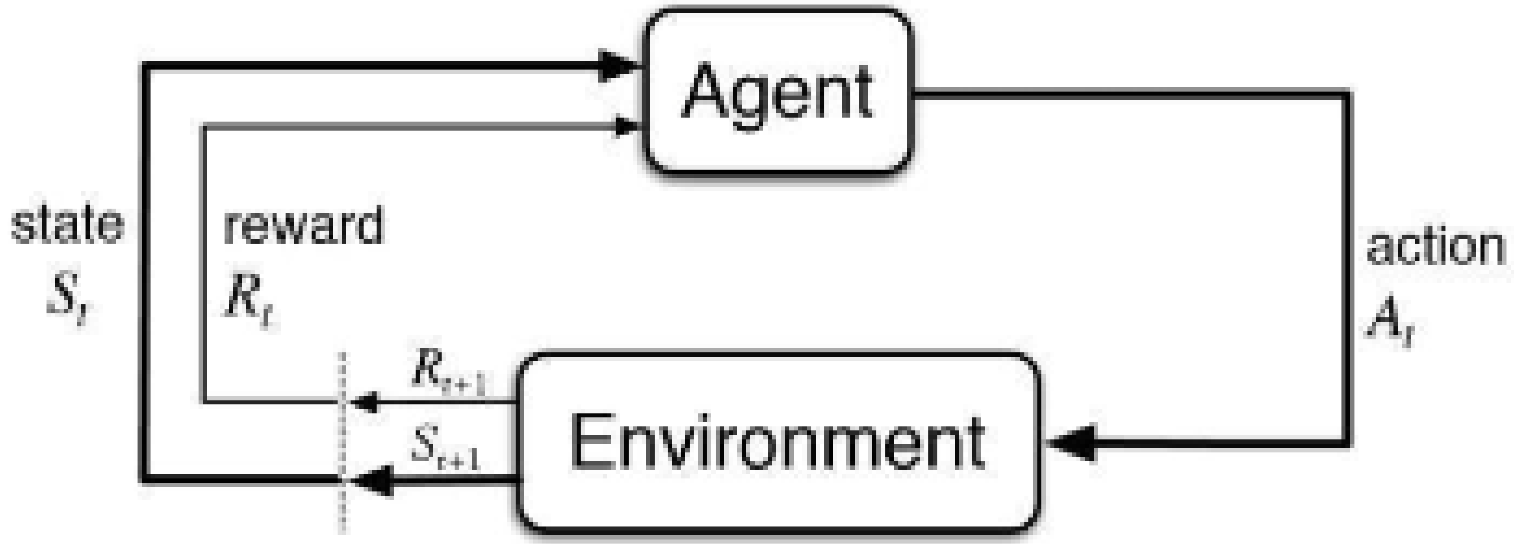


To optimize its own objectif function

we build a RL to optimize the fleet management

METHODOLOGY

Reinforcement Learning



By Markov Decision Process

N	Number of Agents(AEVs)
S	S = (St , Sv, Sh)
A	{A1,A2,A3,...}
P(s,a,s')	The transition probability
R(s,a)	The Reward Function
γ	Between 0and 1

Reference :https://www.kdnuggets.com/2018/03/5-things-reinforcement-learning.html

State Variables

we model the state of the system by the tuple : state of time , state of vehicle , state of destination

$$S = (St\ ,\ Sv,\ Sh)$$

$$Sv = \begin{pmatrix} \text{Battery} \\ \text{Location} \\ \text{Current activity} \end{pmatrix} = \begin{pmatrix} Vq \\ Ve \\ Vc \end{pmatrix} \qquad St = \begin{pmatrix} \text{Time} \\ \text{Day} \end{pmatrix} = \begin{pmatrix} t \\ d \end{pmatrix} \qquad Sh = \begin{pmatrix} \text{Destination} \\ \text{origin} \end{pmatrix} = \begin{pmatrix} xd & yd \\ xo & yo \end{pmatrix}$$

Vq is characterized by the level of battery $\in [0,Q]$;

Ve is characterized by its locations the coordinate of the vehicle

$\in (xv,yv)$

Vc $\in$ { 1:idle , 2:serve , 3 :reposition, 4: preprocess , 5:recharge }

Action for an agent

Serve Request

Request exists with energy feasible

Reposition

No request exists and no waiting demand with energy feasible

Charging

Request exists or not with unfeasible energy

Non -Action

Just finished serving

Reward

The table below summarizes all the rewards of all the process

states	actions	Reward
Vq	Q [100%, 30 % [	= +150
	Q [30% , 10% [	= -10
	Q < 10 %	= -1000
Vc	lose the customer < D	= -100
	pick up don't drop off	= -150
	Do not reposition the AEVs	= 0

