

# Management of Intelligent Vehicles: Comparison and Analysis

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**Abstract:** The main purpose of Connected and Autonomous Vehicles (CAVs) is to ensure optimal safety while improving user comfort. Many studies address the problem of CAVs to improve specific driving situations (intersection management, traffic flow management, etc.). In this paper, we propose both a comparison of these systems according to a set of criteria and an analysis to assist the development of CAVs fleets. This analysis shows that, among other, the *ad-hoc* algorithms use similar data (position, speed, etc.) and that the decisions for vehicles are based on cooperative processing for specific situations. The objective of this paper is to provide a guide for the design of CAVs fleet capable of managing all traffic situations.

## 1 INTRODUCTION

Over the past years, the population of large urban areas has increased significantly. The resulting traffic jams cause stress, considerable time loss and harmful pollution (Pulter et al., 2011). In addition, the majority of road accidents are due to human error such as inattention or drunk driving (French government, 2019). Level 3 to 5 Autonomous Driving System (ADS) equipped vehicles (SAE On-Road Automated Vehicle Standards Committee, 2018) are useful to prevent accidents related to those errors.

Vehicles have now the ability to send specific messages to other vehicles and road infrastructures (Sharif et al., 2018); V2V (*Vehicle To Vehicle*) and V2I (*Vehicle To Infrastructure*) communications are called "connected". Such a vehicle controlled by a computer system is called a Connected and Autonomous Vehicle (CAV).

Although many CAVs fleet have been developed in recent years, it is difficult to obtain an artificial system that can efficiently address all situations encountered during a journey. This problem is increased by the necessary use of simulators to test these CAV fleet. Road traffic encompasses many different situations. It is then very complicated to find a simulator able to model all encountered situations including a large number of vehicles, with characteristics close to reality (Sobieraj et al., 2017). In this paper, different CAVs fleets are first compared. Then based on this

analysis, a guideline for a CAVs fleet capable of managing all road situations is proposed.

The paper is organised as follow: section 2 defines the requirements and criteria required. Then, sections 3 to 5 describe existing CAV fleet dedicated to each traffic situation and analyse them based on the previously defined criteria. section 6 presents the synthesis of all the studied system. Before concluding, section 7 proposes a guideline for designing a robust CAV fleet.

## 2 REQUIREMENTS OF A CAVs FLEET

As a driver, a human or an ADS, has the duty to ensure safety of all passengers. We assume that this point is covered in all the studied systems. The comparison is based on the situations addressed in these systems. Multiple criteria such as the purpose of the system, the traffic mix, and the volume of communications are used to study them.

### 2.1 Focus on the Addressed Situations

During a journey, a vehicle can encounter many different situations such as: (i) **traffic congestion**, (ii) **intersections** and (iii) **lane merging**. These three situations are focused in the current research works.

Whatever the encountered situation, a vehicle has the objective of taking the best decision in coordination with other vehicles to manage the situation in an optimal and safe manner. During the experimentation of a system, scenarios are designed; their consideration is detailed during the analysis.

## 2.2 Criteria of Comparison

For highlighting the strengths and weaknesses of the studied systems, we propose eight relevant criteria identified in the literature.

**1 - System Objectives:** among the compared systems, three main purposes stand out: minimising travel time (Agarwal and Paruchuri, 2016), reducing energy consumption and pollution (Pulter et al., 2011) and smooth driving (Di Vaio et al., 2019). It should be noted, that these issues are not independent.

**2 - Locality of the Decision:** (Barthelemy and Carletti, 2017) being in the context of a CAVs fleet, the implementation of the control process is studied: distributed or centralised.

**3 - Communication Volume:** (Sharif et al., 2018) connected vehicles have the ability to receive and provide data through increasingly efficient communication. The amount of data flow can become very large and be a problem.

**4 - System Robustness:** (Ioannou and Zhang, 2018) robust system can react to unexpected events. The ability of CAVs to act in the event of disruptions is assessed.

**5 - Knowledge of the Scenario:** the experimentation of a system takes place within the framework of a specific scenario that CAVs might know in advance. This knowledge influences the reaction of a CAV after it has detected unexpected events in the scenarios.

**6 - Mixed Traffic:** (Rios-Torres and Malikipoulos, 2016) the possibility of the presence of non ADS-equipped vehicles and other types of users (pedestrians, cyclists, ...) must be taken into account.

