RevEAL: Reliability vs Energy Optimization for Autonomous Vehicles Using Large Language Models

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Abstract

As autonomous vehicles continue to gain traction, the need for highly accurate and energy-efficient systems to enhance safety and performance becomes increasingly critical. Effectively managing the tradeoff between energy consumption and reliability in these systems requires the ability to predict various operational conditions. With the rapid advancements in Large Language Models and models like ChatGPT, new opportunities for improving predictions in autonomous vehicle operations have emerged. This paper proposes RevEAL, which utilizes Large Language Models as map reader co-drivers to predict essential parameters for optimizing the energy-reliability balance during AV operations. Experimental results demonstrate that RevEAL achieved up to 67% driving accuracy and a 53.4% reduction in total energy consumption, depending on the operating scenario. Additionally, RevEAL reduced power consumption by 33% compared to selected baseline configurations, highlighting its strength in maintaining a practical balance between navigation performance and energy efficiency. These findings underscore the potential of RevEAL to contribute to the development of more adaptive and resource-aware autonomous driving systems.

Index Terms

Large Language Models, Energy Consumption, Reliability, Accuracy, Autonomous Vehicles

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1 Introduction

Autonomous Vehicles (AVs), as one of the leading innovations in the transportation industry, are set to revolutionize the future of roads and everyday life. These vehicles, leveraging advanced technologies, are evolving into fully autonomous systems capable of performing all driving tasks without human intervention [1]. The technologies employed in these vehicles integrate multiple sensors such as cameras, LiDAR, radar, and global navigation systems with advanced deep learning algorithms, enabling them to perceive the environment, make decisions, and control the vehicle. AVs utilize intelligent software that processes sensor data to perform tasks such as obstacle detection, lane-keeping, and responding to emergency situations. This level of technology not only enhances features like emergency braking and adaptive cruise control but also marks a significant step toward reducing human errors in driving [2].

Despite these advances, energy consumption remains a critical challenge for AVs [3]. These vehicles rely on an array of high-precision sensors, powerful processors, and complex mechanical components, all of which consume significant energy. Devices such as high-resolution cameras, LiDAR systems, and advanced processors are among the primary sources of energy consumption in these vehicles [4]. Optimizing energy consumption in AVs is of great importance. Reducing energy usage not only extends the range of electric vehicles but also minimizes the need for recharging and improves operational efficiency [5]. At the same time, the accuracy and reliability of these systems must not be compromised. High algorithmic precision can enhance road safety and prevent accidents. Additionally, adaptability to diverse road conditions and lower operational costs are crucial steps toward the sustainable development of this technology [6].

One innovative approach to reducing energy consumption in AVs is the use of Large Language Models (LLMs) as intelligent collaborators for predicting and adjusting critical parameters. These models can optimize autonomous vehicle performance by balancing accuracy, reliability, and energy consumption. LLMs, such as ChatGPT®, utilize advanced deep learning techniques, particularly transformer architectures, and possess the capability to analyze and generate human-like text based on vast amounts of data. Through natural language processing, these models can handle complex tasks such as interpreting environmental data and predicting route challenges [7]. In the domain of AVs, LLMs can serve as advanced assistants for improving navigation and reducing energy consumption. By accurately predicting environmental conditions and providing appropriate decisions, they can create more efficient movement patterns. For instance, they can optimize acceleration and minimize unnecessary braking, resulting in smoother driving and significant energy savings [8].

In this paper, we introduce RevEAL as an innovative approach that utilizes LLMs to optimize energy consumption and navigation accuracy. RevEAL predicts critical environmental parameters and intelligently manages mechanical actuators and computational resources to strike a balance between energy efficiency and reliability. This method employs ChatGPT® as a collaborative navigator, and its performance was tested in real-world scenarios using an autonomous robot car equipped with a Raspberry Pi board and DC motors.

The key features of RevEAL include:

- Using LLMs to predict environmental parameters and make intelligent decisions.
- Incorporating internal obstacle detection algorithms for identifying and navigating both static and dynamic obstacles.
- Introducing a control policy for optimizing motor speed and computational precision.

Experimental results demonstrate that RevEAL improved navigation accuracy by 33% compared to key baseline scenarios, while achieving a 53.4% reduction in total energy consumption. Additionally, RevEAL demonstrated a 33% reduction in power consumption, highlighting its ability to maintain an exceptional balance between precision and energy optimization. These findings underscore the potential of RevEAL to advance the field of AVs by enabling efficient and reliable performance across varying operational environments.

The structure of this paper is as follows: Section 2 reviews related work on AVs and LLM. Section 3 discusses related studies. Section 4 explains the proposed RevEAL approach, and Section 5 presents simulation results.

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Finally, Section 6 concludes the paper.

2 Background

This chapter focuses on the technology of AVs and examines the crucial impact of energy consumption in these vehicles. It will provide an introduction to LLMs and their applications in AVs. The goal is to offer a thorough overview of the technological advancements and challenges related to AVs, as well as the role of LLMs in improving their performance and accuracy.

2.1 Autonomous Vehicle Technology

The technology behind AVs consists of several essential components, including sensors, algorithms, and control systems. Sensors are responsible for monitoring the environment, detecting obstacles, and facilitating navigation. These include cameras, LiDAR, radar, and ultrasonic sensors, which allow the vehicle to accurately assess its surroundings and provide the necessary data for real-time, precise decision-making [9].

