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Adaptive Cruise Control System: A Literature Survey

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ABSTRACT

Adaptive cruise control (ACC) assists automobiles in preserving a safe following distance and adhering to speed limits. This advanced driver-assistance system (ADAS) modifies the car's speed to keep a safe gap from oncoming traffic. All vehicle types include combustion engines, pure electric vehicles, hybrid electric vehicles, and methods of operation; controllers are designed to react to cruise control signals and provide an efficient route profile according to the surrounding environment and instantaneous vehicle performance characteristics. ACC uses a perception system to measure the forward vehicle's current distance, speed, and acceleration relative to the host vehicle. Some of these systems use lasers, radar, cameras, or a combination of these sensors to determine the distance and speed of the leading vehicle. Other systems even use wireless communication to collect data from surrounding vehicles. ACC can help reduce stress on long drives, increase road safety, prevent accidents, and enhance traffic flow energy efficiency. This paper aims to introduce a comprehensive study of the research on ACC and mention different controlling techniques used to deal with the problem. Furthermore, a discussion of each method with its cons and pros is mentioned too. First, an introduction to the ACC system and control approaches with a brief discussion of their main principle is presented. Next, various application cases of ACC are presented. These applications include lateral dynamics, wireless technology, energy vehicles, navigation data, and practical experimental tests. At last, future guidance and challenges are discussed.

Keywords: Cooperative adaptive cruise control, Adaptive cruise control, Electric vehicle, Hybrid electric vehicle, Vehicle's dynamics.

1. INTRODUCTION

In recent years, the rising rate of automobiles has exceeded the expansion rate of roadway resources, which results in serious traffic congestion issues and accidents **(Sun et al., 2017)**. Therefore, it is essential to enhance vehicle controls to lower the number of accidents and ensure safety measures. As a type of Advanced Driver Assistance System (ADAS), ACC

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automatically modifies the host vehicle's velocity to track the preceding vehicle based on estimating the traffic in the vicinity. The main goal of ACC systems is to enhance the functionality of traditional cruise control systems. In addition to preventing congestion and traffic accidents, ACC can enhance economic efficiency and lessen drivers' workloads. This review considers the ACC as a controller that enables the ACC (host) vehicle to track the preceding vehicle, see **Fig. 1**. ACC is an advanced feature that goes beyond the basic functionality of traditional cruise control (CC). Cruise control allows the driver to select and maintain a desired speed without requiring continuous input of accelerator pedals. Unlike ACC, cruise control does not automatically change the vehicle's speed according to the distance from the preceding vehicle. In addition, when a vehicle accelerates, decelerates or cruises at a steady speed, it emits different quantities of pollutants per unit time or distance **(Al-Neami et al.,2006)**. ACC utilizes sensors such as cameras, lasers, radar equipment, and intelligent algorithms to adjust the vehicle's speed to varying traffic conditions, providing drivers with added safety and convenience. Two modes of longitudinal control are used in a typical ACC system. The speed control mode (cruise mode) is used if no vehicle occurs before the host vehicle. Meanwhile, the distance control mode (following mode) becomes active when a preceding vehicle is ahead.

There are four main parts in any typical ACC system: sensors, actuator, human-machine interface, and controller, as shown in **Fig. 2 (Yu and Wang, 2022)**. Several sensors collect and transfer motion information from the host and preceding vehicles to the other system components. Range sensors such as cameras, radar, or lidar send information about the preceding vehicle. Different sensor types, such as vehicle speed sensor, throttle position sensor, etc., send information about the host vehicle. Afterward, according to the processed sensor's data, an appropriate brake and throttle command is made. So, the controller unit is responsible for ordering the powertrain and brake system with the required commands. Finally, actuators take action by implementing the controller's command to follow the vehicle's speed in front of them or maintain the necessary speed. These actuators may be powered by internal combustion engine (ICE) powertrains for conventional fuel vehicles, electric powertrains for electric vehicles (EV), or both types of powertrains for hybrid electric vehicles (HEV). Also, actuators can be electronic, hydraulic brakes, and regenerative brake systems. The Human Machine Interface (HMI) unit informs the driver of the condition of the car's state and possible warnings so he can take necessary action according to a specific situation. Considerable research into the ACC system has been done. A comprehensive overview of the studies done on ACC is given in this review. Different controlling techniques with their algorithms are presented. Also, an explanation of several application cases is introduced. Finally, the future guidance, challenges, and a conclusion are described.

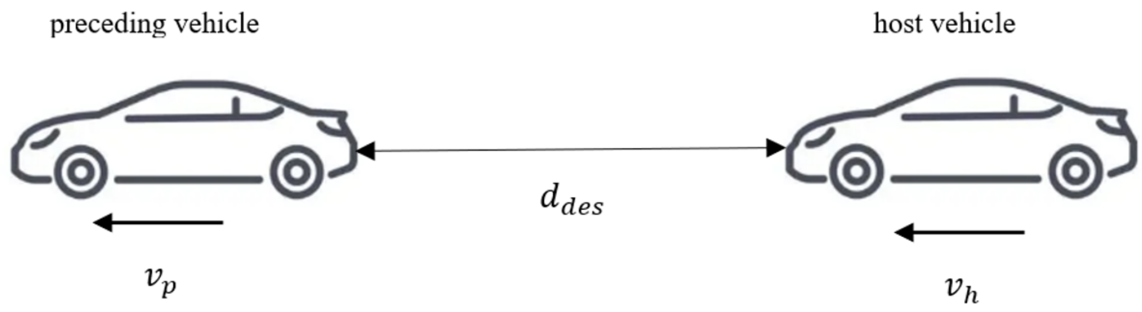

Figure 1. Two vehicles ACC scenario

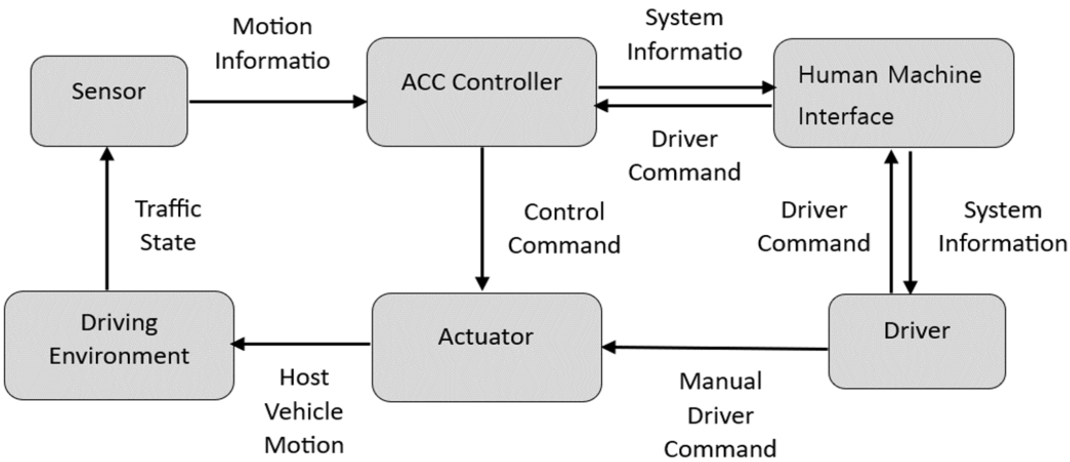

Figure 2. ACC system components **(Yu and Wang, 2022)**

2. CONTROLLING TECHNIQUES

Two control structures exist in the literature: a one-level (end-to-end) controller and a hierarchical (two or three levels) controller. The first type of controller commands a control signal to the actuator directly from the sensor's state information, as shown in **Fig. 3**.

Secondly, the hierarchical controller consists of two control levels, as shown in **Fig. 4**. The high-level controller obtains the required acceleration (or speed) of the host vehicle. On the other hand, the low-level controller commands actuators to follow this produced acceleration (or speed). For example, in **(Zhu et al., 2023)**, the upper controller finds the theoretical safety space between two automobiles and the expected acceleration, while the lower μ integrated controller represents the longitudinal dynamics.

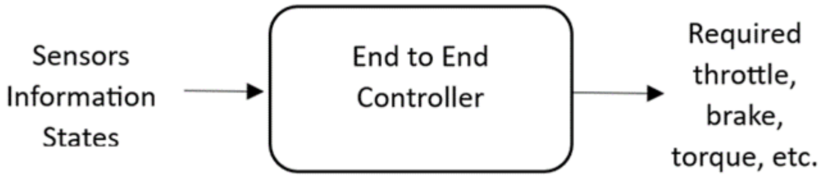

Figure 3. One Level Controller

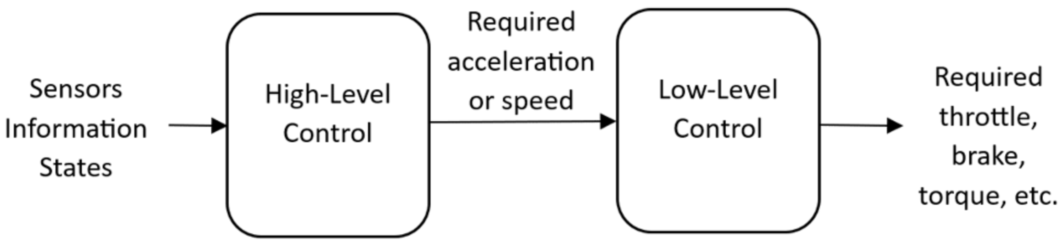

Figure 4. Hierarchical Controller

Few researchers implemented a single-level controller. In **(Shakouri and Ordys, 2017),** the throttle and brake positions are managed by one-level but state-dependent nonlinear model predictive control (NMPC), which makes the control design procedure straightforward. **(Cao et al., 2017)** claims that using a camera's images as input data and the output signal as control (throttle and brake) to mimic the driver's needs in the last driving process gives better control results. Neural networks (NN) are employed in computer vision to identify the lane and the location of the leading vehicle in an image. The suggested NN architecture is predicated on the timed nonlinear autoregressive network with exogenous inputs (NARX) net, which includes a feedback function and a time delay. Subsequently, it can retain the image properties and the generated data in the past time. As a result, the following control command can be predicted more precisely. The simulation's findings demonstrate that NN can identify the feedback and delay functions and define an accurate output close to the desired value. Moreover, the network model achieved the expected acceleration prediction, and no overfitting in the model occurred. Many studies have been conducted for hierarchical controllers with different controlling approaches, such as:

2.1 Proportional-Integral-Derivative (PID)

PID controllers are commonly employed in adaptive cruise control systems. PID controllers can fulfill up to three design specifications, though there are other kinds that can fulfill more variables such as fractional PID **(Abdulwahhab and Abbas, 2017)**. They are used to adjust the speed of the following vehicle based on the acceleration or braking of the preceding vehicle to maintain a safe distance and avoid collisions. The PID controller is a feedback control mechanism that uses three elements: proportional, integral, and derivative. They are calculated individually and combined to determine brake pressure and throttle position. It's essential to note that implementing the PID controller for adaptive cruise control may vary depending on the specific system and requirements. Different tuning methods and additional control strategies can be used to maximize the PID controller's performance **(Chaturvedi and Kumar, 2021)**. First, a dead time nonlinear first-order model is designed in the research mentioned. ITE, ITAE, and ITSE have been chosen as the objective function for optimizing the controller. The teacher learning-based optimization technique and the particle swarm optimization (PSO) method are utilized for the PID designing.