**7 - Scaling:** the number of vehicles influences the reliability of the system and may reveal specific problems that need to be considered.

**8 - Simulation Model:** (Sobieraj et al., 2017) to know its effectiveness, a system is evaluated under certain conditions. Microscopic models are used to observe a situation with a few numbers of vehicles with a close representation of the vehicles' dynamics. Macroscopic models aim at observing a large number of vehicles (the traffic in a big city).

The following section presents and evaluates 16 CAVs systems identified in the literature that address a solution to a road problematic. The purpose is to extract a guideline and the requirements for a system

capable of managing all road situations. Each system is studied according to the eight criteria defined in section 2.2.

## 3 PANORAMA OF CAV FLEET FOR TRAFFIC FLOW

The objective of these CAVs fleet is to maintain a smooth traffic in the 8 following situations.

### 3.1 Learning the Best Path based on Congestion

Large urban areas experience congestion problems on major roads can be mitigated by the use of CAVs and learning mechanisms (Barthelemy and Carletti, 2017). The authors present a Multi-Agent System (MAS) with CAV agents. Some CAV agents are called strategic and choose the best path to improve travel time using a neural network. Each agent uses its knowledge on nearby roads to take its decision. The experiment focuses on the Chicago city network, by varying the proportion of strategic CAV agents in the system. The authors observe that an increase of the strategic CAV agents also increases the traffic flow. Using **local data only** provides a low volume of communications and agents do not need to know the scenario to learn and choose the best route. In this experiment, Matlab is used to simulate at the **macroscopic level** a large number of vehicles and therefore to **successfully scale up**.

### 3.2 Choosing the Best Path using Pheromone Deposit

(Mouhcine et al., 2018) propose a MAS in which agents follow a pheromone based strategy to indicate congestion on an axis. In their MAS called "*Distributed Vehicle Traffic Routing System*" (DVTRS), pheromones are dropped by stopped vehicles. Through communicating infrastructures, non grounded vehicles are aware of the densest roads and can therefore choose a more fluid road. The advantage of this system is that vehicles require few knowledge and communication to take their decisions. On the other hand, this MAS is not defined in a **hybrid context**: the CAVs will then lack information about non connected vehicles. In this DVTRS, each vehicle is an agent with a total control over its own decisions/actions and can be abstracted from the particularities of each scenario through the use of local knowledge only. The DVTRS experiment **at the**

**macroscopic level** is located in the road network of a large city.

### 3.3 Reduce Shock Waves using Communications

A shock wave is often the result of intense actions such as emergency braking and it results in slow-downs and an increase of traffic density. (Di Vaio et al., 2019) propose a control strategy with MAS in which CAVs coexist with non autonomous vehicles, both being connected. CAV agents use the exchanged data to adapt their speed and to be informed as quickly as possible about the actions of others. A better anticipation before the shock wave, prevents vehicles to act urgently: vehicles thus have a more fluid and more ecological driving behaviour. CAVs make local decisions using certain data (velocity, direction, target) obtained every 20 ms. The experiment simulates vehicles dynamics in a **microscopic** simulation and shows that this strategy goes to **scale with a high number of vehicles**.

### 3.4 Reduction of Consumption by Anticipation

In the case of CAVs, communications can provide and process many more information than a human driver. The use of a predictive control model provides to the vehicle anticipation capabilities. This type of model proposed by (Kamal et al., 2015) combines lane change, acceleration and braking data. In a context of perfect communications, CAVs accelerate optimally and predict the best time to change lane: they save fuel while reducing travel time. But as communications must be perfect and data up to date, it requires a large volume of communications and in case of incorrect or missing communications, the system cannot work. A CAV does not have any knowledge of the scenario used for the experiment. This one simulates six vehicles, on two lanes using a **microscopic simulator, the scaling has not been proved**.

### 3.5 Selection of the Least Congested Intersections

The distribution of vehicles at intersections can be uneven and result in traffic congestion. Through the use of intelligent communications and infrastructure controlling intersections, CAV agents can decide to change the route as shown by (Lin and Ho, 2019). This MAS approach allows a better distribution of

CAV agents between intersections, leading to a **reduction of intersection congestion**. Each agent decides locally even if a server may ask it to change its route. Although communication is essential for the proper functioning of the system, **the volume of information exchanged is not high**. The CAV agent **has knowledge about the scenario** through the graph representing all the intersections given as an input at the entrance of the system. The presented experimentation **concerns the macro level and is scalable**.