Algorithms are another critical element of AVs technology. These algorithms process the data collected from sensors and make decisions to guide the vehicle. They encompass artificial neural networks, machine learning techniques, and decision-making algorithms that analyze environmental data, select optimal paths, and respond appropriately to various situations. Advanced algorithms can manage complex behaviors such as lane changes, stopping at red lights, and collision avoidance with high accuracy [10].

Control systems, which are also vital, implement the commands provided by the algorithms. These systems include both electronic and mechanical controllers that interact directly with the vehicle's physical components, such as the steering, brakes, and throttle. Control systems must execute commands with high precision and speed to ensure the vehicle moves safely and efficiently. Their role is crucial in maintaining the stability and accuracy of AVs operations [11].

Integrating software and hardware in AVs is also of great significance. This integration involves the full coordination between sensors, algorithms, and control systems, enabling the vehicle to operate seamlessly and cohesively. Advanced software must process a variety of data rapidly and relay critical information to the control systems in real-time. Moreover, the hardware must exhibit high precision and stability to ensure the accurate execution of software commands [12].

In conclusion, the success of AVs technology relies on the coordinated and effective interaction between all of these components. Each part must function perfectly to ensure the vehicle operates safely and efficiently. Therefore, continuous advancement in sensors, algorithms, and control systems, along with the integration of software and hardware, is essential for the progress and widespread adoption of AVs [9].

2.2 Energy Consumption in AVs

As shown in Fig. 1, the sensors in AVs, such as cameras, LiDAR, and radar, generate vast amounts of raw data that the vehicle's computing unit must process. The data rate produced by these sensors varies based on their technical specifications, including factors such as generation, bit rate, and recording features [1]. For instance, the data rate of a LiDAR sensor may differ from that of a camera, as each sensor captures different types of data from the surrounding environment that require distinct processing.

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These variations directly influence the energy consumption of AVs. Energy consumption in AVs can generally be divided into three main categories. The first category is energy consumption from the vehicle's sensors, computing devices, and mechanical components, which accounts for the largest portion of energy usage. The second category involves energy consumption from infrastructure sensors and vehicular network communications, which are crucial for coordination and data exchange between vehicles and infrastructure [13]. The third category relates to energy consumption in the backend, including Edge servers and local and central servers that store and process historical data. The level of autonomy in AVs plays a significant role in determining energy consumption, as higher levels of autonomy necessitate more sensors, computing units, and controllers [6].

Vehicle autonomy is categorized into six levels, each with specific sensor and operational requirements. At Level 0, there is no automation, and all driving tasks are performed solely by the driver. Level 1 involves driver assistance, where some driving tasks are supported by vehicle sensors, but the driver remains in full control. In Level 2, partial automation is achieved, with certain tasks like adaptive cruise control and emergency braking handled by the vehicle's computing unit, although the driver must stay engaged and ready to take control.

Level 3 introduces conditional automation, where the vehicle can autonomously perform some tasks, but the driver must be prepared to intervene when required. At Level 4, high automation is achieved, allowing the vehicle to handle all driving tasks under specific conditions, though the driver may still take control if needed. Finally, Level 5 represents full automation, where the vehicle can autonomously complete all driving tasks under all conditions, although the driver retains the option to control the vehicle if desired [1].

The high energy consumption in AVs arises from the use of compute-intensive algorithms and processing units, such as graphics processors, which are necessary for perception and visual applications. A highly effective strategy to reduce energy consumption in AVs is route planning and optimization [14], [15]. This technique utilizes advanced algorithms to determine the most efficient route, minimizing both travel time and distance, thereby significantly reducing energy usage. Furthermore, adopting adaptive and predictive models to optimize energy consumption is essential. These models analyze historical data and forecast future energy needs to enhance vehicle energy efficiency [16]. For example, employing LLM to predict road conditions and adjust vehicle speed and accuracy can be an effective approach to optimizing energy consumption [7].

2.3 Large Language Models

LLMs are deep learning models designed to process and generate natural language. These models leverage vast neural networks and massive datasets from a wide range of sources to understand and generate human language [17]. Notable examples of LLMs, such as GPT-3 and GPT-4 from OpenAI, have been trained with billions of parameters and are capable of performing various tasks like translation, text generation, and question answering. These models primarily rely on advanced machine learning techniques like deep learning and Transformers to detect intricate patterns and relationships in words and sentences [7].

These models typically receive input text and analyze it through deep neural networks to extract meaning, detect patterns, and generate appropriate outputs. The results can be delivered in the form of human-readable text (e.g., responses or summaries) or as numerical embeddings that capture semantic information for further processing.

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Such output forms help the model recognize and process complex relationships between concepts, improving both efficiency and accuracy [18].

In the context of AVs, LLMs play a critical role in map reading and navigation. By processing textual and visual data, they can handle complex geographic information, analyze traffic and environmental conditions, and help determine optimal driving routes, ultimately reducing travel time and enhancing efficiency [7].

In addition, LLMs significantly improve the accuracy of autonomous systems. By learning from historical data, these models can analyze diverse inputs and make highly accurate decisions. They can intelligently identify road obstacles, speed limits, and sudden route changes, enabling the AVs to plan appropriate responses. This capability ensures safer operation, reduces the likelihood of accidents, and provides a better experience for passengers. Overall, LLMs play an essential role in enhancing both the accuracy and efficiency of navigation and autonomous driving systems [8].