The proposed controller performs better than the traditional PID and the fuzzy-based controllers, significantly reducing the system's overshoot and rise time. In other papers, advanced tuning techniques, such as adaptive control, optimization algorithms, or model reference adaptive control, can also be used to optimize the performance of the PID controller for adaptive cruise control. **(Mingyang and Gangfeng, 2023)** develops a nonlinear vehicle dynamics model that considers acceleration limits and driving force lag. For a CACC system, a robust fuzzy-based PID controller is used, allowing the host vehicle to effortlessly transition between the cruise and speed modes while adhering to the cutting-in and cutting-out situations of the vehicle ahead. In this paper **(Mingyang and Gangfeng, 2023),** the relative speed of the vehicles and the distance error are taken as inputs to the high-level controller and acceleration as output. The low-level controller receives the required acceleration as input and produces the brake pressure and throttle angle. It also considers the two vehicles' relative speed and the preceding vehicle's acceleration to set the desired spacing. In addition, a logic decision algorithm is proposed to replace the conventional way of creating an additional set of PID controllers in the fixed-speed cruise mode. So, it leads to reduced algorithm complexity and the attainment of the same control outcomes. Various conditions for demonstrating the suggested algorithm's reliability are evaluated, and smooth switching between the distance and constant cruise modes and a small distance error is achieved. The third research **(Islam et al., 2021)** uses a PID controller and an Extended Kalman filter (EKF) to adjust the following vehicle's speed based on the preceding vehicle's acceleration or braking. The control method employs a "Genetic Algorithm" (GA) to improve the ACC function, considering four cost indicators: ride of rear mass, loss in throttle command, distance penalty and collision avoidance. GA was successfully able to locate optimal PID parameters. Moreover, the EKF enabled precise filtering of sensor data, contributing to fast decisions made by a control system. It uses the MAVS software library used for simulating autonomous ground vehicles. Altogether, the results demonstrate good performance and correct following of the leading vehicle. The method of GA is also employed by (Rout et al., 2016) to optimize the PID parameters. The comparison of three other methods (state space, conventional PID, and Fuzzy logic controller) has demonstrated that the combined use of GA with a PID controller outperforms other types with regard to maximum overshoot, rise time, steady-state error, and settling time. The results also indicate that the system rejects high-frequency noise and output disturbance. **(Wu et al., 2016)** have proposed a new "Chaotic Ant Swarm" (CAS) intelligent algorithm as an approach for tuning the PID controller in this study increased the algorithm's convergence speed and enhanced CAS. The proposed controller considers several objectives, such as reducing fuel consumption, shrinking the safety gap, and improving driving comfort. Tests were carried out on vehicle queues with varying speeds under various work settings, cut-in, and cut-out conditions.

Both PRESCAN and MATLAB/Simulink are used to demonstrate that this paper fulfills all objectives previously mentioned. In **(Chamraz and Balogh, 2018),** the structure and characteristics of the controller are modified based on the ACC system demands. This modification is done through two control loops: one controller for speed control, and the second adjusts the host vehicle's speed according to the spacing between the two vehicles. This structure is fitted better when the preceding vehicle has a varying speed. In addition, the disturbance, which increased linearly, is tracked by an observer. Lastly, **(Zainuddin et al., 2022)** present a performance comparison between a traditional PID controller and a "Predictive Functional Control" (PFC) specifically for ACC application. A plant that mimics the control reaction of an actual car is created using a standard nonlinear vehicle longitudinal dynamics mathematical model. An analysis of both controllers' features, such as parameter tuning, disturbance rejection, and constraint handling, is performed. A closed-loop response is carried out to compare the two controllers. The outcomes present that this method gives a better response, addresses the problem of constraints, and rejects disturbance compared to PID. Another conclusion from the comparative study is that the tuning process of PFC is more realistic, which can be very useful for the expansion of the ACC application in the future.

2.2 Fuzzy Control

Fuzzy logic, developed by Prof. L. A. Zadeh in 1965 **(Zadeh, 1965),** is one of the classes of soft computing techniques that has robust learning and a good approximation to human reasoning as well as good tolerance to inaccuracy and uncertainty **(Milanes et al., 2012)**. **Fig. 5 (Jantzen, 1998)** presents an example of a fuzzy controller where relative distance and speed error are the input and acceleration as the output. Three phases are implemented in a fuzzy controller. The first stage is fuzzification, which transfers input and output variables into fuzzy classes. These classes may have five (or fewer) classes: positive large (PL), positive middle (PM), zero (ZE), negative middle (NM), and negative large (NL). Secondly, predefined rules are used by fuzzy inference to generate the fuzzy output. Finally, the fuzzification stage turns these fuzzy outputs into control outputs. A membership function is needed for both input variables, as shown in **Fig. 6**. **(Ko and Lee, 2007).**

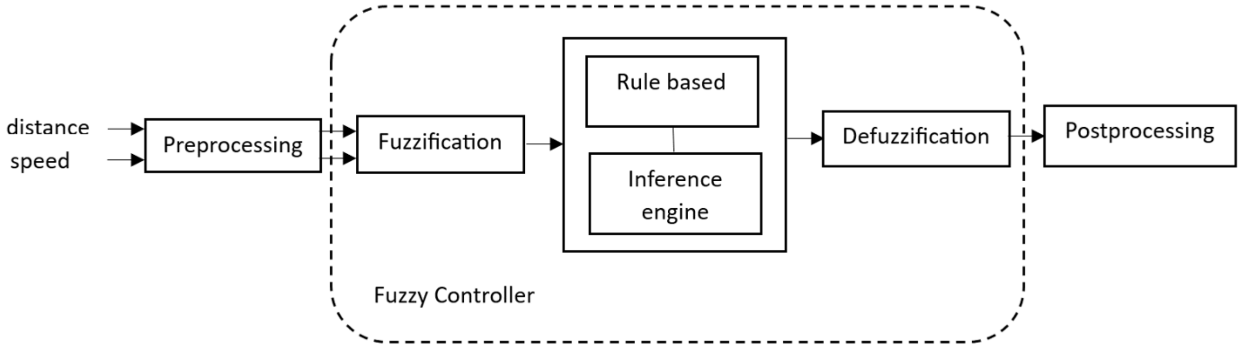

Figure 5. Fuzzy controller **(Jantzen, 1998)**

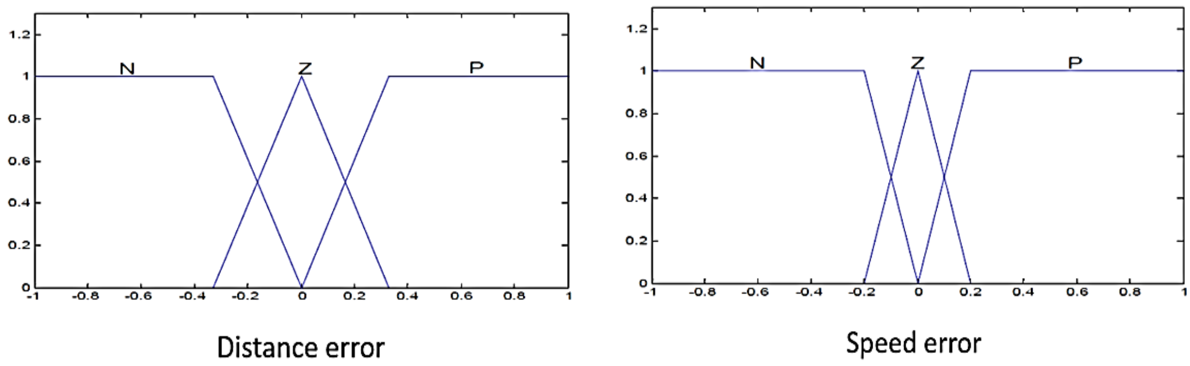

Figure 6. Membership function for input variables **(Ko and Lee, 2007)**

Several research studies have been conducted on fuzzy logic controllers for ACC. In **(Milanes et al., 2012),** the designing and tuning of a fuzzy controller on a longitudinal control for throttle and brake padel in simulation is performed. In addition, two commercial vehicles (fully automated and manually driven) were implemented to determine the behavior of the control algorithm in real experiments. A stop-and-go maneuver, an essential and hard-to-solve topic in the automotive industry, has been accomplished using the proposed controller. An autonomous model car called "AutoMiny" using a fuzzy logic approach (see **Fig. 7**) is presented by **(Khaled et al., 2020)**. The modeled vehicle uses a grid map and a global localization system to navigate and adjust its orientation. The fuzzy controller is used as an upper control to calculate the required acceleration. Then, a lower controller maps this acceleration command to a speed command to drive the vehicle's motor. A comparison with traditional PID controller design is conducted. It shows that many fuzzy controller parameters need to be manually calibrated compared to a PID controller. Yet, the presented fuzzy controller is more convenient for ACC systems (a compromise between performance and simplicity).