### 3.6 Cooperation of CAVs in Squads

*Platooning* is a squad based vehicle formation in which the front vehicle is the leader. The advantage of such a strategy is the fast and secure information sharing between the vehicles of the squad (Llatser et al., 2015). Thus, the vehicles follow the leader and their speed is aligned its. Vehicles have the possibility to be closer than usual and do not risk collisions as they all act in coordinated way, **the driving is smooth**. This type of training was experimented with real vehicles as part of the "Grand Cooperative Driving Challenge 2016" (Englund et al., 2016) in which two CAVs squads aimed to merge into a single squad. The merging action is initiated by leaders of each squad, and from that moment each vehicle wishing to join the squad **binds by communication** to one of the present vehicles. Vehicles then insert themselves one behind the other. The *platooning* method **centralises decisions** (speed and travel) at the leader's level but each vehicle has autonomy for some actions, such as deciding to leave the squad when desired.

### 3.7 Emergency Vehicle in Heavy Traffic

Driving emergency vehicles (EV) in heavy or congested traffic is often problematic, as they are slowed down even if vehicles trapped in traffic try to clear the way for the EV. (Agarwal and Paruchuri, 2016) propose a strategy for the EV that consists in choosing the fastest lane at one time and sticking to it, while asking other Connected Vehicles (CV) to clear that lane. This strategy, constraining other CVs, is not efficient when the traffic density is too high. Another strategy consists in choosing the best lane according to the number of vehicles visible by the EV and the possible speed on the lane. It thus allows EVs to reduce their travel time. As only one message is exchanged between the EV and each vehicle, the volume of communication is low. The experiment of both strategies is carried out on a two kilometres road with the SUMO simulator (Behrisch et al., 2011) allowing **microscopic simulation of vehicles**.

### 3.8 Anticipation of Lane Change in the Event of an Incident

When a vehicle has an incident that brings to a standstill on a lane, the reduction of available lane might lead to a traffic congestion. As a consequence, intense braking and lane changes at lower speeds may arise. That is why (Ioannou and Zhang, 2018) propose to inform the CAVs of the lane impracticability in advance. The CAV agent, the incident initiator or one CV receiving the message, can in turn disseminate the information. Although lane reduction still has an impact on traffic, congestion is reduced. Each CAV agent takes its own decision based on the information received and can communicate with other vehicles, ADS-equipped or not. As only the presence of the incident is exchanged, the communication volume is low. A microscopic **digital** experiment is presented and this **system succeeds in scaling up**.

This study highlights the contribution of communications, and the use of a local control for a CAV in order to take a better decision.

## 4 PANORAMA OF CAVs FLEET FOR INTERSECTION MANAGEMENT

Until now, the road code and traffic signs were sufficient to guarantee the safety of users to manage intersection when all the rules are respected. An intersection may be seen as a dangerous area. In this section, the studied CAVs systems addressing this issue are using two different approaches: the centralised approach with an agent in charge of the intersection, *Infrastructure Management Agent* (IMA), which concentrates decisions, and the decentralised approach in which CAV agents cooperate with each other to find a consensus, with an IMA possibly helping this cooperation.

### 4.1 Coordination of Vehicles by Reservation in an Intersection

In the centralised approach, an IMA communicates with vehicles wishing to cross the intersection by indicating how to proceed, and uses the notion of reservation (Jin et al., 2012; Dresner and Stone, 2008; Pulter et al., 2011). (Jin et al., 2012) propose a Multi-Agent Intersection Management System (MAIMS) using reservations. A CAV agent approaching the intersection has to request a reservation by sending its objective. The IMA reserves a slot that allows

the CAV to cross the intersection without being in conflict with other vehicles. The particularity of the MAIMS is that it uses a vehicle scheduling approach instead of a FIFO one. All the near CAV agents report their speed, position and destination to the IMA, then it organises their crossing order. Authors have noticed that with a large number of CAVs, the volume of communications becomes problematic. The experiments carried out on SUMO with MAIMS show a clear **improvement of the vehicle flow** compared to the FIFO-based approach. However, this system shows no improvement in fuel consumption: the authors suggest that it comes from vehicle trajectories. The presented experimentation uses a large number of vehicles: the **scaling for this scenario is validated**.

