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RESEARCH ARTICLE

A Literature Review of Energy Optimal Adaptive Cruise Control Algorithms

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ABSTRACT Transportation sector and its impacts on climate change have received much attention over the last decade. Energy-optimal vehicle control algorithms such as adaptive cruise control can potentially reduce fuel consumption and the consequential environmental impacts. Adaptive cruise control algorithms optimize vehicles' speed to lower energy consumption considering several constraints, including safety, stability, and comfortability. A wide range of algorithms with different objectives and optimization mechanisms have been reported in the literature. Due to the high diversity of constraints and objectives, a comprehensive study of these algorithms is required. In recent literature reviews, there is no comprehensive summary of the adaptive cruise control algorithms' features, classes, and objectives. This paper presents a holistic literature review of energy-optimal adaptive cruise control algorithms. We gathered relevant publications from well-eminent journals. Information on diversity and the number of publications will be presented to provide data on used references. For each paper, the objectives, features, and relevant classes of algorithms were extracted. Then a classification based on objectives is suggested, and mathematical formulas of representative studies are summarized to provide the required knowledge regarding mathematical modeling and optimization in this field. The study provides a useful insight into the development of the cruise control systems research field, revealing those scientific actors (i.e., authors, developers, and institutions) that have made the biggest research contribution to its development.

INDEX TERMS Adaptive cruise control, energy-optimal vehicle control mechanisms, transportation, transportation sustainability, climate change.

I. INTRODUCTION

Climate change must be addressed holistically in different sectors, including transportation, to prevent adverse environmental effects [1]. Specific to the transportation sector, several technologies, including but not limited to intelligent vehicle control algorithms, collision avoidance mechanisms, and electronic system malfunction indicators may impact vehicle fuel consumption and consequential environmental pollution [2], [3]. Cruise control (CC) is a type of algorithm that can be used to manage the speed and headways of vehicles [4]. Fuel consumption and its consequential environmental pollution can be managed through speed and headway control.

Adaptive CC (ACC) algorithm maintains the vehicle's speed typically set by a driver at a defined and desired point. The primary versions of CC algorithms do not interact with the traffic flow, and the driver maintains the vehicle's safety. ACC is an advanced version of CC that uses radar or camera data to maintain a safe distance from a leading vehicle [5]. In [6], It has been shown that when 10 percent of vehicles utilize ACC algorithms, fuel savings range from 8.5 to 28.5 percent. Different versions of ACC algorithms, such as Cooperative ACC (CACC) [7] and Ecological ACC (ECO-ACC) [5], result in a wide range of fuel-saving reported in the literature. In the literature, adaptive cruise control (ACC) systems are classified in a variety of ways based on different items as explained below.

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- **Sensor types**: There are various types of sensors that can be used to detect the presence and distance of other vehicles, such as radars, lasers, or cameras [8], [9].
- **Control strategy**: In order to maintain a safe following distance from the lead vehicle, ACC systems can use different control strategies, such as proportional-integral-derivative (PID) control, model predictive control (MPC), or fuzzy logic control [10], [11].
- **Adaptability context**: Different driving scenarios and conditions can be accommodated by ACC systems, such as highway, city driving, or different ecological conditions [12].
- **Automation Level**: ACC systems can be classified based on the level of automation which they provide, ranging from driver assistance to fully autonomous control [4].
- **Integration with other systems:** ACC systems can be integrated with other vehicle systems, control systems of other vehicles, or control systems of a smart city [9], [13], [14], [15]. For example, ACC system can cooperate with lane-keeping assistance or automatic emergency braking, to provide a more comprehensive Advanced Driver Assistance System (ADAS) [15].

Designing an energy-optimal ACC algorithm is not easy due to increasing and, at times, conflicting objectives (i.e., safety, stability, and comfortability) [16]. Analyzing the solutions trends and extracting classifications of the existing research and development scopes can support further advancement in energy-optimal ACC algorithms. Currently, there are several existing literature reviews [2], [4], [7], [10] focusing mainly on cooperation aspects, experimental data issues, driver characteristics, and intelligent collision avoidance techniques. On the other hand, the nonlinear dynamic structure of ACC systems require suitable control methods [17], [18]. Hence, optimal control methods are essential for ACC systems. In the literature, numerous controlling structures have been recently reported, including PID controllers [19], PID controller with reference model [20], fractional-order PID controller [21], fuzzy PID controller [22], fuzzy logic controller [23], and state space controller [24]. There is a gap in literature reviews that classifies recent studies considering scopes and objectives while focusing on mathematical formulations of the objective functions.