3 Related Work

This section highlights several studies relevant to our work, which focus on enhancing routing accuracy and optimizing energy consumption in AVs.

In [5], the authors explore an energy optimization controller for mobile robots, utilizing event-based cameras for real-time vision operations. The controller regulates both the CPU's voltage/frequency and the motor voltage simultaneously to minimize energy use. The core concept of this paper is that controlling the robot's speed and CPU voltage/frequency separately does not necessarily yield the most efficient energy use. Instead, optimal energy efficiency is achieved through coordinated management of computational and mechanical controls. To facilitate this, a fast hill-climbing optimization algorithm is introduced, which determines the best configuration for the CPU and motor during runtime, adapting to new environments. Experimental results show that this approach achieves average energy savings of 50.5%, 41%, and 30% in low, medium, and high complexity environments, respectively, compared to baseline methods. These results were observed in a robot equipped with brushless DC motors, a Jetson TX2 computational unit, and a DAVIS-346 event-based camera.

In [17], researchers investigate the potential of using LLM like ChatGPT as driving assistant for vehicles. The study aims to bridge the gap between human intentions, machine comprehension, and execution by using LLMs as a "Co-Pilot" to assist with specific driving tasks. The framework is enhanced using a technique known as black-box tuning. In experiments, the Co-Pilot successfully performed tasks such as path control and route planning through natural language processing. While not without limitations, the study demonstrates the high potential of this framework for broader applications in AVs, particularly in improving human-machine collaboration in driving scenarios.

Wan et al. in [19] present a framework named BERRY, which enhances energy efficiency and bit error resilience in reinforcement learning models for autonomous systems. While reducing the operating voltage saves energy, it also increases the likelihood of bit errors, which can compromise system performance and safety. BERRY combines offline and onboard robust learning, enabling systems to operate reliably at lower voltages, thus achieving notable energy savings. The experimental findings indicate that BERRY can reduce energy consumption by up to 15.62% and increase mission success rates by up to 18.51%.

In [13], the authors propose the EcoFusion method, which aims to reduce energy consumption in AVs while

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maintaining object detection performance. EcoFusion dynamically adjusts sensor fusion and the fusion location based on environmental conditions, thereby optimizing both energy use and detection accuracy. The core idea is that different driving conditions, such as city driving or rainy weather, require different sensor configurations. By identifying these conditions, the system can adapt sensor fusion to achieve optimal energy consumption. The method demonstrates a 9.5% improvement in object detection performance compared to traditional sensor fusion approaches. Furthermore, EcoFusion reduces energy consumption by around 60% and latency by 58% when compared to the Nvidia Drive PX2 platform.

4 RevEAL in Details

Energy consumption and reliability are critical factors in the performance of AVs. Each component, including sensors, computational units, and mechanical systems, independently impacts the energy usage of these vehicles. However, independent control of speed (managed by the mechanical unit) and CPU processing (handled by the computational unit) does not necessarily lead to an optimal solution. In other words, merely reducing speed or processing accuracy cannot guarantee reduced energy consumption. Achieving maximum efficiency requires coordinated and simultaneous control between computational and mechanical systems [5].

Therefore, it is essential to design a system capable of dynamically adjusting speed and processing accuracy based on environmental conditions and road changes. Such a system can significantly reduce energy consumption while maintaining navigation accuracy and establish an optimal balance between energy efficiency and reliability, where reliability in this study is defined as navigation accuracy and obstacle detection in the environment. To achieve this goal, we introduce RevEAL. This system utilizes LLM chat bot as co-driver map readers to analyze the operational route, identify obstacles and appropriate strategies for handling them, and finally adjust critical vehicle parameters such as speed and image processing accuracy to achieve an optimal balance between accuracy and energy consumption.

Fig. 2 illustrates the architecture of RevEAL, which consists of two main components: the computational unit and the mechanical unit. In the computational unit, data such as environmental conditions, road images, existing obstacles, current speed, and image processing accuracy are sent to the Prompt Generator. This component generates a prompt based on the received data and sends it to the LLM Chatbot. The chatbot analyzes the travel environment, including road curvature, straightness, and obstacles, and generates an appropriate response, which is then forwarded to the Management Unit. Based on the road, the chatbot makes decisions such as increasing or decreasing the speed or accuracy. The Management Unit decodes the chatbot's response and extracts the necessary information.

The extracted data, which includes vehicle speed, and the desired frames per second (FPS) for image processing, is sent to the respective control units. For straight paths, the chatbot suggests specific values for speed and FPS, while different values are recommended for curved paths. FPS-related data is forwarded to the Image Processing Unit, while speed-related data is sent to the Speed Control Unit. The processed information in the Image Processing Unit is applied to the Direction Control Unit to adjust steering and vehicle navigation.

The Speed Control Unit calculates the defined speed and transmits the necessary commands to the mechanical unit's motor. The motor activates either the right or left motor (or both) depending on the direction and degree

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of curvature.

Another essential component of the RevEAL architecture is the Energy Measurement Module, which monitors the energy consumption of the Computational Unit and the Mechanical Unit (motors). The measured data of each unit's power consumption is sent to the Energy Measurement Unit, where power consumption is calculated. The results are also sent and stored on a cloud server using the MQTT protocol.

This stored information can later be used to improve algorithms and further optimize energy consumption, as well as enable deeper analysis of the collected data to understand energy consumption patterns and improve overall system performance. The calculated energy is also passed to the Feedback Management Unit for making decisions that adjust the system's speed and accuracy.