### 4.2 Optimisation of Trajectories in an Intersection

(Kamal et al., 2014) propose a Vehicle-Intersection Coordination Scheme (VICS) to obtain a more fluid traffic at an intersection and a reduced fuel consumption. To reach these objectives, they optimise the trajectory of each vehicle agent using an IMA located in the intersection, which schedules the CAVs. The authors experiment VICS on Matlab, which is **distant from real vehicle conditions** and show that VICS eliminates almost all the stops at the intersection: this **significantly improves traffic flow and fuel consumption** for each vehicle. An experiment with a large number of CAVs shows **the transition to system-wide**. However, VICS operates in the context of a **traffic composed solely of CAVs** that are cooperative with the IMA and the **volume of communications may become too large**.

A centralised approach leads to significant data exchange and to possible congestion of communication flow. CAVs, equipped with V2X perception and communication devices, can also negotiate to facilitate the resolution of non-cooperative situations.

### 4.3 Negotiations between CAVs in an Intersection

(Gaciarz et al., 2015) propose a negotiation mechanism between CAV agents wishing to cross an intersection. In this mechanism, the intersection is divided into cells and CAV agents communicate in order to obtain a coherent configuration. The IMA of this system has a greater knowledge than CAV agents and has the ability to propose configurations that improve the overall fluidity without impacting local agent satisfaction. Each agent is free to accept or refuse the

IMA proposition according to its preferences and objectives. Negotiation includes all the agents present in the intersection at the current time and it does not generate a high volume of communications; however the presence of non-cooperative vehicles is not considered. Experimentation with this mechanism shows that the length of queues in the intersection is reduced. The simulation using *threads* does not allow **to have a simulation close to reality** but the number of vehicles is sufficient to **validate the scalability**.

These studies underline that the CAVs can negotiate together the appropriate time to cross an intersection with a low volume of communications. Cooperation between CAVs and infrastructure improves the smoothness of the crossing.

## 5 PANORAMA OF CAVs FLEET FOR THE MANAGEMENT OF LANE MERGING

The third situation that a CAVs must be able to handle is the lanes merging. It is difficult because a vehicle that wants to join a lane has to adapt its speed to the other vehicles in that lane and to find the best place to insert into it with a minimum of discomfort for other vehicles.

### 5.1 Coordination of CAVs at Merging Point

The merging zone of the two lanes may be managed by an agent present in a connected infrastructure. (Rios-Torres and Malikipoulos, 2016) propose a controller that organises vehicles in FIFO for this area by giving each of them an identifier to organise them. This system seeks to optimise fuel consumption by calculating the most appropriate time and speed to insert smoothly and safely at the merging point. A controller ordering the insertion allows the management of CVs but not CAVs. Experiments with this system, carried out under Matlab, have shown a **reduction in fuel consumption and a more fluid merging** regardless of the number of vehicles. However, the authors highlight a **limit when the vehicle speed is too high**.

### 5.2 Cooperation Upstream of the Merging Point

(Wang et al., 2018b) propose a protocol for cooperation between vehicles before reaching the merging point of the lanes. Each CAV agent sends its data (acceleration, speed and position) to an infrastructure

agent which sequences the vehicles and indicates to each of them which vehicle is in front of it. A CAV agent receives data from the vehicle in front of it in order to adapt its speed to reach the merging point at the optimal time, even if both are on two different lanes. A **large volume of data** is required to build this system. An agent-based simulation made of **six vehicles** in *Unity* (Wang et al., 2018a) compares the use of this system to human conductors; it results in a **reduction of travel time and energy savings** for CAV agents.

Although the previous approach presents very interesting results, it requires the presence of a controller and therefore an infrastructure to host it. Some decentralised approaches avoiding infrastructures are presented.

### 5.3 Decentralised Cooperation before the Merging Point

(Mosebach et al., 2016) propose a decentralised lane merging control algorithm in which CAVs use communications to determine if a vehicle is present in the area preceding the lane merging. If a CAV has detected vehicles, it slows down and calculates a trajectory to cross the merging point without collision. When the CAV considers that this trajectory is correct, it follows it by re-accelerating. The required communications concern the other vehicles as well as their speed. The CAVs **know the road typology** and cross the merging zone in FIFO. The simulation of two lanes merging with **40 vehicles** shows that the CAVs are inserted **smoothly** while maintaining a safe distance.