METHODOLOGY

Flowchart

The System is formed by a set of Autonomous Electric Vehicles

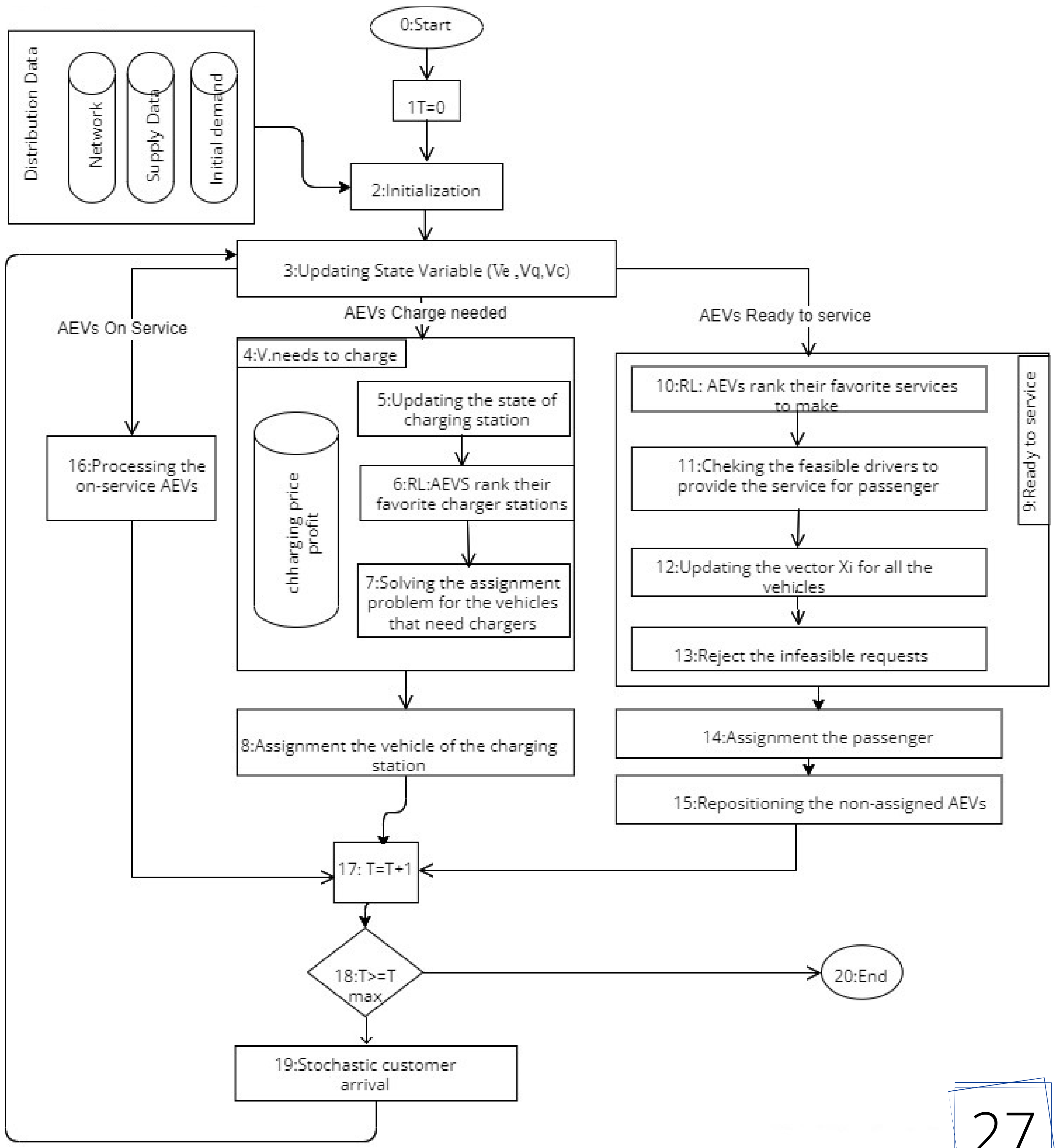
Vehicle needs to recharge
Vehicle needs to be repositioned
Vehicle ready to serve