In this paper, we conduct a thorough literature review of energy-optimal ACC algorithms. The article serves as a comprehensive reference of publications in the area while presenting a systematic classification of energy-optimal traffic systems objectives. The next section covers the background knowledge. In section III, the motivation of this research is explained. Section IV focuses on the proposed method. Section V is dedicated to discussion. Conclusions and future directions are explained in Section VI.

II. BACKGROUND

In this section, the most common terms in this study are defined. These terms are often used differently in the literature. Therefore, it is crucial to have a unified definition going forward. For example, while most studies use eco-driving to explain general energy optimal driving [25], some studies use the term to describe ecological energy optimal driving (i.e., including topographic data in finding the optimum speed) [5], [26]. We define the terms based on the most commonly used definition in the literature.

- Energy optimal driving: It is an advanced technology that computes the most fuel-efficient trajectory for the vehicle based on the available information (e.g., speed limit, traffic condition, traffic signal, and topographic information) [27]. It finds the most fuel-efficient trajectory by optimization [28] or a rule-based system [29]. Energy-optimal driving algorithms are developed for fuel types (e.g., gas, hybrid, and electric) and control technologies (e.g., CC, ACC, CACC, and CAV).
- Ecological cruise control (ECO-CC): It is a type of energy-optimal driving technology with CC, which uses topographic information to minimize fuel consumption [5]. ECO-CC does not consider the surrounding traffic, and the driver must maintain the vehicle's safety [28], [30]. However, some studies developed ECO-ACCs, which use radar or camera data to adapt their speed and avoid collision [31], [32].
- Energy-optimal ACC and energy-optimal CACC: These are energy-optimal driving technologies based on ACC and CACC. They calculate the most fuel-efficient trajectory for a vehicle based on data from radar, camera, Vehicle-to-Vehicle (V2V), or Vehicle-to-Infrastructure (V2I) communications. They also adapt vehicles' speed to avoid collision [27].
- Model predictive control (MPC): It is a class of control algorithms that use a process to estimate the future status of an object (e.g., the status of a traffic light or a leading vehicle's location) [7].

It is difficult to draw a clear boundary between these technologies since most combine the abovementioned features. For example, an ECO-CC that receives traffic light data through V2I communication to pass the intersection at the right moment can also be classified as CACC [32].

III. MOTIVATION

The number of vehicles that deploy ACC algorithms and their variation is rapidly increasing [33]. These algorithms can significantly decrease energy consumption in vehicles [34]. Therefore, designing energy-optimal ACC algorithms has received much attention recently [34]. Several methods, such as improving powertrain/battery control [35], [36], [37], [38], smoothening acceleration and deceleration [35], [36], optimizing vehicles' trajectory [28], [37], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], and harmonizing vehicles' speed [43], [49], [50], [51], [52] have been proposed to

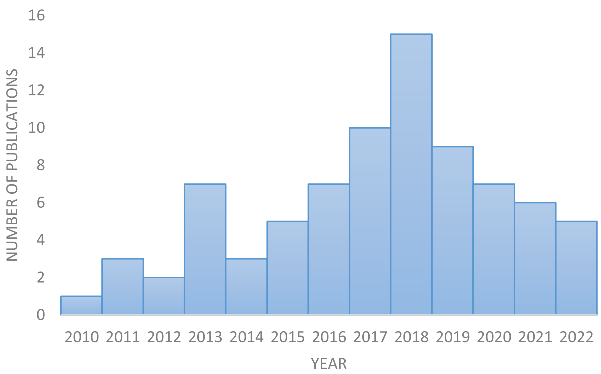

FIGURE 1. Number of publications from 2010 to 2022.

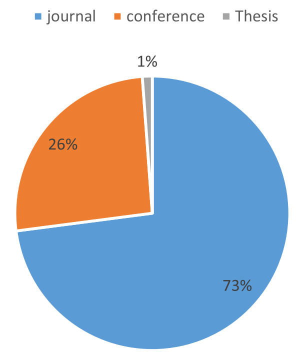

FIGURE 2. Types of publications.

reduce fuel consumption in energy optimal algorithms. Due to the increase in optimization methods, constraints, and objectives, the diversity of solutions and their categories have increased recently. A few papers [2], [4], [7], [10]) focus on this issue, but they cover limited aspects such as cooperation, collision avoidance, experimental data, and stop-and-go strategy. To our knowledge, there is no comprehensive summary of these algorithms' features, classes, and objectives. In addition, no literature review focuses on mathematical formulations of objective functions. We believe understanding the mathematical formulations of the objective functions and their classifications is crucial in understanding the algorithms, their strengths, and weaknesses, and how they can be further improved. Therefore, we took it upon ourselves to conduct a thorough literature review to conduct an in-depth analysis and classification of the energy-optimal objective functions.