### 5.4 Decentralised Merging in Mixed Traffic

(Sobieraj, 2018) proposes a cooperation protocol between CAVs. In an area, known by the CAV agents and close to the merging point, the CAVs of two different lanes communicate to form pairs. Then, the CAV agents of each couple coordinate their acceleration to position themselves at a safe distance one behind the other. **The resulting communication volume is low** and acceleration calculations are based on models that allow fluid insertion. The experimentation consists in merging two lanes crossed by a dense vehicles flow. The presence of CAV agents **improves traffic flow** and waiting times have almost disappeared. This approach can be used in a mixed traffic despite lower performance.

## 5.5 Change of Cooperative Path with Confidence Index

(Monteil et al., 2013) have designed a mechanism for cooperation between CAVs agents by considering unreliable communications. This method is based on a confidence index that each CAV agent calculates for each vehicle communicating with it, thus it may evaluate the quality of the communications. In the case of missing or unreliable communications, the CAV can only use its own perceptions to make decisions: **the presence of unconnected vehicles is considered**. The **local control** and the ability to use only its perceptions **validate the robustness** of this method. Adding to this mechanism a connected infrastructure (Guériau et al., 2016), provides access to additional information to the CAV agents with an **increase of the volume of communications**. The simulation of a flow of a **large number of vehicles** shows that the presence of CAVs and infrastructure **smooths** the merging zone.

## 6 SYNTHESIS AND ANALYSIS

**Table 1** summarises and synthesises the results (with ratings ranging from - - to ++; - - means *not at all* and ++ *totally*, while NA means *not addressed*).

We note that the majority of systems only work in a fully connected and cooperative environment. The presence of unconnected, so eventually uncooperative vehicles, makes difficult for CAVs to determine their behaviour. Nevertheless, CAVs and non ADS-equipped Vehicles will very probably have to coexist before the traffic becomes fully autonomous.

First of all, only the system of (Wang et al., 2018b) has an explicit influence on the **travel time, the pollution emitted and the fluidity of the traffic flow**. However, it only concerns the insertion in a lane merging. Systems that aim to find the best route mainly influence **travel time** even if it is not clearly stated.

Managing an intersection requires a substantial **volume of communications** when a large number of vehicles are present. The studied systems need that either IMA or CAV agents have some scenario knowledge. Thus, each intersection must be specified and the modification structure of an intersection requires a new specification.

Only systems whose objective is to find the best path are **robust** because it does not require to make a quick decision. This is due to the complexity of the real vehicles and all the factors that need to be considered when decisions are made within a very short

time frame.

In all three situations, the fact that a CAV agent shares its objectives, speed and position allows other vehicles to have a better anticipation and understanding of this vehicle. Most of the conflict situations that a vehicle may encounter in these systems involve the sharing of space.

The presence of unconnected entities is often not considered in the studied systems (see Table 1). If we consider that a not connected entity in a traffic is a mobile or an unpredictable obstacle, then a CAV will only have to avoid that entity.

A CAV that only needs local information and a small amount of knowledge can adapt to unexpected situations. As shown in Table 1, only systems with a positive assessment for these two criteria also have a positive assessment for robustness.

Among the 16 systems presented, 12 are MAS in which CAV agents use a cooperative process when confronted with one of the three situations.

## 7 A GUIDELINE TO SATISFY THE REQUIREMENTS OF A CAVs FLEET

From the requirements (Section 2) and the analysis of the different systems, we propose a guideline to design CAVs fleet, which consists in high level design principles concerning decentralisation, communication, robustness, knowledge of the scenario, mixed traffic and scalability.

All the CAVs in the studied systems have the same design and consequently the same behaviour in a given situation. However, in real life they have several designs leading to different behaviours in the same situation. Thus, the results given in these studies have to be taken with hindsight.

Because centralised systems use a lot of information considered as safe, regardless of uncooperative behaviour or incidents, **a local control of the CAV** using partial perceptions and able to adapt to unexpected situations is mandatory.