In RevEAL, the process of energy measurement begins with calculating the input voltage using the digital output of an Analog-to-Digital Converter (ADC), as shown in Eq. (1) [20]:

$$InputVoltage = \frac{Dout \times Vmax}{Dmax} \tag{1}$$

Here, *Dout* represents the digital output from the ADC, *Vmax* is the maximum measurable analog voltage, and *Dmax* is the maximum digital value the ADC can output.

Next, the current is calculated by dividing the obtained input voltage by the value of the shunt resistor 2 as shown in Eq. (2):

$$Current = \frac{InputVoltage}{Shunt\ Resistance\ Value} \tag{2}$$

Finally, the power consumed by a device (either mechanical or computational) is calculated using the following Eq. (3):

$$Power = Current \times Device\ Voltage \tag{3}$$

These calculations enable precise energy tracking for both mechanical and computational components, forming the basis for adaptive control and optimization within the system.

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5 System Setup and Results

To evaluate the performance of the RevEAL method, we designed and implemented an AVs robot in a real-world environment. Fig. 3 shows the implemented robot. This implementation consists of two main parts. The first part is the processing unit, which uses a Raspberry Pi 4B board to handle computational tasks, prompt generation, and server communication. Additionally, a Raspberry Pi camera is used for video capture and image processing. The second part is the mechanical unit, responsible for controlling the speed and movement of the robot. The motors are controlled using an L298N motor driver, while the wheels are powered by DC motors.

To implement the computational unit's code, Python programming language was used. Line detection algorithms and the OpenCV [21] library were utilized to identify road lines and adjust the navigation direction. Motor control commands were sent using the RPi.GPIO library, which manages the Raspberry Pi's output pins. The wheel rotation speed was controlled through Pulse Width Modulation (PWM).

Road line information was obtained via image processing and used to adjust the robot's movement direction by sending control commands to the motors. Additionally, obstacles on the road were initially detected using the OpenCV library. However, advanced obstacle detection was handled by a chatbot.

Fig. 4 shows the test environment and the AV evaluation. The test track was designed in an infinity shape, including straight and curved sections and four crosses. For performance evaluation, the AV was tested on this track, with various obstacles such as stationary objects (e.g., trees) and moving ones (e.g., vehicles or pedestrians) placed along the road.

A module was designed using a shunt resistor to measure the energy consumption of computational and mechanical units within the energy management system. This module is positioned between the power source and the computational and mechanical units to measure the voltage consumed by each section, ultimately calculating the power consumption of each unit.

As shown in Fig. 5, we illustrate how a LLM performs step-by-step logical reasoning and decision-making in an environment with obstacles. For LLM Chatbot, we use chatGPT by OpenAI to get image information and pictures from vehicles and process that. The autonomous vehicle captures an image of the road and environment using an onboard camera. then, Basic visual analysis (e.g., road curvature, object presence) is performed locally, and the extracted context is encoded into a structured natural language prompt. This prompt is sent to the LLM, asking it to decide whether to increase or reduce vehicle speed and whether high or low image processing precision (FPS) is needed, based on the visual context. In the provided image, the road is identified as curved, requiring the AV to make appropriate adjustments. For safe navigation, the vehicle should reduce speed to maintain control while negotiating the curve. Adjusting speed ensures the vehicle remains stable and avoids deviation from the road. The image processing quality is high, as the road's path and curvature are clearly detected, allowing the vehicle to make accurate decisions regarding its trajectory. This decision-making is based on analyzing the road's direction and ensuring smooth movement while minimizing risks. Additionally, an internal obstacle detection algorithm ensures that whenever an obstacle is detected, the vehicle steers around it and passes safely alongside.

To evaluate the effectiveness of the proposed method, it was compared against the Self-Contained Logic approach, where all processing and decision-making are performed on a Raspberry Pi, as well as four different

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baseline scenarios: 1) high speed with high FPS (speed: 1.26 km/h, FPS: 30), 2) low speed with high FPS (speed: 0.98 km/h, FPS: 30), 3) high speed with low FPS (speed: 1.26 km/h, FPS: 5), and 4) low speed with low FPS (speed: 0.98 km/h, FPS: 5). The experiments were conducted under similar conditions for all scenarios, including the proposed method, with the same distance considered for testing. To assess reliability and navigation accuracy, the ability to stay on the designated path, and obstacle avoidance were evaluated.

As illustrated in Fig. 6, the proposed RevEAL method achieved superior results compared to other scenarios. In terms of Non-Collision Probability, the RevEAL approach experienced no collisions, outperforming all other scenarios, particularly the Low FPS conditions at High and Mid Speeds, which recorded a 0% Non-collision rate.

For Driving Accuracy, as shown in Fig. 7, the RevEAL method achieved a driving accuracy of 0.67, which is substantially higher than High FPS at High Speed (0.25) and Low FPS at High Speed (0.14). It also outperforms both High FPS and Low FPS scenarios at Mid Speed (each at 0.40), and shows a better balance than the Low FPS configuration at Low Speed (0.50). Although its accuracy is lower than the best-performing scenario—High FPS at Low Speed (1.00)—the RevEAL method offers a strong compromise between accuracy and energy efficiency across all speed conditions.

This result demonstrates that while RevEAL may not always achieve the highest raw accuracy, it provides a consistently reliable and adaptive performance that is well-suited for dynamic environments, especially when considered alongside its substantial energy savings and collision-free operation.