Figure 7. AutoMiny: a model car developed at Freie University, Berlin, Germany **(Khaled et al., 2020)**

(Hassan and Collier, 2014) also, model and implement the ACC system for a robot-like car using a fuzzy logic control strategy. LabVIEW, a graphical programming environment toolkit, is used for system identification to extract the transfer function of the two robot-like cars (DaNI2 robots). Real-time implementation and simulation tests show good performance for the proposed control strategy **(Ko and Lee, 2007)**. **(Rizvi et al., 2014)** introduces an integrated speed sign detection (SSD) in combination with a fuzzy logic-based ACC. This system, capable of distance measurement and lane detection, can also read the road signs to determine the speed limit on the road. The fuzzy logic controller modifies the speed during driving by adjusting the brake and throttle values. A car-racing platform called Open Racing Car Simulator (TORCS) is used as a simulation platform. The results were positive, and the controller adapted to both vehicle-varying parameters and different speed limits. **(Kudamble and Jabeen, 2018)** used an ultrasonic sensor to obtain the spacing from the leading vehicle. The fuzzy logic controller accepts relative velocity between two vehicles and distance error as inputs. Then, two outputs are produced: velocity command (throttle valve dependent) or brake command (a DC motor applied command). The proposed controller for the ACC is designed and modeled using MATLAB Simulink. Also, in **(Samani and Shamekhi, 2022),** a hierarchal structure controller is designed but with fuzzy as the low-level controller that determines the throttle valve opening value or brake pressure necessary to find a required acceleration and a model predictive controller as an upper-level controller that calculates this desired acceleration. **(Mo et al., 2022)** synthesizes the variable time headway model, employs inverse longitudinal dynamics model of a vehicle, type-2 " feedforward fuzzy control" plus "fuzzy proportion integration feedback control" (F+FPIF) to introduce a new hierarchical ACC strategy. Type-2 fuzzy control is a high-level controller to imitate the driver's behavior. In contrast, F+FPIF is used as a low-level controller to reduce the effect of nonlinearity and enhance the tracking accuracy for the desired acceleration. MATLAB Simulink and CarSim software are employed to build and run the model, and the results revealed the superiority of the suggested method over four other control schemes. **(Ondoğan and Yavuz, 2019)** studied the limitations of the environment so the vehicle keeps a specific speed defined by the diver. If there is no danger else, the vehicle decelerates using an interactively determined formula that uses both acceleration and velocity limitations. Although this study uses fuzzy logic-based low-speed tracking, it can be extended by defining more IF-THEN rules and fuzzy subsets for high-speed ranges. The effectiveness of the design is analyzed in a simulation scenario, which shows that the designed strategy meets the required performance.

2.3 Neural Network (NN)

Neural networks are a machine learning model that can learn patterns and forecast according to input data. In the context of ACC, neural networks can be used for various purposes, such as target selection, parameter learning, speed prediction, and lane change intention prediction. Neural network-based ACC involves training an NN controller to produce the required acceleration or speed, and then a lower controller commands a suitable throttle and brake single (see **Fig. 8 (Lu et al., 2019)**). Overall, using a neural network in ACC can improve safety, comfort, and accuracy while providing flexibility in design. Neural networks are being used for adaptive cruise control in several research papers. **(Wang et al., 2022)** describes a design of an ACC system based on a backpropagation NN (BPNN) to recognize several driving scenarios and situations and solve poor vehicle following performance problems. The developed model is obtained by training the characteristic parameters after being normalized. Eight different drive cycles were used as other working conditions. Moreover, these drive cycles are redivided to control the car's speed better. As a result, the fuzzy control high-level controller (for low-speed) and the MPC high-level controller (for average to high-speed) are proposed, respectively. The simulation tests reveal that the proposed algorithms obtained better tracking performance and comfort. Another paper **(Samani and Shamekhi, 2021)** uses a data set obtained from a multi-objective ACC system simulation for training neural networks. Firstly, model predictive control is used to design ACC with several objectives, such as preserving the driver's goal speed and safety gap with the vehicle ahead, improving ride comfort, and lowering fuel usage. Secondly, the extracted data from the MPC simulation trains the NN since implementing MPC (online) needs powerful and expensive hardware. The proposed method achieves the control objectives, and a significant reduction in computation time is obtained as well. A third paper **(Wang et al., 2019)** proposes an ACC technique based on NNs trained using data representing the driver behavior for cutting-in/cutting-out scenarios. Model Predictive Control (MPC) for an ACC strategy is also proposed for vehicle-following conditions. This dual mode is combined to form an intelligent ACC for Electric Vehicle (EV).

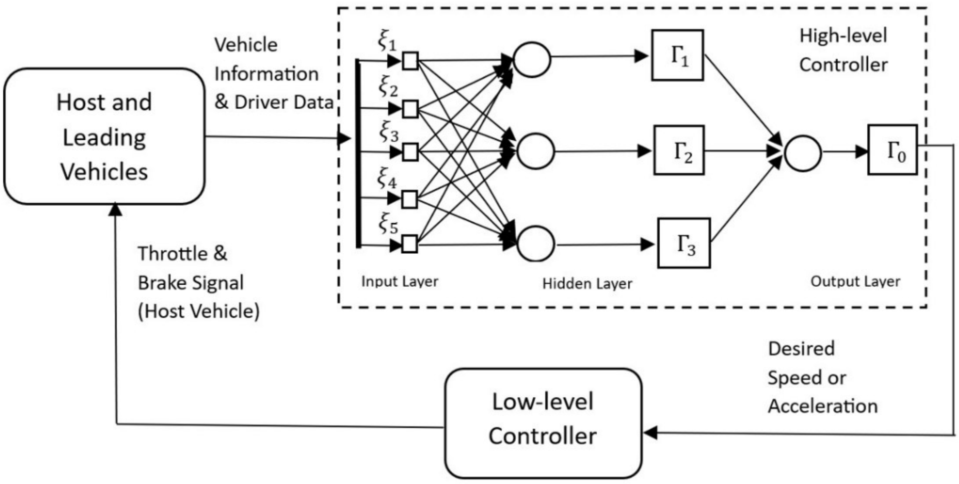

Figure 8. NN Structure **(Lu et al., 2019)**

The three-level control structure is designed. A high-level adopted dual mode operation, the middle level organizes the hydraulic braking and the regenerative braking, and the low level commands both the hydraulic braking device and the electric motor. The simulation tests show that the controller has superior trajectory tracking action, preserves a safety gap, and has better braking energy recovery. Overall, many objectives are improved, including safety, energy saving of EVs, and riding comfort. **(Mahadika et al., 2020)** also used two approaches: NN to emulate vehicle dynamics and model predictive controller to achieve minimum error between future reference tracks and predicted outputs. The proposed controller represents an inner loop that produces throttle and brake pressure required to track a desired acceleration commanded from an outer loop controller. This outer controller is based on a decision algorithm and a PI controller to calculate the set speed required to keep a safety distance. The results obtained from the simulation show good tracking of the leading vehicle with relatively small errors, yet a new data training set is needed if a rapid change in speed is encountered. This limitation can be overcome if a large training set from the NN is used. The fourth research **(David et al.,2021)** used NN to evaluate deceleration model parameters for the ACC unit with both static and dynamic obstacles in front of the vehicle. Furthermore, a braking system mathematical model, one of ACC's basic functions, is created. Various versions of sensors used in ACC and collision avoidance systems are described. The ACC system's most important long-range sensor is the 77-frequency GHz radar, as shown in **Fig. 9. (David et al.,2021).** But with bent roads and heavy traffic, infrared (or video) cameras effectively capture and analyze the road ahead. The research also deals with road conditions (weather conditions) and tires' adhesion coefficient, characterizing braking efficiency and road inclination. A unique hierarchal NN structure is designed with three levels (ANN1, ANN2, and ANN3). All the road parameters mentioned above and other information (vehicle type, brake status, and vehicle load) are the input to the NN, while the output is the allowable deceleration intervals. As a result, an improved ACC system is implemented with better safety driving.

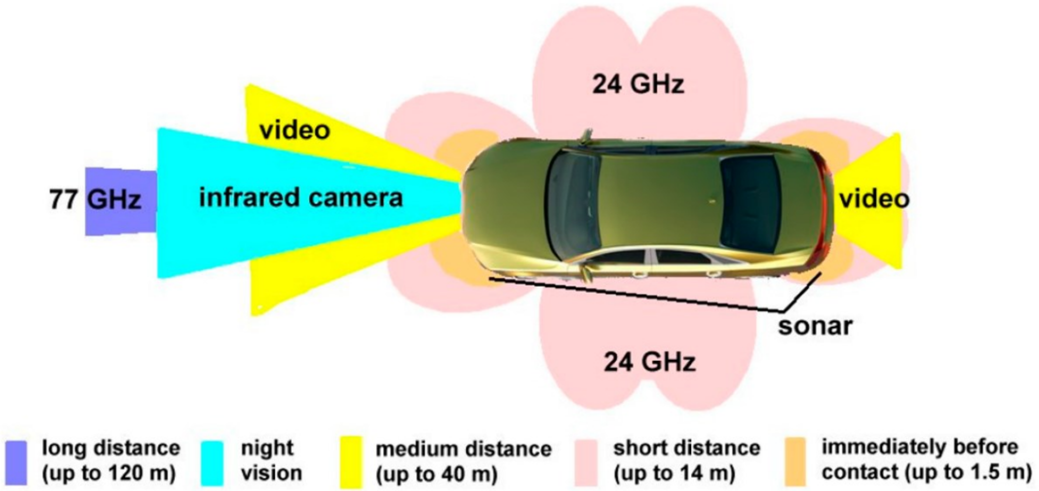

Figure 9. Schematic diagram of different sensors' range **(David et al., 2021)**

This paper **(Xiang and Shao, 2022)** explores simplifying the safety verification of NN systems using a reachability-based algorithm. This method accurately finds the model minimization precision. The simplified model aims to minimize the computational efforts of the original NN system. The reduced-size NN controller is applied to the ACC system, and feasible and efficient results can be obtained. In **(Sathiyan et al., 2020),** a hardware implementation of the ACC system using an NN controller is done using dSPACE DS1103 for real-time testing and validation. Two types of sensors are used: a proximity sensor to determine the speed (attached to the wheel of the host vehicle) and an ultrasonic sensor MB1340 as a range sensor to measure the actual distance between the host and the leading vehicles. Speed error is the input to the NN controller, while the output is throttle and brake values. Then, the corresponding actuators accelerate or decelerate the vehicle accordingly. The results show a satisfactory response when the proposed controller is implemented using HIL testing with dSPACE. A traditional ACC system cannot handle the cut-in/cut-out situations, so an ACC system model and backpropagation (BP) NN layered control algorithm are designed **(Li et al., 2022)**. It can recognize the change in lane of the leading vehicle. Offline training for lane change identification is implemented, and online identification of the ahead vehicle, depending on sensor information, is done. A hierarchal controller with low-level and high-level control is adopted. The high-level control is represented by a variable-weight linear quadratic controller (LQR) with distance, speed, and acceleration as performance indicators for the controller. On the other hand, a fuzzy PID control is adopted as a lower controller to ensure that the reference acceleration can truck the predicted acceleration stably. These steady, different lane-changing conditions are tested to investigate the proposed strategy. Results show ACC vehicles can change their positions to follow the leading vehicle, and other objectives, such as driving safety and riding comfort, are fulfilled, too. Another work **(Singh et al., 2015)** trained neural networks (BPNN and RBNN) as a reference and fuzzy logic approach to output the required acceleration and braking pressure. The three methods were tested through simulation, and the results show that the fuzzy-based controller was superior to NN as it got minimum MSE, much faster response, and less complexity than BPNN and RBNN.