Our organization chart designed by 3 parts

1: Initialization

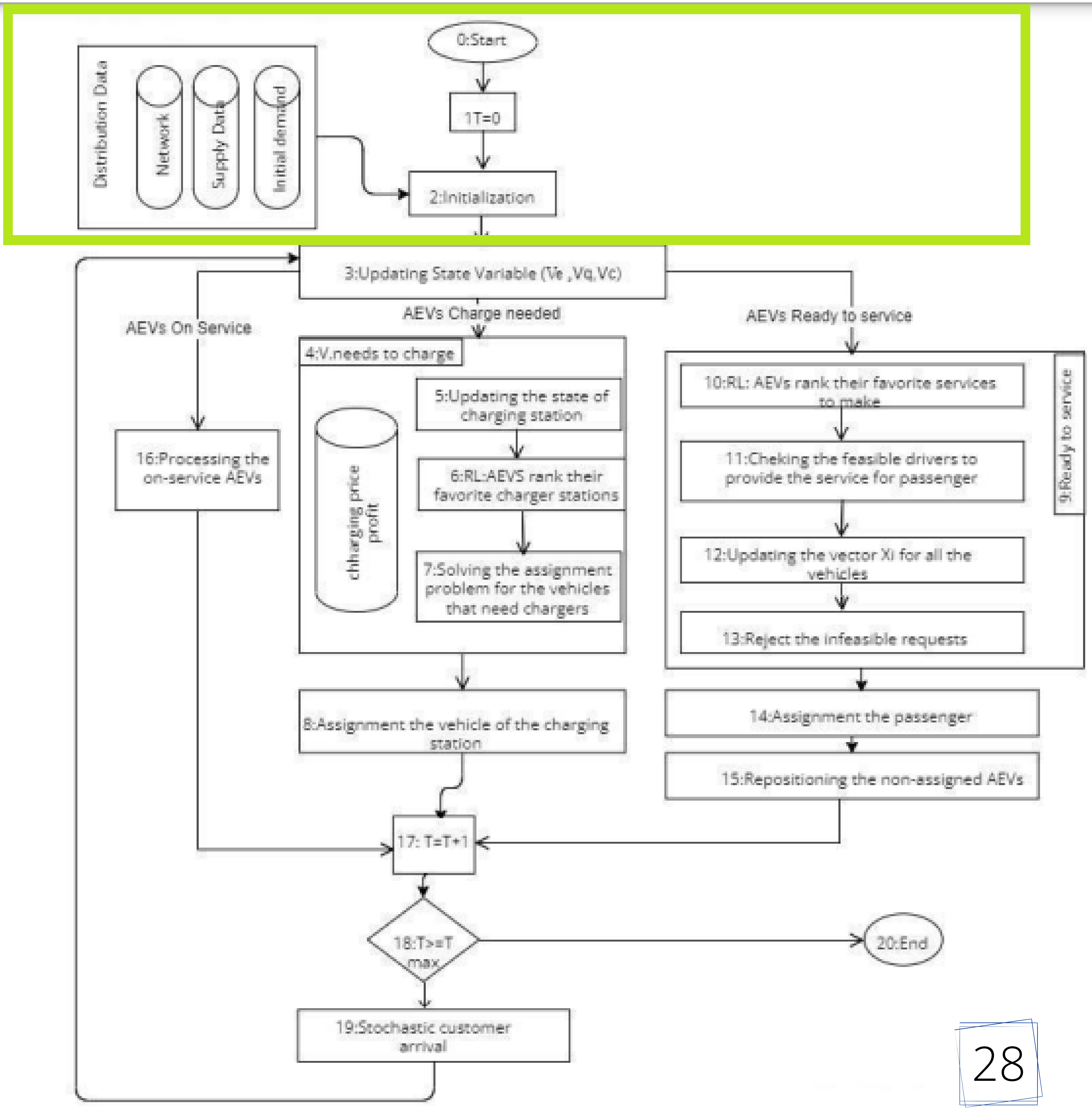
2: Assigning process

3:Stopping Condition



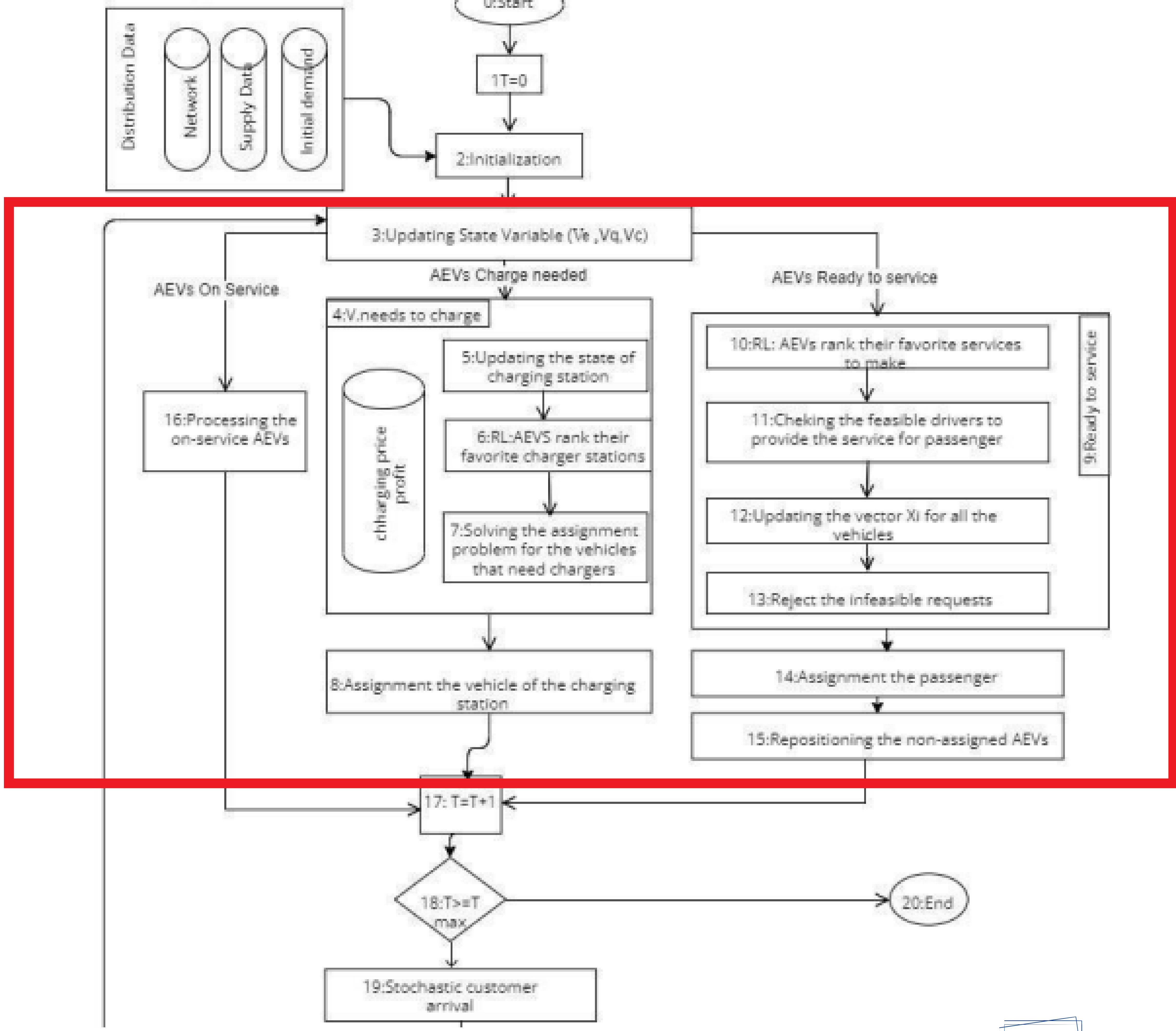
1: Initialization

Distribution data :The network graph , the initial demand ..