As illustrated in Fig. 8, the RevEAL method demonstrates significant improvements in both power consumption and energy efficiency compared to other scenarios. In terms of Power Consumption, the RevEAL approach achieves a balanced trade-off between Computational Power (5.73 W) and Mechanical Power (5.07 W). Compared to the High FPS scenarios across different speeds, the computational power remains lower than the 4.18 W observed for High FPS and closer to the Low FPS values (3.07 W).

For Energy Consumption, as shown in Fig.9, the RevEAL method achieves 350 J, which is significantly lower than all other scenarios. Specifically, compared to the worst-case scenario (Low FPS at Mid Speed with 751 J), the proposed method reduces energy consumption by 53.4%. Compared to High FPS at High Speed (535 J), RevEAL achieves a 34.6% energy improvement. Overall, the RevEAL method reduces total energy consumption by up to 53.4%, while maintaining an efficient balance between computational and mechanical power. This highlights the method's superiority in achieving energy optimization without compromising performance.

6 Conclusion

The proposed RevEAL method presented in this paper demonstrates substantial improvements in both AVs navigation and energy efficiency. Through comprehensive testing and comparison with baseline methods, RevEAL has shown superior performance in both navigation accuracy and energy optimization. The integration of advanced algorithms for map reading, route optimization, and energy-efficient models has resulted in a robust system that enhances AVs operations.

One of the key advantages of RevEAL lies in its ability to dynamically manage energy consumption across computational and mechanical subsystems, while still ensuring competitive navigation accuracy. The experimental results reveal that although RevEAL does not always outperform every baseline in isolation, it achieves 67%

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accuracy in dynamic conditions, surpassing several static high/low FPS configurations in more rigid settings.

Furthermore, RevEAL achieved remarkable energy savings, reducing total energy consumption by up to 53.4%. The method demonstrated a 53.4% reduction in energy consumption compared to the worst-case Low FPS at Mid Speed scenario and a 34.6% improvement in energy efficiency compared to High FPS at High Speed. Additionally, the system showed an efficient balance in power consumption with a 33% reduction compared to baseline methods. These results emphasize the effectiveness of the approach in optimizing energy usage without compromising performance or accuracy.

In conclusion, RevEAL represents a promising advancement in AVs technology. By effectively managing the trade-off between energy consumption and navigation accuracy, this method opens new possibilities for more efficient and reliable autonomous systems. Future work may focus on refining optimization techniques and expanding the application of the approach across various platforms and environments, leading to further improvements in AVs capabilities.

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List of Figures and Tables Captions

Figures

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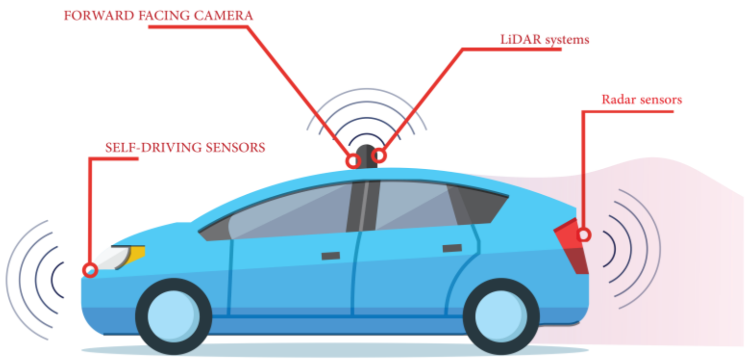