Overall, while using a neural network in ACC can provide several benefits, it is vital to consider the limitations, such as complexity and requiring significant computational resources to train and run. Also, overfitting is another problem when a model conforms too closely to the training data and poorly generalizes to new data. In addition, limited data to train effectively and limited real-world testing are additional issues when dealing with NN.

2.4 Model Predictive Control (MPC)

The MPC's main working principle is to forecast a plant's future behavior and compute control signals to fulfill a particular objective. The error between actual and predicted values can be optimized (minimized) using feedback. An online optimization problem is solved to obtain the optimal control sequence. Only the initial value of this sequence is employed to regulate the plant. Then, the MPC control procedure is repeated as the control horizon shifts a step ahead. as shown in **Fig. 10 (Maciejowski, 2002)**. MPC mathematical equations can be written as Eq. (1) and as Eq. (2) **(Wang, 2009)**,

$$x(k+1) = \mathrm{A}\, x(k) + \mathrm{B}\, \mathrm{u(k)} \tag{1}$$

$$y = \mathrm{C}x(k)$$

Cost function equation:

$$J_N(x_0, u) = V_f\big(x(N)\big) + \textstyle\sum_{k=0}^{N-1} l(x(k), u(k) \tag{2}$$

$$s.t. \quad u \in \mathbb{U}, x \in \mathbb{X}$$

Where:

$$V_f(x(N)) = x(N)^T S x(N)$$

$$\sum_{k=0}^{N-1} l(x(k), u(k) = \sum_{k=0}^{N-1} x(k)^T Q x(k) + u(k)^T R u(k)$$

where $x(k)$ and $u(k)$ are state vector and control variable at time k respectively, S, $Q$and R are weight matrices, and N is prediction Horizon. By solving the cost function with both state and control variable constraints, the optimal $u(k)$ is then obtained. This cost could be car following, safety, comfort, and energy economy. For transitional maneuvers, the spacing-control laws of the ACC vehicle are derived using a model predictive controller **(Bageshwar et al., 2004)**. A transitional maneuver (TM) is required to keep a safe space behind a preceding vehicle. The specified safety distance, acceleration limits, and collision avoidance are constraints. In **(Li et al., 2011),** a two-stage control architecture is utilized. A lower controller uses the inverse dynamics control design, adapts to nonlinear vehicle dynamics, and tracks a desired acceleration. The high-level controller is synthesized by MPC theory. Conflicts such as tracking error, low fuel consumption, and ride comfort are considered when formulating a quadratic cost function. In **(Memon et al., 2012),** a nonlinear model for the vehicle is deemed to form an ACC system for TMs with a hieratical structural controller using MPC. This model is exploited in the continuous-time domain and holds the vehicle dynamics for both steady-state and transient states. In **(Nie and Farzaneh, 2020),** the MPC algorithm is also designed for the ACC system. Many objectives include eco-driving, driving safety, tracking capability, and comfort driving. The optimal control variable is sometimes calculated beyond the constraints, so the constraint softening method is applied **(Guo et al., 2020)**.

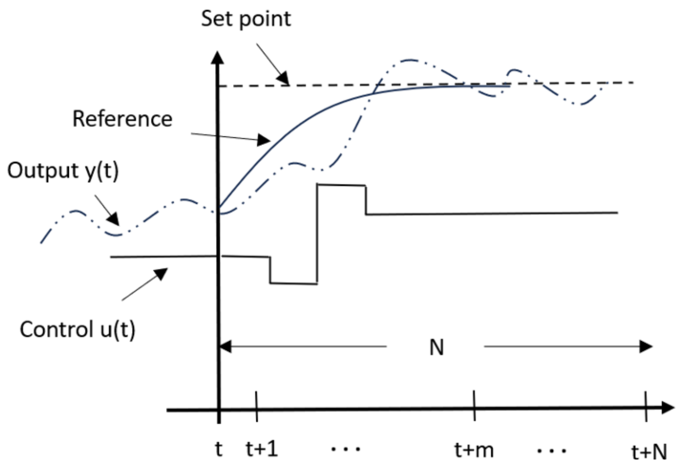

Figure 10. MPC prediction horizon. **(Maciejowski, 2002)**

A new technique for ACC's low-level controller **(Mahadika et al., 2020)** uses artificial neural networks (ANN) to emulate vehicle dynamics and MPC to obtain the minimum error between reference values and expected output signals. The upper controller is based on a decision algorithm, and the PI finds a reference speed. So, NNPC manipulates throttle and brake pressure to adjust the host vehicle's speed. In **(Feng et al., 2022),** an explicit MPC (EMPC) controller design with "an extended state" Kalman filter to assess the state and disturbance amounts based on "a binary search tree" is suggested. The online computational load of MPC is transferred to offline calculations using "multi-parametric quadratic programming" (MPQP). In **(Gonzalez and Rossiter, 2020),** a novel ACC algorithm is proposed based on MPC as a high-level controller and active disturbance rejection control (ADRC) as a low-level controller. An MPC for the high-level controller assists by predictive acceleration calculations (to increase accuracy), and ADRC is implemented to improve precision and decrease internal or external disturbance.

2.5 Sliding Mode Control (SMC)

Sliding mode control is a reliable and robust approach that was first proposed in the 1950s **(Sloiton and Li, 1991),** and since then, it has attracted significant attention. It has been adopted by many researchers in different applications of control engineering **(Ganji et al., 2014)**. The method establishes a hyperplane for control, where state quantities are converged onto the hyperplane and controlled towards a balanced point. It is known for its quick response, insensitivity to parameter variations and disturbances, and insufficient online identification **(Ya et al., 2013).** The main features of sliding mode control include:

1- Sliding Surface: Choosing a hypersurface or manifold (the sliding surface) such that the system behaves as required when confined to this manifold.
2- Feedback Gains: The system's trajectory intersects and remains on the manifold.
3- Robustness: Sliding mode control is known for its robustness against system uncertainties and perturbations, ensuring the trajectory remains on the sliding surface even when model uncertainties or external disturbances exist.

The SMC method regulates a dynamical system's behavior by pushing the system's state onto a predefined sliding surface (see **Fig. 11 (Tagne et al., 2013)**).

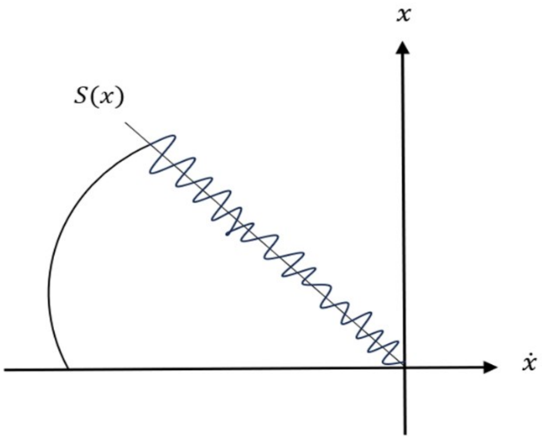

Figure 11. SMC principle **(Tagne et al., 2013)**

The dynamic equation of an nth-order single input system Eq. (3) is as follows **(Ganji et al., 2014)**:

$$\dot{x} = \varphi(x) + \beta(x)u \tag{3}$$

$$x = [x\ \dot{x}\ \ddot{x}\ \ldots .\ x^{n-1}]$$

x is the state vector or variable of interest (relative speed), $\varphi(x)$ is a nonlinear function of x, and $\beta(x)$ is a continuous function of x. A sliding variable s Eq. (4) needs to be identified to design a sliding mode controller as:

$$s = c_0 x + c_1 \dot{x} + c_2 \ddot{x} + \cdots + c_{n-2} x^{n-2} + x^{n-1} \tag{4}$$

where $c = [c_0\ c_1\ c_2 \ldots c_{n-2}\ 1]$ is the vector of the sliding mode parameter and should be chosen to make the solution $(s = 0)$ asymptotically stable.
SMC has attracted the attention of many researchers to solve the ACC problem **(Ganji et al., 2014).** First, a PID controller is applied to a mathematical vehicle's model, and the "particle swarm optimization" (PSO) method is used for the PID parameters tuning. Secondly, a time-varying nonlinear second-order system is considered, and SMC is implemented instead of the PID controller. The output speed of the simulation result is stable and has zero overshoot, while the output of the PID approach has oscillation and overshoot **(Sharma and Bhushan, 2019).** A sliding mode considering uncertainties and external disturbances is proposed. A two-axle vehicle model is adopted. So, a high gain observer (HGO) based SMC is designed and integrated into the vehicle dynamics to adapt to the system uncertainties. Simulation results show good speed tracking and a decrease in relative distance error. **(Hajjami et al., 2022)** proposed an optimal control technique aimed at controlling an autonomous vehicle. This method uses a super-twisting algorithm to overcome the chattering effect associated with using SMC. Furthermore, a meta-heuristic optimization algorithm called the "Butterfly Optimisation Algorithm" (BOA) was used to determine the parameters of SMC. A frequent speed scenario is applied to verify the efficiency of the proposed method. It shows that the vehicle accurately tracks the desired speed profile, guaranteeing stability **(Tagne et al., 2013)**. Also, a super-twisting technique with high-order SMC was used to control an autonomous vehicle. The super-twisting method reduces the car's lateral displacement regarding a given path. Vehicle DYNA collects experimental data equipped with several sensors such as the "Inertial Measurement Unit" (IMU) (for the yaw rate and acceleration measurement), four laser sensors (for the chassis' height measurement), a CCD camera, and GPS, etc. These data are used as reference data to compare to the results obtained using simulation. Several tests are carried out to verify the robustness of the controller during three scenarios: average, high, and varying speed. In addition, different cornering stiffness and variable vehicle mass are tested to implement the vehicle's uncertain parameters. All simulations confirmed the robustness of the developed control algorithm. In **(He et al., 2019),** SMC variable structure control theory is used to investigate the stability of the control scheme. Three different road conditions were tested through the simulations: (dry concrete, icy, and wet asphalt) road surfaces. A 3DOF vehicle model to facilitate the vehicle's vertical, horizontal and yaw motion is considered. Different simulations with several driving speeds and road conditions show that the controller achieves good vehicle maneuverability and stability. Finally, SMC is designed to develop Cooperative Adaptive Cruise Control (CACC), as we will discuss later in a subsequent section.