IV. METHOD

The goal of this study is to study the classifications, objectives, and mathematical formulation of recently reported solutions for ACC algorithms. In this regard, we gathered relevant papers from different databases including Scopus, Web of Science, IEEE, MDPI, and Google Scholar. The papers have been sorted based on their priority considering impact factors and year of publication. 85 publications, including 62 journal papers, 22 conference papers, and 1 dissertation have been reviewed in reviewing the literature. We also covered 8 books and reports. Figure 1 shows the years of publications utilized in this study. Figure 2 illustrates the type of publications, most of them belonging to high-impacted journals. This section is organized into two parts, explained as follows. Thirty-two publications on ACC algorithms and their variations are categorized in the first part. Then, the second part summarizes the modeling method and objective functions reported in the papers.

A. ACC ALGORITHMS

ACC could reduce fuel consumption and emissions by maintaining a constant speed and smoothening vehicle acceleration/deceleration [28], [40], [41]. Some studies applied optimization algorithms to achieve minimum fuel consumption for a given path, known as energy optimum ACC presented in [53], [54]. Energy optimal ACC uses optimization algorithms to find a speed trajectory that minimizes fuel consumption while maintaining a safe distance from the leading vehicle. Distance to the leading vehicle is calculated by radar or camera data. In [53], Park et al. estimated up to 60% fuel saving possibility, which could lead to 13.8 billion gallons of gas per year, equivalent to $38.0 billion per year in the U.S. TABLE 1 summarizes the recently reported related works of ACC algorithms. According to this table, safety and tracking efficiency are considered as other objectives of designing energy-optimal ACC. Another thing shown in TABLE 1 is that quadratic programming, neural networks, and simulation techniques are used to propose solutions. These solutions consider vehicle lane change, fluctuation of vehicle acceleration, safety distance, and indirect fuel consumption.

1) CACC ALGORITHMS

CACC algorithms invest in cooperation among vehicles. In CACC, information propagation among vehicles leads to flowing valuable information that provides the required information for each vehicle to improve its accuracy with respect to energy consumption, safety, and stability, as shown in TABLE 2. This table summarizes the related works of CACC algorithms. Compared to ACC, CACC requires hardware and software infrastructure to support V2V communication, and this issue may lead to an increase in the cost of deployment of these algorithms. In addition to optimization methods presented for ACC, a machine learning method based on the Kalman filter is reported, as shown in TABLE 2. The scope of optimization is increased due to the availability of vebicle data; therefore, we need machinery methods to process a large amount of data. In addition to papers that focus on energy efficiency, safety, and comfortability, some papers, such as those reported in [45], [46], and [47], focus on security issues because most recently reported approaches require information sharing among different vehicles, and therefore these mechanisms must be secured.

TABLE 1. Feature and objectives of ACC algorithms.