Fig. 1: Data generated by the automotive sensors

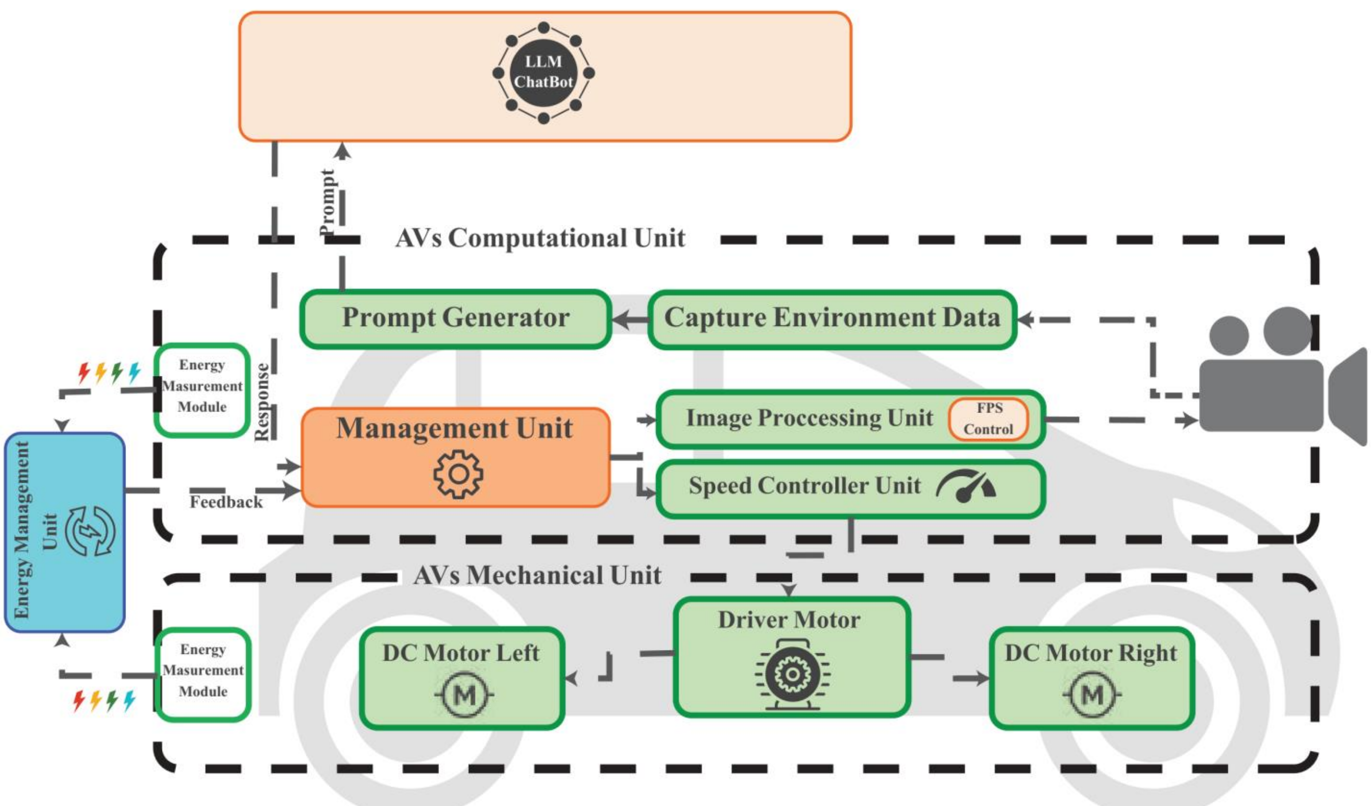

Fig. 2: RevEAL Architecture

Fig. 3: RevEAL AVs Implemention

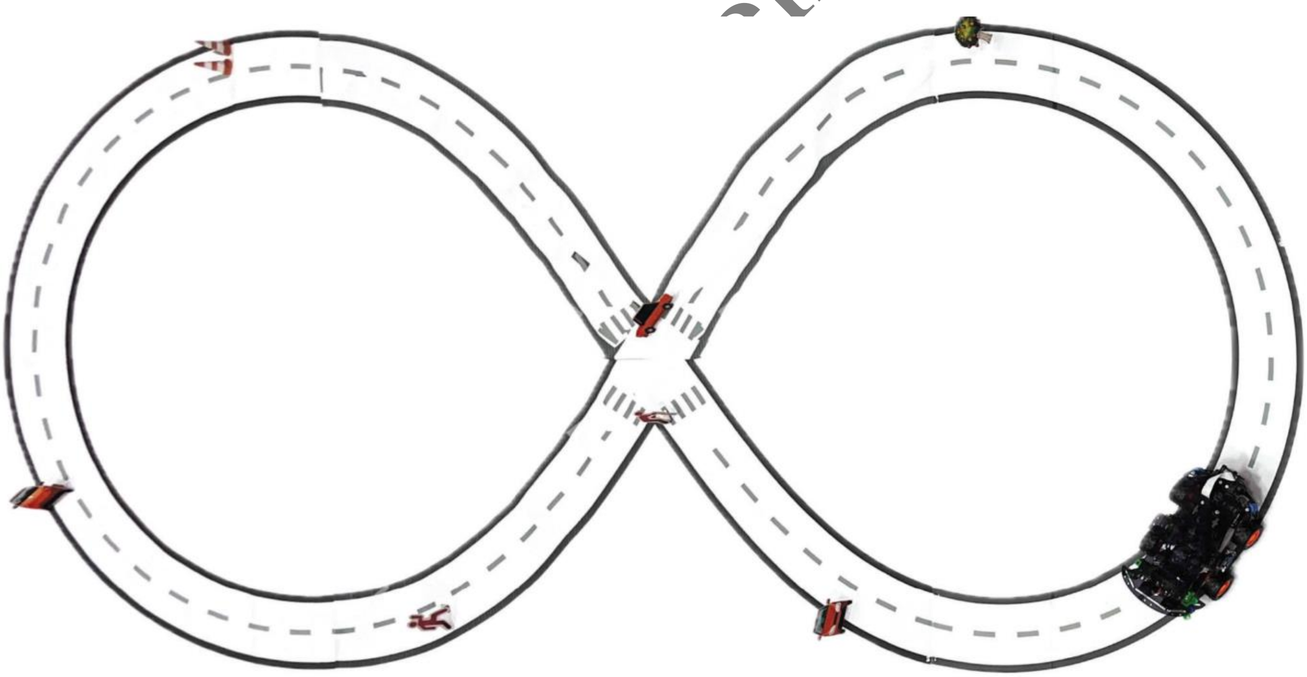