2.6 Linear Quadratic Regulator (LQR)

Linear Quadratic Regulator (LQR) is a form of optimal control that utilizes state space representation and an important function of control engineering **(Al-Mulla, 2012)**. It is a feedback controller that improves the system's performance and maintains a stable closed-loop system by providing optimal feedback gains. So, by choosing closed-loop characteristics essential to the system, the optimal K is found **(Mohammed et al., 2020)** as in **Fig. 12**.

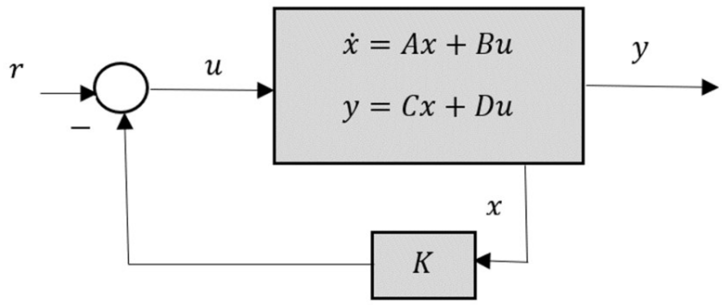

Figure 12. LQR structure **(Mohammed et al., 2020)**

The state space representation is as Eq. (5):

$$\dot{x} = Ax + Bu \\ y = Cx + Du \tag{5}$$

The optimal gain (K) is determined by a cost function J as Eq. (6):

$$J = \int_0^\infty (x^T Q\, x + u^T R\, u)dt \tag{6}$$

Where R and Q are weight matrices. The optimal gain associated with the lowest cost is obtained by solving the LQR problem as Eq. (7):

$$u = -Kx \tag{7}$$

The gain matrix (K) is evaluated by solving the algebraic Riccati equation associated with the LQR problem. The LQR has been widely adopted in ACC systems design. For example, in **(Kim et al., 2012)** the system's structure is simplified to handle the unnecessary switching between cruise control and distance control. It introduces a virtual preceding vehicle, and the controller decides the speed and position of that vehicle depending on the situation ahead. The proposed method provides a smoother response than the conventional mode-switching design and shows improved reaction in cut-in or cut-out scenarios. On the other hand, researchers have proposed various methods to improve the LQR, including using time-varying parameters **(Jiang, 2020)**, where Q and R vary with time based on the current traffic flow. The constraints on the Q and R parameters are determined using the phase-plant method, and the constrained optimization problem is resolved using the coefficient descent method. A Q-function (cost function), consisting of a Markovian state and action penalty, is presented. Here, an incremental PID controller is utilized as the ACC lower controller, and an LQR controller is utilized as the ACC upper controller. The time-varying parameter LQR used in the simulation demonstrates its superiority over other controllers. However, these methods have not fully addressed the issues of process and measurement noise and the tedious tuning problem in ACC system design. However, this study **(Jiang et al., 2019)** presents linear quadratic Gaussian where the Kalman filter is applied to compensate for the noise. In addition, a genetic algorithm is used to improve the efficiency of the tuning process. The LQR controller can also be used with other control methods, such as in **(Naeem and Mahmood, 2016)**. A model using bond graph formulation is developed. This model combines both state space representation and actuator dynamics. The nominal model is modified to the standard format to deal with parameter uncertainty. Then, a synthesized model using LQR and H_2 is done. LQR solves one Reccati equation while H_2 solves two

Reccati equations simultaneously. The simulation tests show that the H_2 scheme responds better by stabilizing the control input in the minimum time. It is worth noting that the LQR controller can be added with other control techniques, such as PID control or fuzzy logic control, to improve the ACC system performance. For instance, **(Shakouri et al., 2011)** investigate two control approaches: the gain scheduling Linear Quadratic (GSLQ) and the gain scheduling proportional integral (GSPI) control as a lower controller. A linear model for the vehicle is extracted from its nonlinear model. Tests were conducted for scenarios covering a high range speed to validate and compare both controllers separately.

3. ACC APPLICATION CASES

3.1 ACC with Lateral Dynamics

Lateral dynamics refers to studying a vehicle's motion in the lateral direction, perpendicular to the vehicle's longitudinal axis. It involves understanding how a vehicle behaves during cornering, lane changes, and other maneuvers that involve lateral motion. The lateral dynamics of a vehicle can affect its stability during cornering, and this has an impact on adaptive cruise control. Integrating lateral control with longitudinal control is crucial for achieving both lateral stability and advanced adaptive cruise control functionalities **(Fu et al., 2019)**. Current Adaptive Cruise Control systems have limitations in handling lateral dynamics. One of the major drawbacks of commercially available ACC systems in the automotive industry is their restricted abilities in cornering **(Idriz, 2015).**
Lateral dynamics can be modeled using a state-space model, which includes the vehicle's lateral acceleration, which can affect its stability during cornering, especially for heavy vehicles. The bicycle model is a commonly used lateral dynamic model in the ACC system, as illustrated in **Fig. 13 (Ji et al., 2019)**.

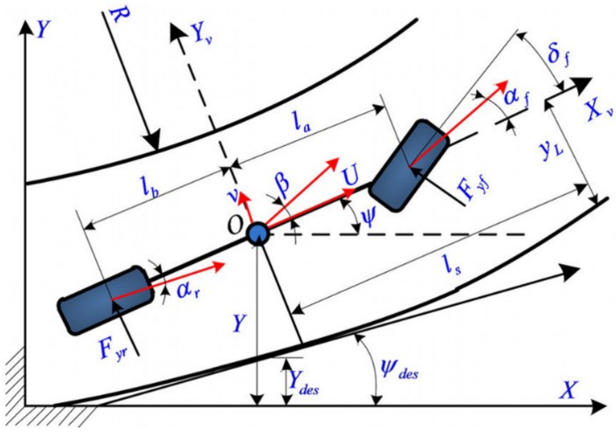

Figure 13. Lateral and Longitudinal dynamics **(Ji et al., 2019)**

The vehicle's lateral motion relative to the road can be described as Eq. (8):

$$m(\dot{v}_y + v_x\dot{\varphi}) = 2F_{yf}(\alpha_f) + 2F_{yr}(\alpha_r) \quad (8.a)$$

$$I_z\ddot{\varphi} = 2aF_{yf}(\alpha_f) - 2bF_{yr}(\alpha_r) \quad (8.b)$$

$$\dot{Y} = v_y + v_x\varphi \quad (8.c)$$

$$\alpha_f = \frac{v_y + a\dot{\varphi}}{v_x} - \frac{\theta_{sw}}{N_s} \tag{8. d}$$

$$\alpha_r = \frac{v_y - b\dot{\varphi}}{v_x} \tag{8. e}$$

where the description of each parameter is shown in **Table 1**.

Table 1. Lateral dynamic model parameters description

Parameter	Description
a	center of gravity (COG) to the front axle distance, m
b	COG to the rear axle distance, m
F_{yf}	lateral force of the front axle, N
F_{yr}	lateral force of the rear axle, N
I_z	yaw moment of inertia, kg · m^2
m	vehicle mass, kg
N_s	reduction ratio of the steering system
v_x	lateral velocity, m/s^2
v_y	longitudinal velocity, m/s^2
Y	the vehicle's lateral displacement, m
α_f	lateral slip angle (front wheels), degree (°)
α_r	lateral slip angle (rear wheels), degree (°)
θ_{sw}	steering wheel angle, degree (°)
φ	yaw angle, degree (°)

Change in lane lateral and longitudinal dynamic is considered **(Wang et al., 2019)**. A multi-objective control scheme that tracks weighted virtual cars is presented with two-level controllers to plan the lateral trajectory. A hierarchical controller algorithm, which integrates parametric function and the Gaussian Mixture Model (GMM), is proposed for the higher controller. Uncertain behavior of the driver in various traffic conditions is taken into consideration. A lower controller based on MPC theory tracks the trajectory of the higher controller plans. This controller uses a force input model to predict the vehicle's movement and handle all possible constraints. **(Yao et al., 2021)** also deals with lane-changing issues, so it proposes an algorithm to select a target vehicle based on the lane-changing of the leading vehicle called a "Support Vector Machine" (SVM). This algorithm is trained by the "Next Generation Simulation" (NGSIM) dataset and determines the size of the sliding window. After that, the algorithm must select three possible situations: lane-changing cancellation, safe lane-changing, and unsafe lane-changing.

At last, a co-simulation design was constructed using Prescan software, CarSim, and Matlab/Simulink to validate the algorithm. The results show that the presented method identified the lane-changing intention of the preceding vehicle earlier and that the highest longitudinal deceleration of the subject vehicle was smaller during the entire control process than that of the traditional algorithm. In addition to fast response, the algorithm prevented accidents under dangerous lane-changing situations.

A curved road needs a unique controller design considering longitudinal cruising capability and lateral stability. **(Zhang et al., 2012)** considered curved roads in their design, so they presented a curved ACC design that collaborated with a "direct yaw-moment control" (DYC) system. At first, a model for the vehicle reflecting longitudinal and lateral dynamics is constructed. Then, a cost function is formulated with all possible constraints associated with the driver's car-following range and road conditions. Finally, a linear matrix inequality method obtains the desired acceleration and yaw moment. A driver-in-the-loop (DIL) simulator with a real steering reaction tests the Curving ACC controller. These tests confirmed that the Curving ACC has improved lateral stability by reducing the brake pressure on the wheels and has better comfort and safety due to satisfying the distance error range. In the same context, **(Yang and Jie, 2023)** proposed a curving ACC system that collaborated with a differential steering control (DSC) system of a "differential steering vehicle" (DSV). The curved ACC system is implemented based on the "fuzzy model predictive control" (FMPC) algorithm (as upper controller) and PID (as lower controller). The sliding mode control and preview algorithms are employed to design the lateral stability controller. In this paper, two simulation scenarios representing constant speed and varying speed are tested. A comparison with the direct yaw moment control system shows the advantages and effectiveness of the proposed ACC system.