In order to avoid bottlenecks of communications, the use of a centralised system for communications should be avoided. However, each CAV should not share all its data to all other CAVs because the volume of communications will explode. It is required for a **CAV to learn which information is useful** to share for a situation in order to limit their amount and to facilitate the decision process.

Even faced to unknown situation, a robust CAV must be able to take a correct decision. Moreover,

Table 1: Synthesis of Connected and Autonomous vehicles Systems.

System	Locality	Travel Time	Pollution	Smooth Driving	Data volume	Robustness	Scenario Knowledge	Mixed Traffic	Scaling	Simulation Model
<b>Traffic flow : Choose the best path<sup>1</sup> or Smooth driving<sup>2</sup></b>										
Barthelemy et al. <sup>1</sup>	++	+	NA	NA	+	+	+	+ -	+	Macro
Mouhcine et al. <sup>1</sup>	+	+	NA	NA	+	-	+	-	+	Macro
Di Vaio et al. <sup>2</sup>	++	NA	+	+	-	+	+	+	+ -	Micro
Taguchi et al. <sup>2</sup>	++	NA	+	+	-	-	+	-	-	Micro
Lin et al. <sup>1</sup>	+	+	NA	NA	+	-	-	-	+	Micro
Englund et al. <sup>2</sup>	+ -	NA	NA	+	+ -	+ -	+	-	-	Real
Agarwal et al. <sup>2</sup>	- -	+	NA	+	+	+ -	-	-	-	Micro
Ioannou et al. <sup>2</sup>	++	+	+	NA	+	+	+	-	+	Micro
<b>Intersection</b>										
Jin et al.	- -	NA	-	+	+ -	-	+	-	+	Micro
Kamal et al.	- -	NA	+	+	+ -	-	+	-	+	Micro
Gaciarz et al.	+	+	NA	+	+ -	+	+ -	-	+	Macro
<b>Lane merging</b>										
Rios-Torres et al.	+ -	NA	+	+	+	-	-	+ -	-	Micro
Wang et al.	+ -	+	+	+	-	-	-	+ -	-	Micro
Mosebach et al.	++	NA	NA	+	++	+	-	-	+ -	Micro
Sobieraj et al.	++	NA	NA	+	+	-	+	++	+	Micro
Gueriau et al.	++	+	NA	+	+ -	+	-	++	+	Micro

it should be able to learn which behaviour is better for the next time a similar situation will be encountered. Because the amount of information available is continuously evolving and it seems unlikely that the same data would be expressed in the same way by two different vehicles, a CAV should **learn continuously the usefulness of information without semantic**. At first, the CAV would drive safely, like a new driver, and it will gradually acquire experience while driving, improving its behaviour. A CAV that aims at managing every road situation needs to be able to exchange its data and to negotiate with other vehicles. Moreover, it needs to be able to cooperate with other connected entities to refine its knowledge of the context and thus, it will lead to have a better behaviour (Di Vaio et al., 2019; Barthelemy and Carletti, 2017).

It seems that situation awareness can be a barrier because it is impossible to model all the possible situations in beforehand. It is desirable for a CAV to be able to understand the current situation so that it can adapt its behaviour to it. Coordination between vehicles will make it possible to solve many traffic situations. So, **cooperation and negotiation must be implemented in each CAV** (Llatser et al., 2015; Gaciarz et al., 2015; Wang et al., 2018b).

The presence of non CAV could be addressed by considering them as non cooperative entities with unpredictable behaviour. The CAV must be able to **identify them and learn how to interact with them**, with avoidance strategy (Degas et al., 2019) and the exchange of information without communication.

In the validation step, the evaluation of the CAVs fleet must be done **simultaneously at the micro and**

**macro levels**. The first one is necessary to observe how a CAVs fleet manages a precise situation while the second one would be used to observe the result at a larger scale.

If the CAVs fleet design follows the guideline, an improvement of the road traffic (pollution, travel time and smooth driving) will be observed.

## 8 CONCLUSION

This paper proposes a state of the art of CAVs systems. An analysis of the papers is made according to a set of criteria that are presented beforehand. It is shown that communication exchange and coordination between vehicles allows them to better manage the situations they encounter. After comparing and analysing different systems, a guideline is proposed, mainly: local control and interactions, cooperation and negotiation between CAVs and lifelong learning.

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