2: Assigning process

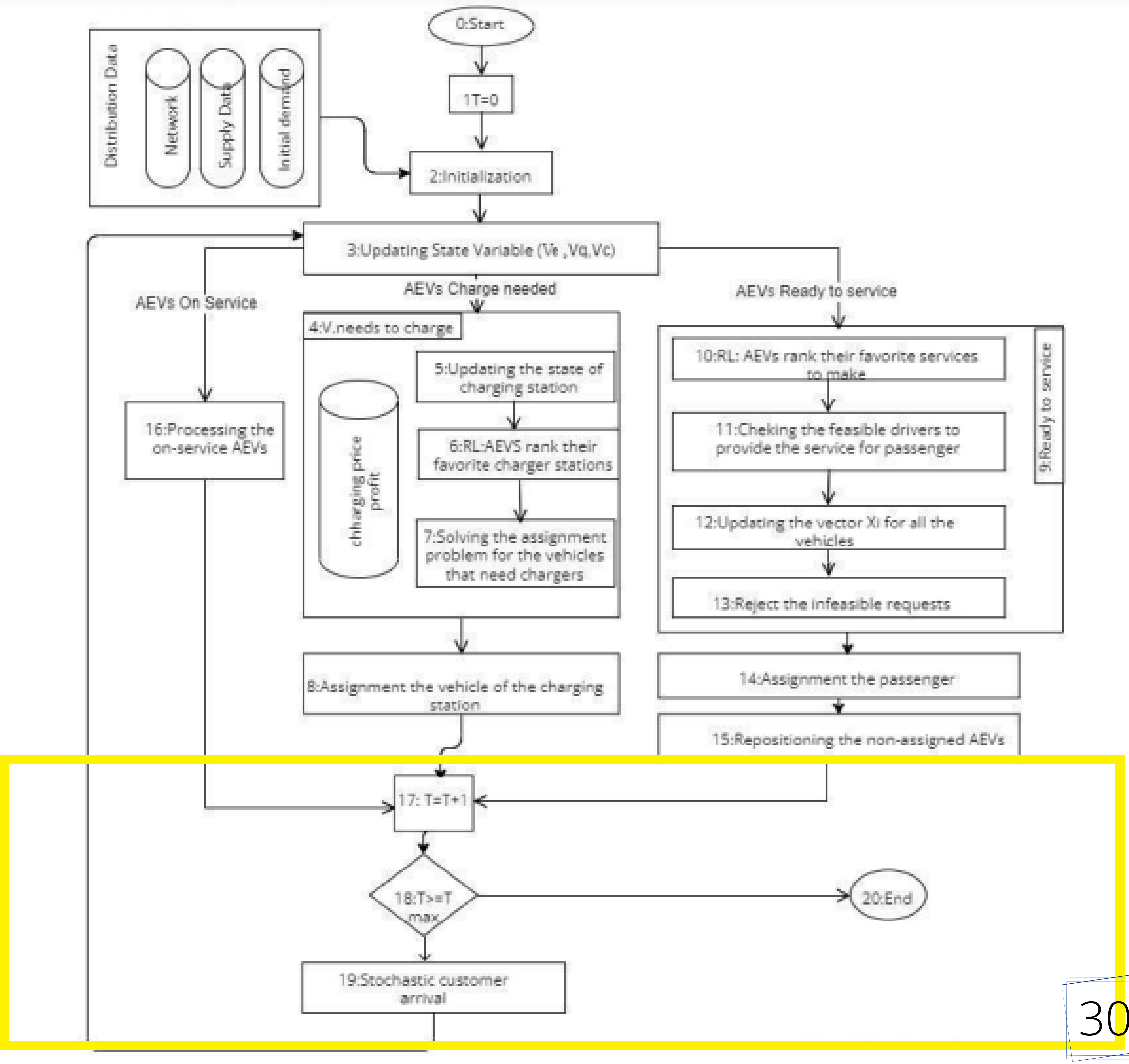
Update the different numbers of vehicles in the fleet by updating the variable status