3.2 ACC using Connection Technologies

ACC system involving communication is also known as "Cooperative Adaptive Cruise Control" (CACC). It is an expansion of the traditional adaptive cruise control. It can be classified into vehicle-to-vehicle (V2V) CACC, infrastructure-to-vehicle (I2V) CACC, and vehicle-to-everything (V2X). V2V CACC uses communication to enhance vehicle information exchange, allowing for more accurate following, faster response, and shorter gaps. On the other hand, the I2V CACC system received guidance and information (such as the speed limits) from the infrastructure **(Shladover et al., 2015)**. At least two vehicles need to communicate and exchange data through a wireless communication link, as shown in **Fig. 14**.

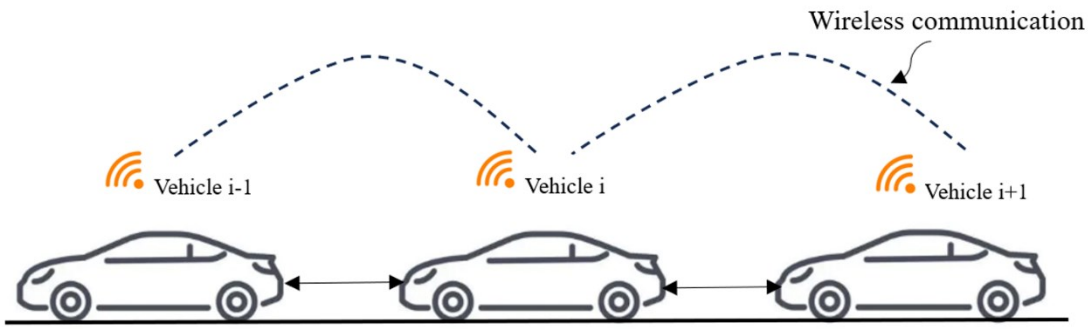

Figure 14. CACC in vehicle platooning

When the vehicle ahead is not a CACC (i.e., it has no wireless communication), the host vehicle activates the ACC mode. As the CACC preceding vehicle is detected, the controller switches into the CACC mode **(Bu and Chan, 2012),** as shown in **Fig. 15.**

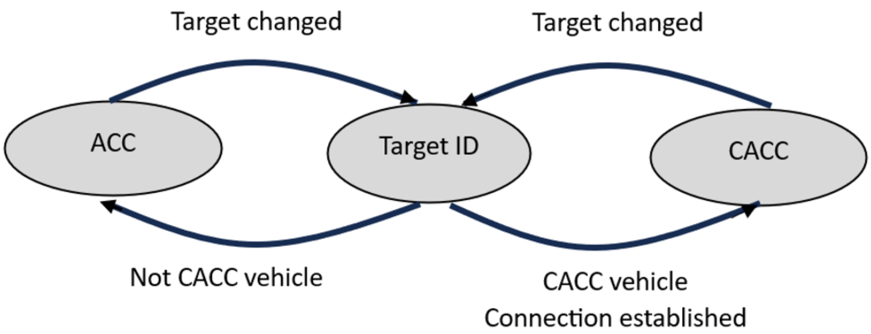

Figure 15. Transition diagram of CACC system operation modes **(Bu and Chan2012)**

CACC allows multiple vehicles or systems to work together in a coordinated manner. It aims to improve traffic safety, efficiency, and decision-making in human-machine driving or vehicle platooning systems. In the context of human-machine driving **(Li et al., 2023),** a non-cooperative game theory that cooperated with an adaptive dynamic allocation strategy was proposed to resolve decision conflicts between the controlled system and the driver. A multi-objective optimal control problem with the cooperation of the human-machine was established. Typical and emergency situations were tested to confirm the effectiveness of the proposed strategy. It achieved harmonious human-machine cooperative driving and reduced decision conflicts by improving the driving experience and reducing the car's collision. For vehicle platooning systems, a control-aware communication solution was proposed by **(Razzaghpour et al., 2023),** which combines control-aware communication with Model-Based Communication (MBC) to reduce communication resources while maintaining desired performance. V2X technology helps increase awareness of traffic conditions for connected and autonomous vehicles (CAVs). However, as the number of interconnected vehicles grows, this has a negative effect on communication reliability. So, a method to minimize the amount of communication resources used is introduced. The proposed method significantly reduces the average communication rate, and the behavior of a platoon of 10 vehicles is investigated in terms of vehicle efficiency and safety. Regarding uncertainties arising within the CACC system, especially those presented as perturbations affecting the system and measurement equations, **(Coskun et al., 2021)** suggest a predictive controller that preserves stability under disturbances. A Kalman filter handles the state estimation problem, while a quadratic programming method is adopted to solve the optimal control problem. A platoon consisting of four vehicles (one leader and three followers) linked together via predecessor-following topology is presented for the test scenario. Root Mean Square (RMS) error is used in this study to evaluate the performance of ACC and CACC. Moreover, different platoon sizes are verified to demonstrate the effectiveness of the algorithm and for the deployment of real-time platoon possibility. **(Wang et al., 2021)** Also deals with a linked and automated vehicles platoon problem in the CACC system. Here, two control systems based on a "robust adaptive non-singular terminal" SMC approach are presented: the first controller is a parameter adaptive SMC, and the second is a time-delay compensation Smith predictor. Several parameters were considered when designing these controllers, such as nonlinearity of vehicle dynamics, engine model, road profile, uncertainties, and external disturbances. Finally, a platoon of seven-vehicle CACC is simulated, and tests showed reduced speed overshoot, less settling time, and approximately zero steady-state deviation for distance error. Comparative studies with a "coupled sliding mode control" (CSMC) controller verified the superiority of the proposed approach.

An important issue associated with CACC is the string stability of the vehicle platoon. It means that spacing errors between two consecutive vehicles in the platoon will not be increased. String stability reduces "shock waves" and guarantees smooth traffic flow. Research plans and recommendations have been developed to investigate the safety issues, potential advantages, technical gaps, and difficulties in deploying CACC systems. This paper **(Wang et al., 2014)** presents an improved CACC algorithm to maintain string stability in cases when V2V communication is not entirely valid based on the SMC theory. Thus, when the communication of one vehicle is lost, the controller parameters should be modified to preserve communication stability and ensure that the entity stays in the platoon. As a result, chain collisions can be avoided, and safety and comfort are assured. The controller action is confirmed through an automatic five vehicles platoon simulation, and it preserves string stability and overcomes the partially invalid connection of one of the vehicles. Sometimes, wireless communication for individual vehicles in a platoon is exposed to cyber-attacks to disrupt the platoon. To solve this problem, **(Jahanshahi and Ferrari, 2018)** proposed a method for detecting and estimating such threats using an adapted sliding mode observer. The V2V network receives data, and the observer uses the local measurements to assess the vehicle's dynamics ahead. A CACC for interconnected buses along the "exclusive bus lane" (XBL) (see **Fig. 16 (Gao et al., 2019)**) exists too. An XBL is one of the most common bus travel systems in the United States due to its importance in transportation. **(Gao et al., 2019)** proposed a novel data-driven CACC approach to optimize a cost function for XBL using reinforcement learning (RL). Online headway, speed profile, and acceleration data gathered from system paths are used to learn a distributed controller. This real-time learning takes into account the continuously varying topology. The closed-loop transient performance and traffic flow are improved for the proposed method.

Figure 16. The exclusive bus lane (XBL) **(Gao et al., 2019)**

3.3 ACC in EV and HEV

Vehicles with conventional internal combustion engines (ICE) use adaptive cruise control systems widely, but in EVs, it needs to be related to the electric motor control block **(Petri and Petreuș, 2022)**. According to the passenger vehicle market, electrified vehicles are the most common new energy vehicles. The EVs are categorized according into different types based on three elements. First, the energy converter (i.e., ICE or electric motor) propels the vehicle. Second, they are categorized according to the power source (i.e., "Fuel Cell Electric Vehicle" (FCEV), "Battery Electric Vehicle" (BEV), or gasoline). Finally, they are classified according to their charging infrastructure (i.e., on-board or off-board, such as "Plug-in

Hybrid Electric Vehicle" (PHEV)). **Fig. 17 (Nour et al., 2020)** shows the basic structure of several EV types. EVs generate no tailpipe emissions and are more efficient than conventional ICE vehicles. In addition, its components, such as motors, batteries, and other electronics, typically require less maintenance.

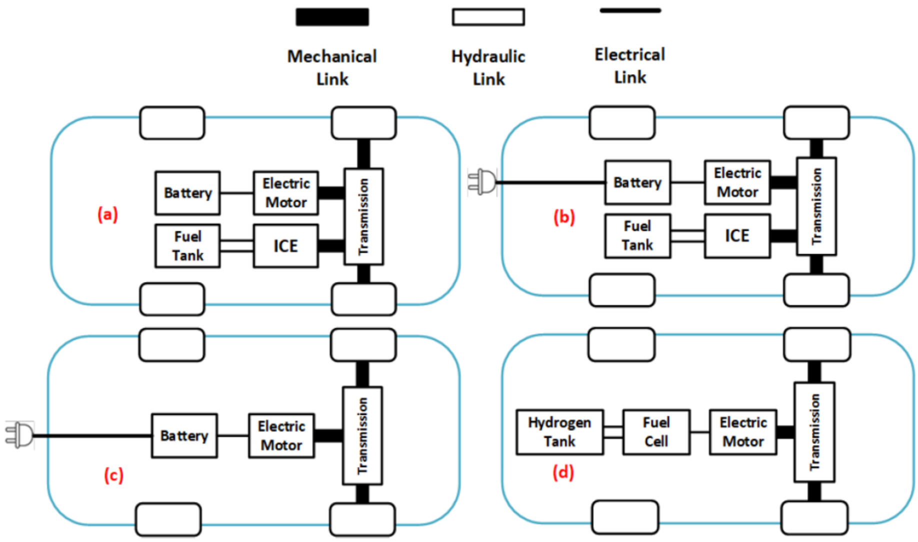

Figure 17. Different EV type's structure (a) HEV, (b) PHEV, (c) BEV, and (d) FCEV. **(Nour et al., 2020)**

Hierarchical controllers, which consist of upper and lower controllers, are used for ACC of EVs as in a conventional vehicle. However, there are several differences between EV and ICE vehicles. Firstly, in EVs, the kinetic energy is captured during braking by the regenerative braking systems and stored in the battery. Secondly, the powertrain system has a different structure, too. As a result, various ACC controllers can be designed accordingly. For instance, BEV needs to consider state of charge (SOC) when developing a control strategy to improve the overall performance. In HEV, the electric motor and the internal combustion engine collaborate to output the required torque. So, a tailored control strategy must be included for ACC functions to increase the efficiency and performance of the "Energy Management System" (EMS).