Fig. 4: Experiments and Test of AVs

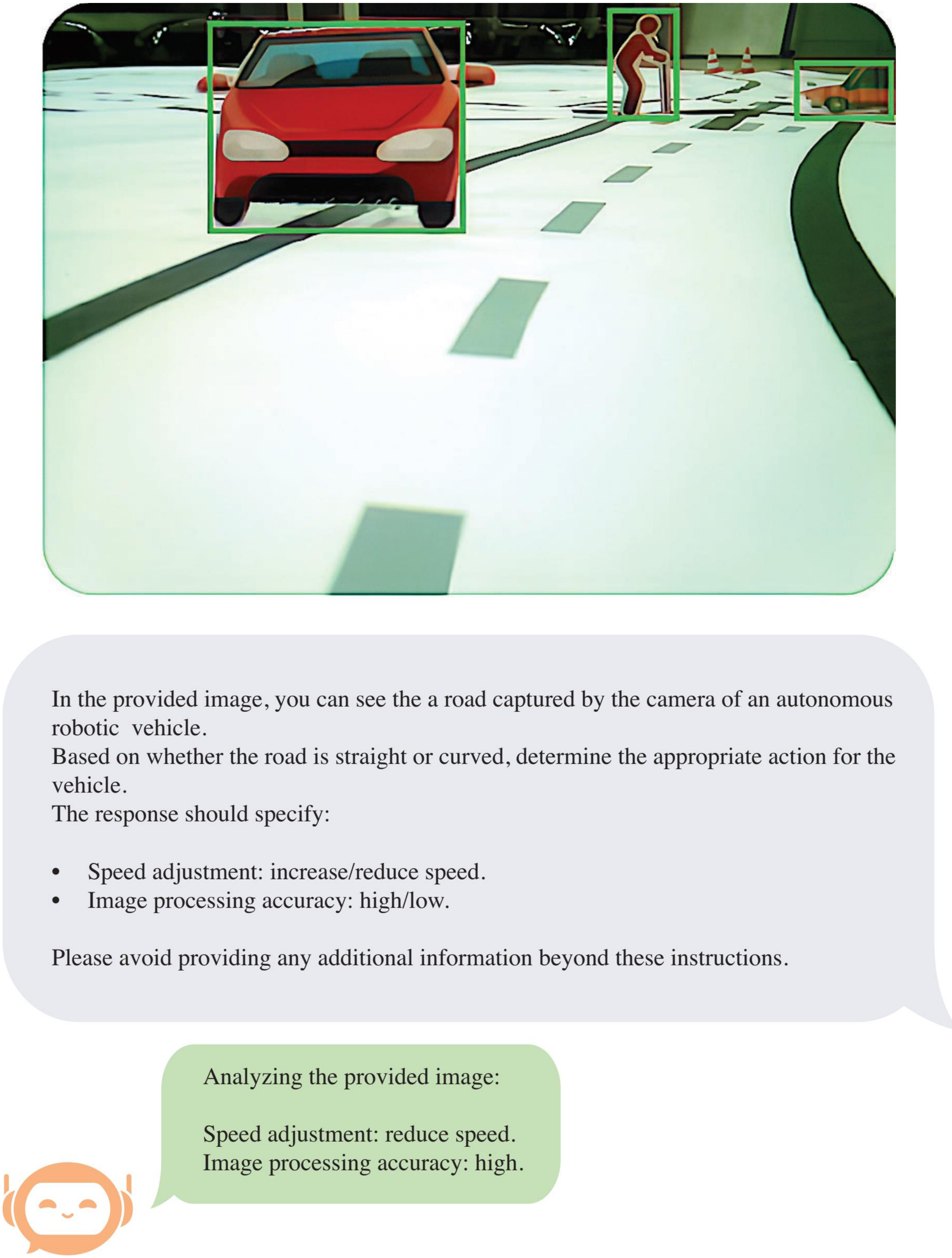

Fig. 5: Example of step-by-step reasoning and decision making in a complex environment