3:Stopping Condition

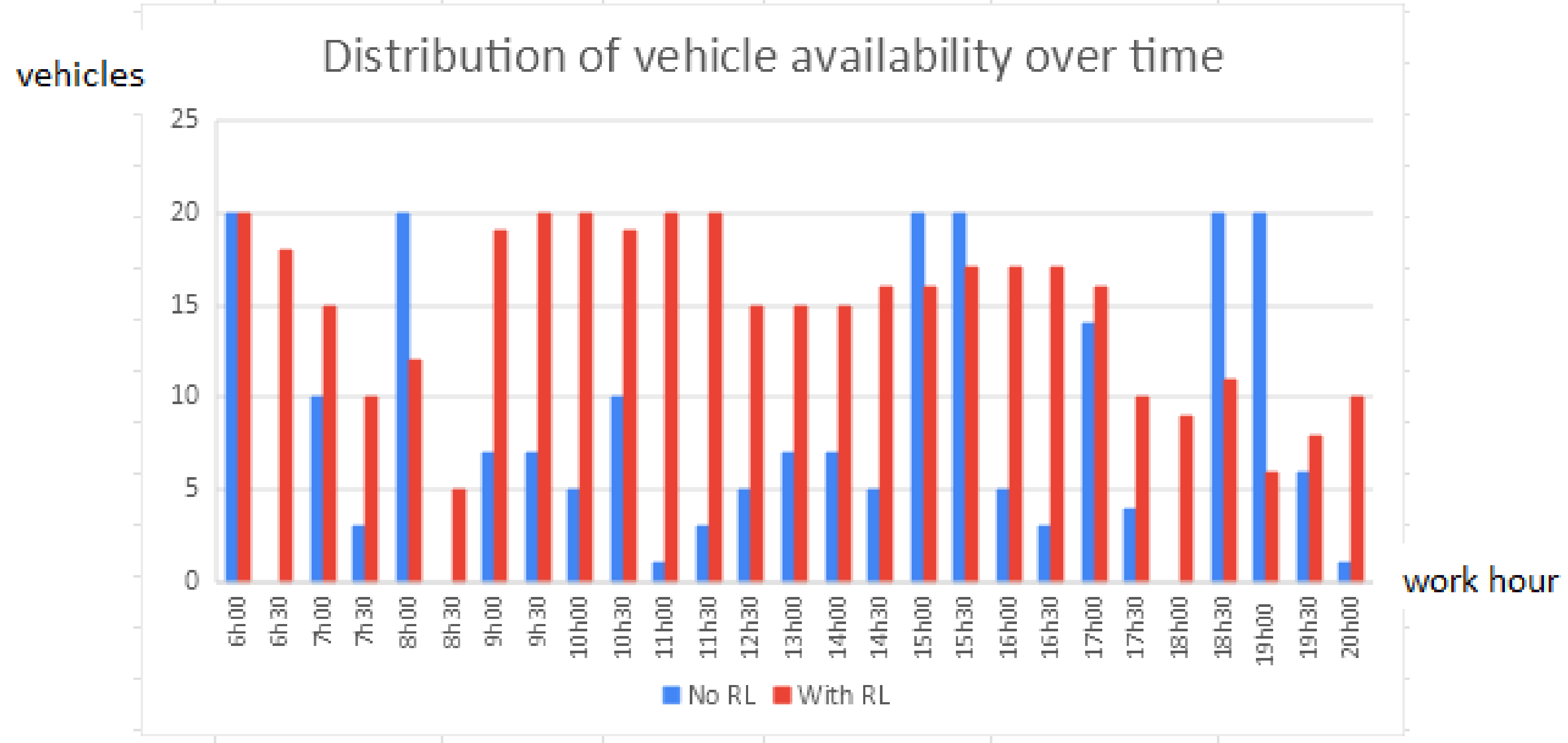
-we finish the whole system service

-we get a stochastir customer from the model generator and go again to step (3) to update the state variable for every time