Regarding EV, various approaches have been adopted for ACC problems, including the "Reference Model Adaptive Control" (RMAC) system. RMAC features two feedback loops: one for regulator parameters setting and the other which is composed of the process and regulator. This paper **(Balaska et al., 2019)** presents a "fractional order model reference adaptive control" (FOMRAC) system for a DC motor EV. A hierarchical control strategy to regulate the lower controller's current and track the higher controller's desired speed is designed. Numerical simulations reveal the effectiveness of the proposed strategy, showing performance improvements in current regulation and desired speed tracking. This paper **(Petri and Petreuş, 2022)** presents a relationship between an ACC system and the EM control in an EV case. The system consists of "an indirect filed-oriented" control of an induction machine.

The ACC block computes the required acceleration to guarantee several objectives. These objectives include the velocity the driver sets, a safe distance, the car's actual velocity, and the relative distance between the two cars. The system was carried out in MATLAB/Simulink and dSPACE platform (a low-scale laboratory experimental setup), as shown in **Fig. 18**.

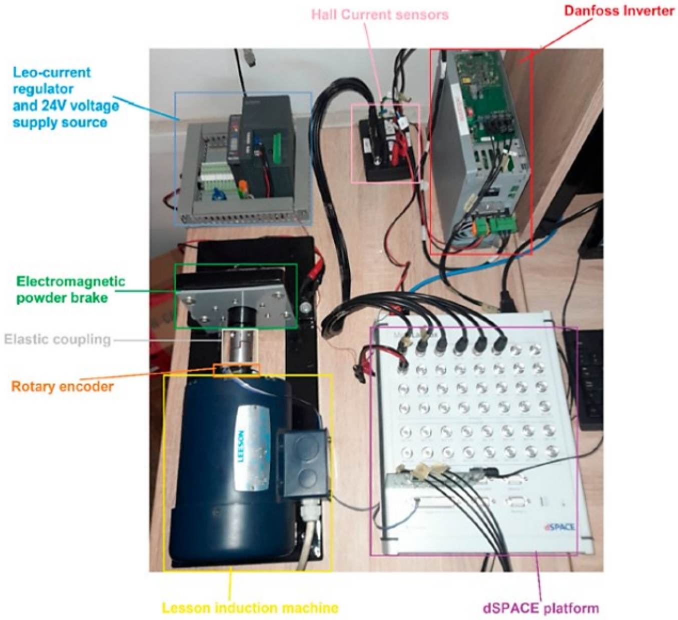

Figure 18. Components for the low-scale Lab. setup **(Petri and Petreuș, 2022)**

The control strategy successfully maintained a safety gap between the ACC vehicle and a preceding vehicle by adjusting the acceleration based on the relative distance and safe distance values. A study published **(Jia et al., 2019)** developed an "energy-optimal" adaptive cruise control (EACC) system for EV. An MPC controller is utilized to estimate an optimal speed path for the ACC car to improve energy efficiency and track a preceding vehicle. Four methods are used in this study to formulate the MPC problem for its cost function in both time and space domain. In the first method, a convex function represents the power consumption. The second method replaces the approximated power map by penalizing the host car's speed variation. In method three, the cost function is rebuilt. The key difference is to define positive traction force value. Also, an estimate of the power consumption map (upper half only) is used to make the percentage error smaller. Compared with the previously mentioned ways in the time domain, the fourth way is proposed in the space domain. The reason behind using this method is the power map appears similar to a flat surface, so a convex function formulation of a more accurate map approximation is possible. For HEV, adaptive cruise control is also an area of research and development. Several studies have focused on developing adaptive cruise control systems that simultaneously optimize energy management, route, speed, and powertrain control. One approach **(Li et al., 2023)** is fuel economy for connected (through vehicle-to-vehicle communication) plug-in hybrid electric vehicles achieved by a learning-based method. An advanced approximate dynamic programming (ADP) scheme is designed specifically for PHEVs driving in car-following situations. A data-driven model generates reinforcement signals for ADP, taking into account the nonlinear efficiency features of the powertrain system.

Furthermore, V2V communication transfers the cooperative information from the leading vehicle as an input to the controller. This action will dampen the host vehicle's velocity fluctuations and reduce energy consumption. Simulation results show that the fuel economy is significantly improved through cooperative driving information. Another research **(Vajedi and Azad, 2015)** investigates an ecological ACC for the Toyota Prius PHEV

developed for fuel economy and safety. Moreover, trip data information is captured using an on-board sensor. Accordingly, this data is utilized to adjust the host vehicle's speed. Nonlinear MPC (NMPC) is used to manage the vehicle's speed optimally. The proposed controller can be considered applicable in real-time by developing a fast and efficient control-oriented model. Also, "Pontryagin's minimum principle" (PMP) method is used to calculate the global optimum solution for the cruise control problem. Two driving scenarios are conducted to explore the performance of the proposed strategy: driving over the hill and car-following scenarios. Finally, to endorse the efficacy of the NMPC, a comparison of the three controllers is made. The simulation results show that NMPC surpassed all the prementioned controllers. The distribution of traction power, the energy recovery through regenerative braking, and the buffering of the energy for rechargeable batteries all lead to queries about how this energy flows among various HEV powertrain components. Since the ACC system with MPC predicts the velocity and acceleration profile (inherent prediction), both MPC predictive information and sensor information can be used to find the optimal control for better energy recuperation **(Kural and Güvenç, 2015)**. Thus, "second-order" approximation curve fitting is employed for the cost function of "Equivalent Consumption Minimization Strategy" (ECMS) behavior.
The approximation produced an estimated action of traditional ECMS, so the pre-emptive control approach was used throughout deceleration. This approach leads to the full benefit of the restoration energy throughout deceleration profiles. The vehicle model is carried out in IPG CarMaker and AVL CRUISE, a realistic co-simulation toolchain.
Finally, an investigation of ACC with energy management strategy (EMS) is proposed in **(Li et al., 2023),** where a model predictive mixed integer control method for a plug-in hybrid electric vehicle reduces fuel consumption during car following. The "control-oriented" EMS model is built considering clutch engagement and disengagement. Then, the co-optimization structure is converted into mixed integer nonlinear programming (MINLP). A WLTC drive cycle is used for the simulation test. The simulation shows the best performance in the energy management system and less fuel usage compared to sequential optimization.

3.4 ACC with Navigation

A more advanced version of ACC that combines speed sign recognition, road topography, restrictions, and navigation map information to adjust the cruise set speed is developed. Unlike conventional ACC, which detects only the surroundings of the vehicle using radar, camera, lidar, etc., it can benefit from the integration of navigation data to enhance performance and meet the driving requirements. as seen in **Fig. 19**. **(Gáspár and Németh, 2014)**.
One approach is to use navigation data to predict the trajectory and speed of the subject vehicle **(Goodall and Lan, 2020)**. Automated vehicles will behave differently from human-driven vehicles because of differences in precision control, perception abilities, and reaction times. So, this paper employs empirical data to study the car-following characteristics of ACC systems through an analysis of a previously untested manufacturer and model of the vehicle. ACC can utilise high-definition (HD) maps to access additional road and traffic information as shown in **Fig. 20 (Chu et al., 2018)**. So, a study by **(Chu et al., 2018)** provides a novel control scheme of "predictive cruise control" (PCC), which utilizes real-time HD maps to reduce fuel usage. First, the PCC problem is reformulated as an NMPC, then a fast solver is implemented. Second, a shift map method is presented to provide a schedule for various scenarios to allow the application of the proposed system. Finally, the control scheme is

determined through the simulation and practical application, revealing the reduction of fuel consumption.