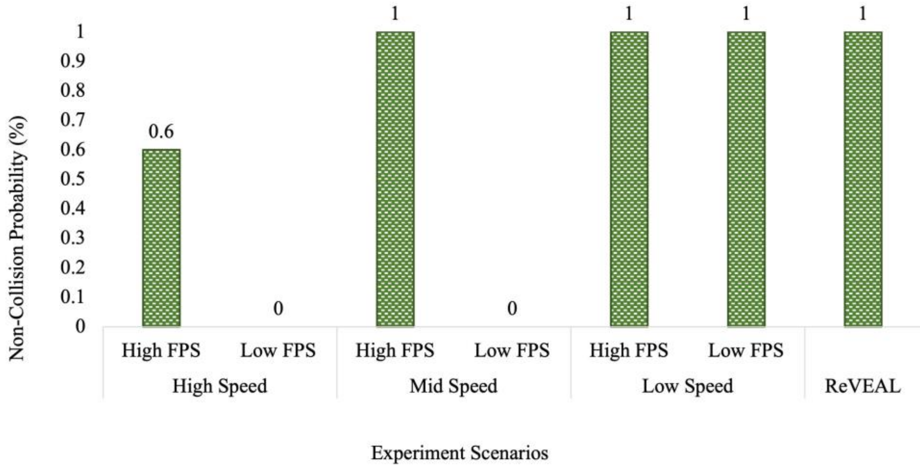

Fig. 6: Probability of Non-Collision: RevEAL Compared to Other Scenarios

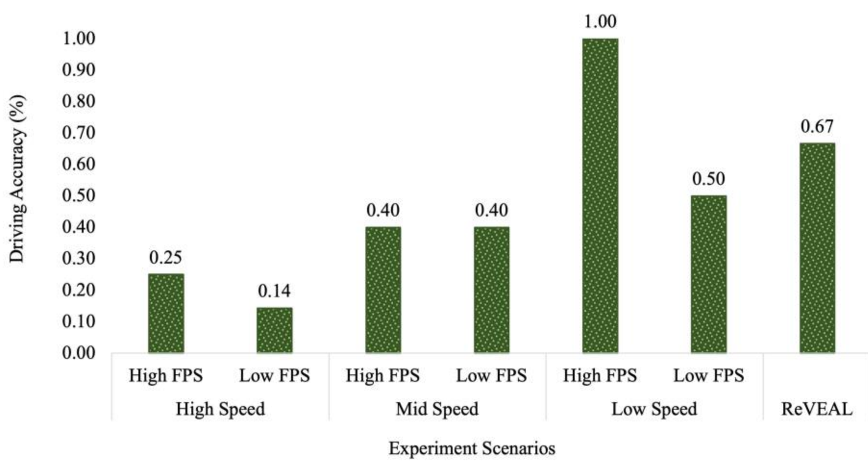

Fig. 7: Driving Accuracy of RevEAL compared to other Scenarios

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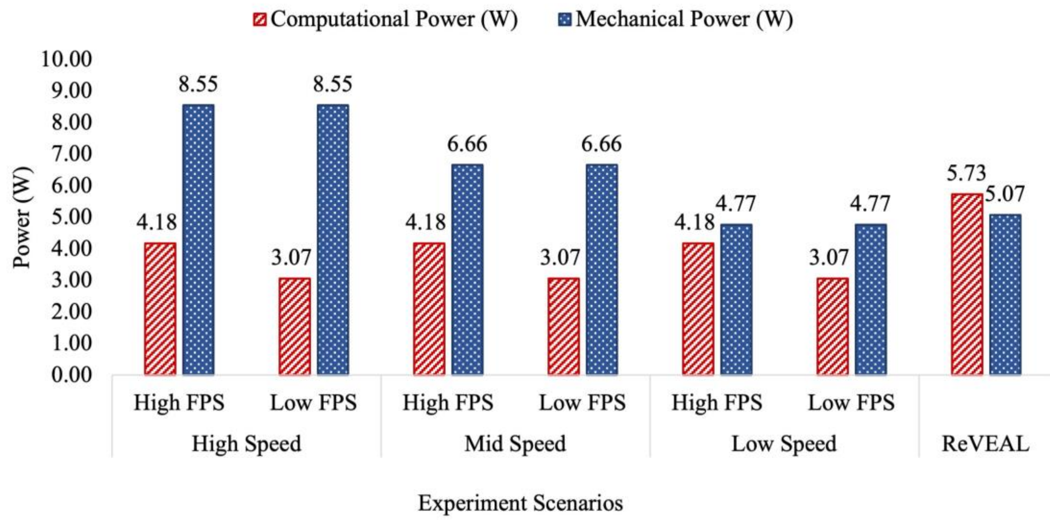

Fig. 8: Power Consumption of Mechanical and Computational units

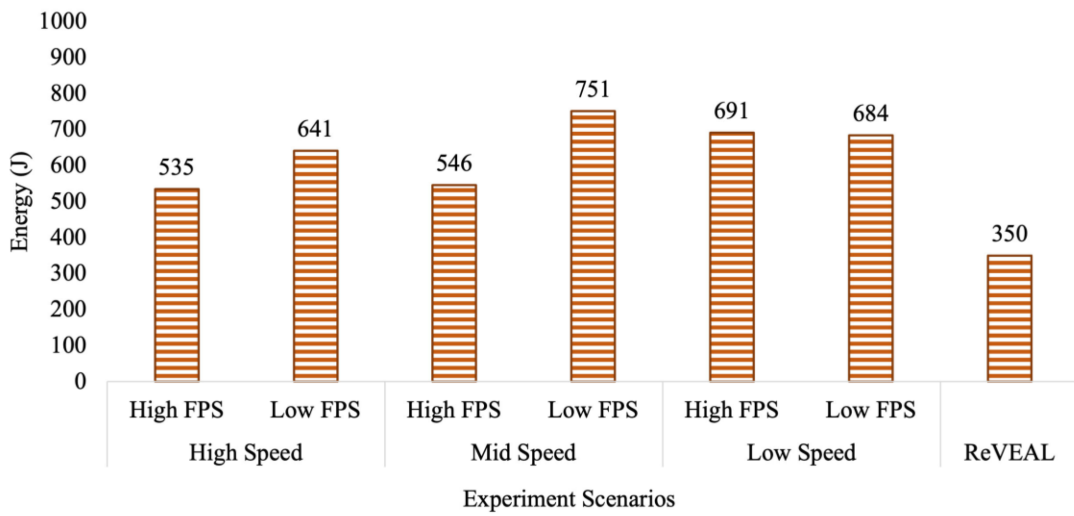

Fig 9. Total energy consumption of RevEAL compared to other scenarios.

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Mahdieh Aliazam received her M.Sc. degree in Computer Architecture Engineering from the Iran University of Science and Technology (IUST), Tehran, Iran, in 2023, and is currently pursuing her Ph.D. degree in Computer Architecture. She is a member of the Cyber-Physical Systems Laboratory (CPSLab) at IUST and has been involved in several hardware development projects. She has also served as a visiting lecturer. Her research interests focus on energy efficiency, performance optimization, and reliability in cyber-physical and embedded systems. She also works on fault-tolerant system design, low-power architectures, and edge computing infrastructures. In addition, she is interested in the applications of artificial intelligence and machine learning in emerging domains such as autonomous vehicles, healthcare, and smart cities.

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