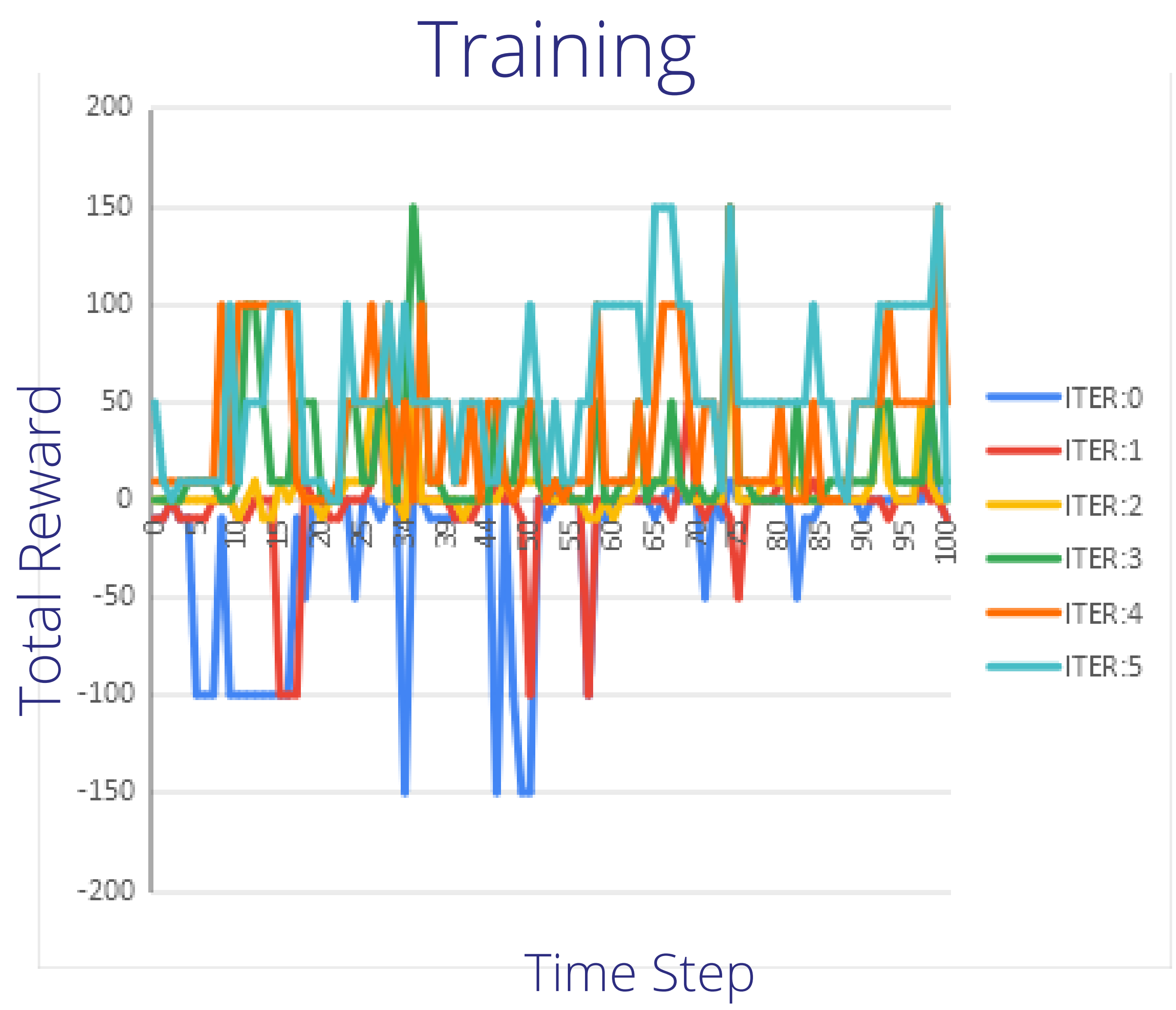


Numerical Result

Programming :**Python**
Math tools :**Equatio**
Data collection:**Google Scholar**
Project management :**Google calendar**



With RL we manage better the work hour



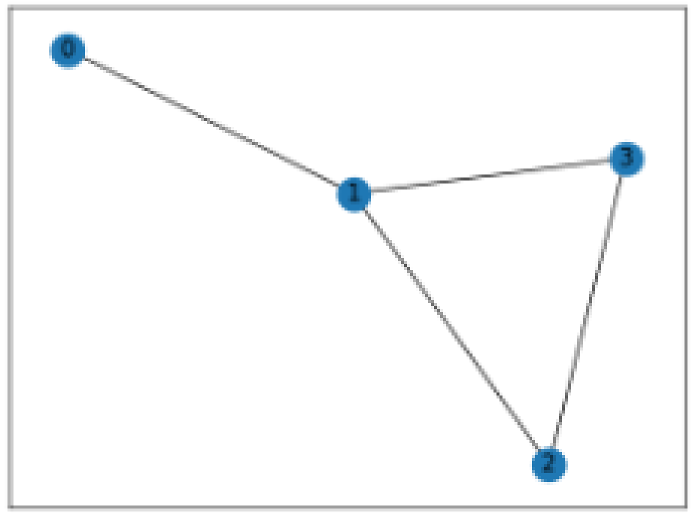
states	actions	Reward
Vq	Q [100%, 30 % [	= +150
	Q [30% , 10% [	= -10
	Q < 10 %	= -1000
Vc	lose the customer < D	= -100
	pick up don't drop off	= -150
	Do not reposition the AEVs	= 0

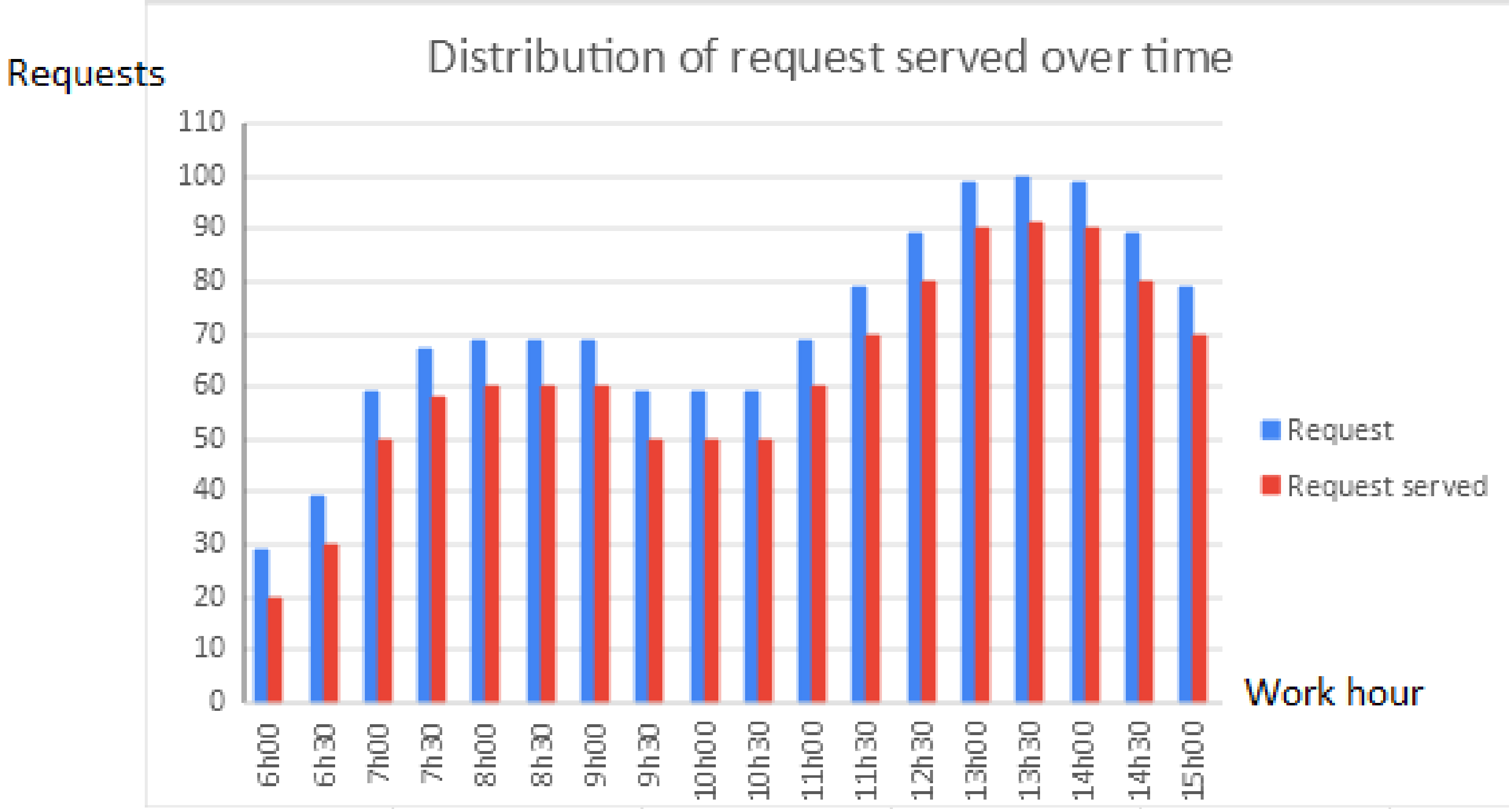
```
Node 1:
Demands [3]: Taxis available [2, 3
Demands [1]: Taxis available [4, 6
Demands [3]: Taxis available [2, 3
Demands [0, 3]: Taxis available [0
Demands [1, 0]: Taxis available []
Demands [1]: Taxis available [4, 6
```

```
Node 2:
Demands []: Taxis available [0, 1, 5, 7, 8]
Demands [3, 1, 2]: Taxis available [4, 7]:
```

```
Node 3:
Demands [1]: Taxis available []
Demands [1]: Taxis available [4, 6
Demands []: Taxis available [2, 3,
Demands []: Taxis available [0, 1,
Demands [1]: Taxis available []: A
Demands [1]: Taxis available [4, 6
Demands []: Taxis available [2, 3,
Demands []: Taxis available [0, 1,
```