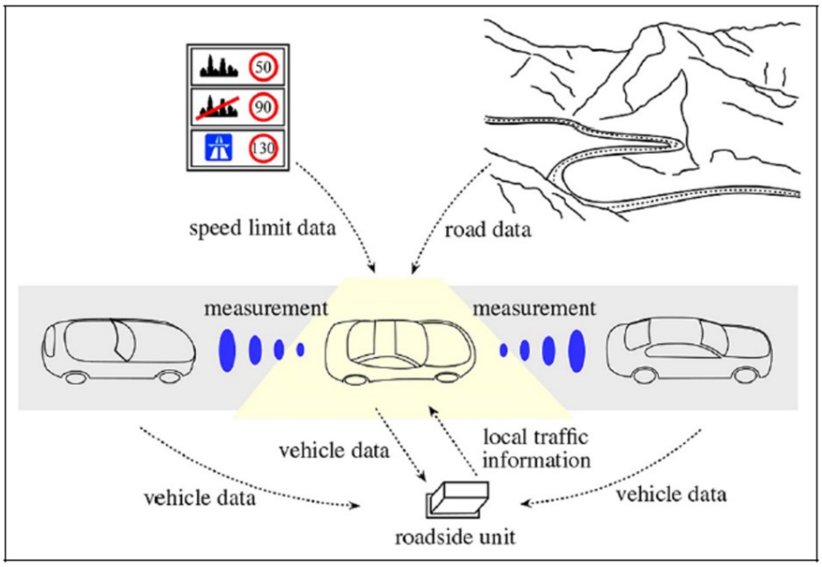

Figure 19. Navigation data usage in ACC system **(Gáspár and Németh, 2014)**

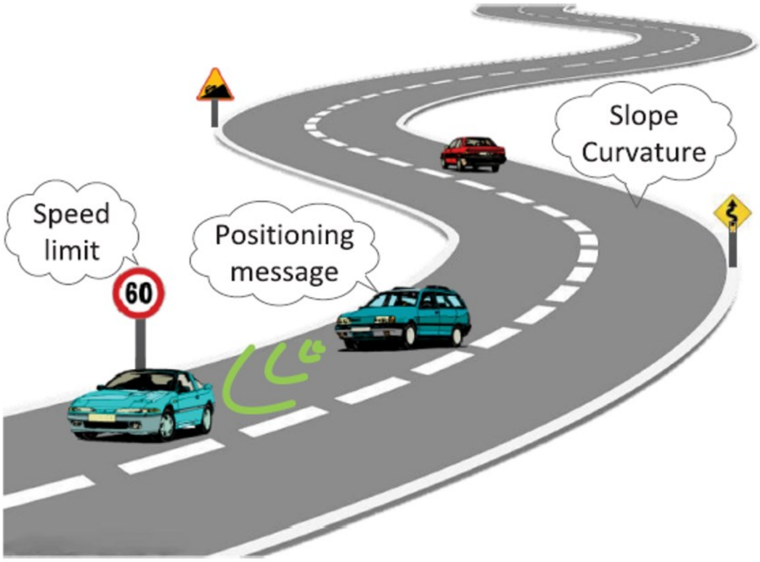

Figure 20. HD map usage in ACC system **(Chu et al., 2018)**

On the other hand, road information about the geometrical characteristics and traffic of the oncoming road sections, such as speed limits, slopes, and road curvature, can also be used to adjust the vehicle's velocity in advance. As a result, reducing the energy required for vehicle motion and improving fuel efficiency is fulfilled. In this context, **(Mihaly and Gáspár, 2013)** designed an "augmented look-ahead" ACC system by including two pieces of data information: the first one is forward traffic gained by floating car data (FCD) systems, and the second one is road curvature information gathered by geometrical data of the roadway. So, the energy consumed by the vehicle is considerably decreased, and the safety of the vehicle's motion is enhanced as well. The traffic flow in the environment of the host vehicle changes throughout the journey. Although several types of research emphasize traffic flow impairment caused by speed reduction, the other vehicles movements on the road are not considered. To overcome this problem **(Gáspár and Németh, 2014)** proposed an optimal look-ahead control strategy that forms a complex multicriteria optimization able to adapt to the movement of the surrounding traffic and solve the congestion problem. This strategy ensures a balance between fuel usage and the speed limits on the roadway.

3.5 ACC with Experimental Data

In literature, several published simulation studies for ACC systems exist; nevertheless, inadequate building of models leads to wrong or unrealistic conclusions. Few researchers implement real experimental data (accurate ACC models) and assess their practical effects on roadway capacity and traffic flow stability **(He et al., 2019)**. Several studies have focused on modeling adaptive cruise control dynamic responses based on experimental data. These studies have used experimental data from different commercially available ACC vehicles to develop accurate models that match real behavior. For example, **(Gunter et al., 2019)** used experimental data from seven commercial ACC cars to adjust the microscopic modeling behavior of each car. This method helps minimize the error between the simulated vehicle paths and the experimental information. Three different typical cars following models are used. Since the dynamic response of the ACC system can affect highway capacity and traffic flow, developing an accurate model is needed. A study by **(Milanés and Shladover, 2014)** developed models for ACC and CACC where four production vehicles with Intelligent Driver Model (IDM) equipped with a commercial ACC system and a newly developed CACC controller. Various traffic scenarios were tested to evaluate how the vehicle responds. The results from the experiments confirmed that CACC (Cooperative Adaptive Cruise Control) significantly enhances highway capacity and improves the stability of traffic flow. To validate and demonstrate controllers for ACC researchers used a scale model car as a testing platform **(Mehra et al., 2015)**.
These controllers are based on optimization techniques. Come with formal guarantees of correctness. Safety constraints, such as maintaining a following distance are represented by control barrier functions (CBFs) while control Lyapunov functions (CLFs) encode control objectives like achieving a desired speed. The effectiveness of the cruise controller was experimentally validated by implementing the CBF CLF based controller on scale model cars. Using a program (QP) this control framework optimally balances safety requirements, with control objectives. The research showcases real-world implementation and validation of these ACC controllers. Another study **(Lád et al., 2017)** developed an affordable experimental platform consisting of several autonomous slot cars fitted with on-board controllers and communication capabilities. The platform allowed for the demonstration of various distributed and decentralized control schemes for car platoons, such as predecessor following and CACC. Due to the fast dynamics of these cars, this platform also enables the observation of string instability.

4. FUTURE GUIDANCE AND CHALLENGES

Research on Adaptive Cruise Control systems has been conducted extensively. The first ACC-equipped vehicles have been available in the market for over two decades. However, the ACC system has limitations in several aspects. For instance, it has inaccurate tracking in bad

weather, the presence of obstacles, sudden lane changes, or bad road conditions. Improvements need to be added to the ACC system to overcome these limitations.
Many researchers try to improve ACC controllers by focusing on vehicle dynamics. Some studies focused only on longitudinal dynamics and ignored lateral dynamics. Others ignored the adverse weather conditions and road conditions. Considering more vehicle dynamics when designing ACC controller can be a future work suggestion. Several control algorithms were applied to solve the ACC problem. Each method has its advantages and weaknesses. For example, PID has a simple structure and is widely used in literature but cannot handle uncertainty or nonlinear behavior. On the other hand, MPC is an elegant approach and can run nonlinear systems successfully, but it has a computational burden. Thus, there is a tradeoff between controller design performance and simplicity. As a future work suggestion, such systems must be enhanced to improve the speed and reduce the computational effort so that it will become applicable in real-time.
Wireless technology conducted with the CACC controller helped to improve highway capacity and traffic flow. Adopting more such technology will upgrade CACC to the next level. The ACC system has become more robust and economically efficient thanks to HD digital maps and navigation technology, especially for EVs and HEVs. So, this technology needs to be investigated intensively by the ACC controller.

5. CONCLUSIONS

This survey aims to summarize the main academic accomplishments on adaptive cruise control to offer more useful experience-based guidance for the new deployment. An introduction to the ACC system, control algorithms used in ACC, and application cases are introduced separately. The paper highlights different vehicle dynamics and models presented by the researchers when designing the ACC controller. Many control approaches and algorithms are implemented. Also, it compares each method by reviewing its advantages and disadvantages. The robustness of the presented methods against external disturbances and model uncertainty needs to be further investigated.
Furthermore, it shows the contradiction between the controller's performance and complexity. Regarding the computational load of some algorithms that make them unsuitable for real-time implementation, more studies to simplify them need to be carried out. Application cases were also introduced, including EV and HEV, actual data experiment vehicles, and platooning using CACC are introduced too. Additional features of V2V and I2V technologies can be added to the controller design to improve performance and safety issues. Finally, the most important results related to ACC systems and future work suggestions have been summarized from vehicle dynamics, control algorithms, and new communication technology perspectives.

NOMENCLATURE

Symbol	Description	Symbol	Description
a	center of gravity (COG) to the front axle distance, m	v_x	lateral velocity, m/s²
b	COG to the rear axle distance, m	v_y	longitudinal velocity, m/s²
F_{yf}	lateral force of the front axle, N	Y	the vehicle's lateral displacement, m
F_{yr}	lateral force of the rear axle, N	α_f	lateral slip angle (front wheels), degree (°)
I_z	yaw moment of inertia, kg · m²	α_r	lateral slip angle (rear wheels), degree (°)
m	vehicle mass, kg	θ_{sw}	steering wheel angle, degree (°)
N_s	reduction ratio of the steering system	φ	yaw angle, degree (°)

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Credit Authorship Contribution Statement

Farah M. Ali: Writing – review & editing, Writing – original draft, Methodology. Nizar H. Abbas: Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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نظام التحكم التكيفي في السرعة: دراسة استقصائية

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قسم الهندسة الكهربائية، كلية الهندسة، جامعة بغداد، بغداد، العراق

الخلاصة

يساعد نظام تثبيت السرعة التكيفي (ACC) السيارات في الحفاظ على مسافة متابعة آمنة والالتزام بحدود السرعة. يقوم نظام مساعدة السائق المتقدم (ADAS) بتعديل سرعة السيارة للحفاظ على مسافة آمنة من حركة المرور القادمة. لجميع أنواع المركبات محركات الاحتراق، والمركبات الكهربائية البحتة، والمركبات الكهربائية الهجينة، وطرق تشغيلها؛ تم تصميم وحدات التحكم للتفاعل مع إشارات التحكم في السرعة وتوفير ملف تعريف مسار فعال وفقًا للبيئة المحيطة وخصائص الأداء الفوري للمركبة. يستخدم ACC نظام إدراك لقياس المسافة الحالية للمركبة الأمامية وسرعتها وتسارعها مقارنة بالمركبة المضيفة. تستخدم بعض هذه الأنظمة الليزر أو الرادار أو الكاميرات أو مجموعة من هذه المستشعرات لتحديد مسافة وسرعة السيارة في المقدمة. حتى أن الأنظمة الأخرى تستخدم الاتصالات اللاسلكية لجمع البيانات من المركبات المحيطة. يمكن أن يساعد نظام ACC في تقليل الضغط الناتج عن الرحلات الطويلة، وزيادة السلامة على الطرق، ومنع وقوع الحوادث، وتعزيز كفاءة استخدام الطاقة في تدفق حركة المرور. تهدف هذه الورقة إلى تقديم دراسة شاملة للبحث عن ACC وذكر تقنيات التحكم المختلفة المستخدمة للتعامل مع المشكلة. علاوة على ذلك، تم ذكر مناقشة كل طريقة مع سلبياتها وإيجابياتها أيضًا. أولاً، يتم تقديم مقدمة لنظام ACC وأساليب التحكم مع مناقشة موجزة لمبدأها الرئيسي. بعد ذلك، يتم عرض حالات تطبيق مختلفة لـ ACC. وتشمل هذه التطبيقات الديناميكيات لحركة المركبة الجانبية، والتكنولوجيا اللاسلكية، ومركبات الطاقة، وبيانات الملاحة، والاختبارات التجريبية العملية. وأخيرا، تمت مناقشة التوجيهات والتحديات المستقبلية.

الكلمات المفتاحية: نظام تثبيت السرعة التكيفي التعاوني، نظام تثبيت السرعة التكيفي، مركبة كهربائية، مركبة كهربائية هجينة، ديناميكيات المركبة.