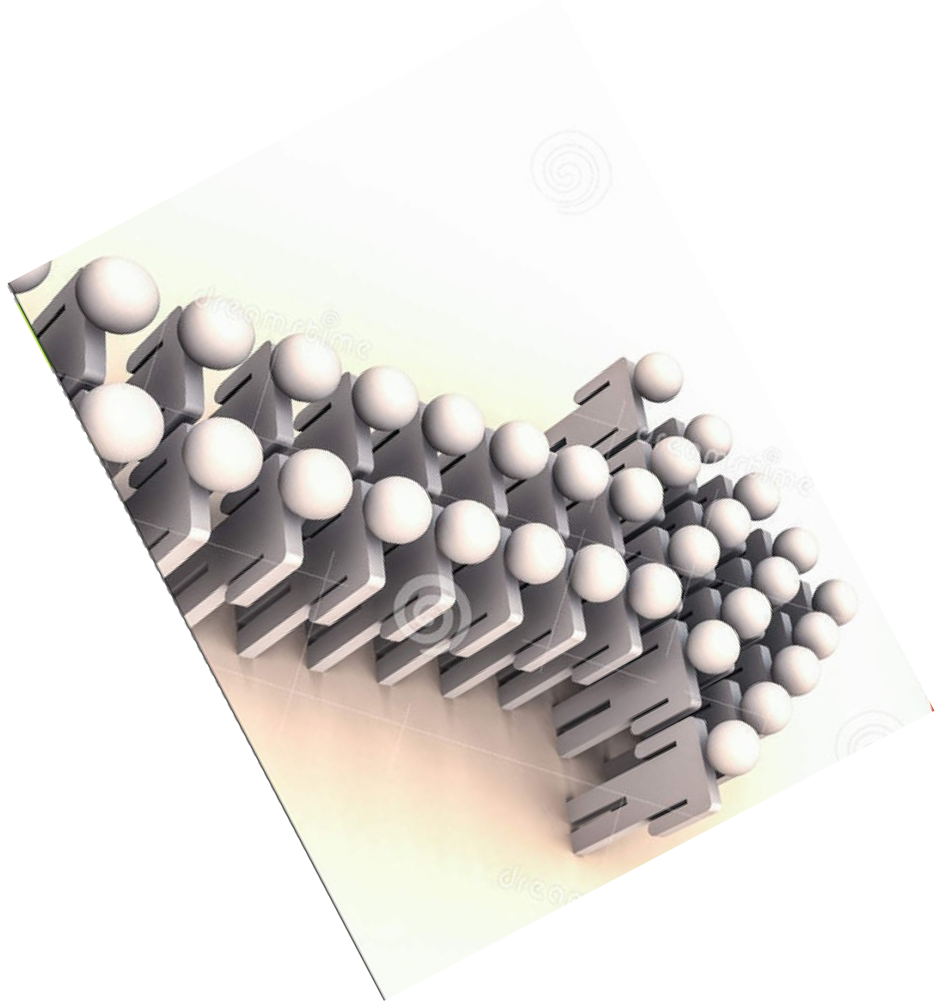
```
Node 4:
Demands [3, 1]: Taxis available [4, 7]
Demands [3, 2, 3]: Taxis available [0]
```

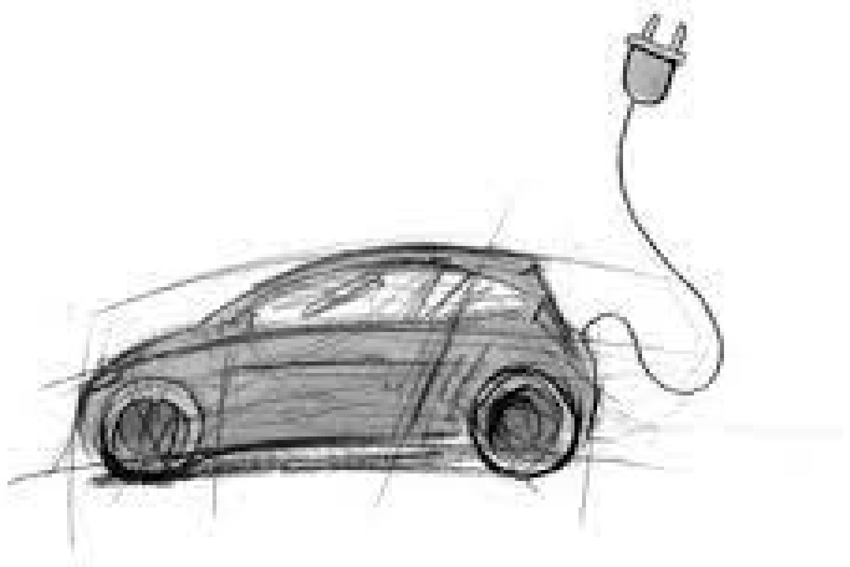




we have more 85% we could response

The goal of the system is to answer all the requests





The goal of Each Agent is to optimize its own performance in term cost and profit

Conclusion

–An operator of a ride–hailing system composed of Autonomous Electric Vehicles

– Reinforcement Learning algorithm

–Repositionning/ Serving demand / recharging

–Other dynamic mobility services ride–sharing in a dynamic environment

– A the traffic congestion in the model : that we take to acompt of the traffic gym of other vehicles not only our taxis.

THANK YOU FOR YOUR ATTENTION

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Notation :

t	Interval of epochs t∈ T=[1,T]
θ	Vehicles set in the area (environnement)
K	Chargers set in the zone (environnement)
p	Set of points where each vehicle can reposition (P)
e_t	Energy level at the start of each epoch t
$e_{\max}$	Maximum vehicle energy level
$e_{\min}$	Minimum vehicle energy level
e_L	Initial energy level for the vehicle to begin its mission

$q_{\max}$	Maximum amount of energy
q_t	Amount of energy at the beginning of each epoch t
q_c	Amount of energy charged
f	Factor representing the relationship between the amount of energy that the charger needs and the charging rates of the charger
λ_t	Energy consumption
ρ_e	Energie Price (euro/KWH)
$d^{p'}$	Travel distance from the location of vehicle "o" to the point "p"
d_1	Travel distance from the location of vehicle" o" to the charge "k"
d_2	Travel distance from the location of vehicle "o" to the client "c"
N_1	Travel time from the location of vehicle "o" to the charge "K"
N_2	Travel time from the location of vehicle "o" to the client "c"
$N^{p'}$	Travel time from the location of vehicle "o" to the point "p"
V_{0k}	Vehicle "O" is assigned to charge "K"
V_{OM}	Vehicle "O" is assigned to client "c"

V_{op}	Vehicle "O" is assigned to point "P"
α	The waiting time of the client to have a vehicle
α'	The waiting time of vehicle "O" at charge "K"
γ	The time of recharging
D_t	demand of number of customer of new request of each epoch t
v	vitesse de véhicule (km/min)

M	random set of customers per day
M_t^p	number of users should answer of each epoch t
R_{t-1}	Total number of users answer
Δ	the time interval [1,7[

2. Algorithm :

1)Our environment is about a road network graph in which our autonomous electric vehicle can travel between adjacent cells (vertically, horizontally up,down) or can stay in the same place .

2) Initially, we start with a number N of taxis distributed arbitrarily.
3) The temporal dimension is discretized into time steps.
4) A vehicle V is characterized by – Its current position at time t ci(t). – Its state si(t) (i.e. 1:idle , 2:serve , 3:reposition , 4: preprocess , 5: recharge).
5) Passengers' requests P appear stochastically in the environment at every time step.

6) Each request P is characterized by two tuples and a time stamp:

– The pickup Location.

- The drop off location .

- The distance between the starting point of the client and the vehicle .

7) The assignment between taxi V and request at time t is denoted by the Boolean variable VoM(t). It will be true if taxi i is assigned to request j at time t, and false otherwise.

8) Requests can only be assigned to an inactive taxi or recharging taxi if the energy level > 30% or if the taxi is in a repositioning state.

9) After the assignment is done the taxi state will change to busy until it drops off the passenger.

10)At each time step a taxi can move to any of the passenger addresses if it will respect the waiting time of months equal Δ if not it is not worth moving.

11) Several requests can come at the same time. So the taxi will take the closest distance to it so as not to lose customers and not let them wait too long and also to optimize the battery.

12) The total number of requests is limited by a predefined upper bound, if reached the simulator will stop generating more requests.

13) The time to get to a given passenger within the same cell is the same and it is equal to one time step.

14) A taxi will be available at the next time step after dropping off its current customer if the load level is greater than 30% and the travel time N_2 is less than or equal to Δ

15) if the taxi has finished its mission and it has no other requests and its charge level is more than 30% in this case it will reposition itself in its place in the parking lot .

16) if the taxi finishes its mission and it has another mission pending but its charge level is below the limit then it is obliged to cancel its requests and go to the nearest charger station