Authors/ References	Objective	Features
Li et al., 2022/ [55]	Safety tracking efficiency	• In this work, a simulation dataset and neural network are used to train the vehicle lane change recognition model to recognize the lane change behavior of the preceding vehicles. • A weighted linear quadratic optimal control is used to reduce the fluctuation of vehicle acceleration.
Yang et al., 2021/[56]	tracking efficiency	• This work suggests an ACC algorithm based on MPC and active disturbance rejection control. • MPC algorithm is used for the upper controller of the ACC system. • This work can accurately control the tracking of the host vehicle with less acceleration fluctuation than other existing methods.
Jia et al., 2020/ [57]	energy consumption	• Speed predictor is based on traffic simulation data • MPC is based on long short-term memory (LSTM) deep recurrent neural network (RNN).
Weibmann et al., 2020/[58]	energy consumption and safety distance	• MPC is used to track the energy-optimal speed trajectory based on dynamic programming. • MPC is furthermore used to maintain the safety distance.
He et al., 2020/[34]	fuel consumption	• They performed a road test with 5 ACC-equipped vehicles when the ACC is on and off. • The result shows that ACC quickly responds to fluctuations in speed and causes traffic instability. As a result, at the follower level, fuel consumption has increased by 12% for the immediate followers and by 14% for the following platoon.
Tajjedin et al., 2019/[32]	safety, energy consumption, and desire velocity tracking	• A non-linear MPC problem is reported for Multi-Lane Adaptive Cruise Controller. • To handle the computational load of solving multiple MPCs in real-time, a method based on Newton and generalized minimal residual numerical methods is used.
Jia et al., 2019/[16]	energy consumption	• Time and Space Domain based on Model Predictive Control is considered. • Two approaches are used to simplify the original non-line system dynamics in the space domain. Linear-constrained quadratic programming is used to formulate the problem.
Jia et al., 2018/[59]	fuel consumption safety distance	• MPC-based ACC in the time domain utilizing multi-objective optimal control theory and quadratic programming is reported.
M. Mamouei et al., 2018 /[54]	fuel consumption	• This study proposes a model based on IDM car-following model. They optimize IDM parameters to generate an ACC model that minimizes fuel consumption. They developed two ACC models; 1) minimize user-oriented fuel consumption (self-centered ACC) and 2) minimize fuel consumption for the whole network (collective or system-oriented). They used a simulation-based optimization that tries different IDM parameter sets to find a set that minimizes fuel consumption.
Park et al., 2011/[53]	fuel consumption	• The model receives a cruising speed from the driver and optimizes fuel consumption, variation from the cruising speed, and gear change penalty. They used a regression model to estimate fuel consumption and MPC to predict traffic conditions.

TABLE 2. Feature and objectives of CACC algorithms.

Authors/ References	Objective	Features
Flores et al., 2022/ [63]	string stability and robustness	• A linear parameter varying feedback system to provide loop stability, robustness and enforce a variable time gap policy is reported. • By dealing with string heterogeneity, the system processes V2V information data to enhance string stability and response bandwidth.
Zhang et al., 2022/[64]	safety	• In this work, a Human-Lead-Platoon controller for CACC is reported for connected and Avs considering human drivers in platooning process. • This method utilizes human drivers' perception to enable full conditional autonomy and accommodate actuator delay in system dynamics to improve actuator control accuracy.
Liu et al., 2021/[65]	fuel consumption	• This study adopted a state-of-the-art traffic flow modeling framework to explore the impacts of CACC on vehicle fuel efficiency in mixed traffic. • The analyses at a freeway merge bottleneck indicated that the CACC string operation resulted in a maximum of 20% reduction in energy consumption compared to the human driver only case.
Coskun et al., 2021/[66]	energy consumption safety comfortability	• This work deals with developing CACC under uncertainty using an MPC strategy. • This work aims to design a predictive controller under a common goal such that the equilibrium from the initial condition of vehicles will remain stable under changes. • A Kalman filter handles the state estimation problem. • The control problem is formulated by quadratic programming.

2) ECO-ACC ALGORITHMS

These algorithms added topographic information of the road to maximize fuel saving [28], [30], [31], [37]. In these algorithms, vehicles adjust their speed on a hilly road to use gravity and maximize fuel-saving. It is reported that this technology could save up to 5% more fuel than classic CCs. Other studies combined ACC with ECO-CC, in which the algorithm receives road data through radar or camera and topographic data through topographic maps [37], [67]. These ECO-ACC algorithms could maintain a safe distance from the leading vehicle while driving fuel efficiently. The studies reported up to 27% fuel saving, depending on road slop and traffic conditions [5], [29], [32], [67]. TABLE 3 summarizes the related works of ECO-ACC algorithms. Although these studies reported significant energy impacts of their algorithms, they were generally tested in small traffic simulations with only a pair of subject-leading vehicles. These studies usually lack comprehensive investigations on their collective (network level) impacts. Thus, the energy impacts of these technologies at the network level and read-world conditions are unclear. The importance of studying the network impact of energy-optimal algorithms has been highlighted by several studies [29], [54], [68]. Huang et al. reviewed several approaches to reduce vehicles' fuel consumption and emissions (e.g., driver training programs, smartphone apps, and cruise control systems). They concluded that ''current eco-driving studies mostly focus on individual's driving behaviors, but lacks consideration at network levels'' [68].

B. ACC ALGORITHMS

In this section, the energy-optimal traffic systems are classified. Then, the objective functions and their formulations are studied. Figure 3 shows the proposed classification for energy optimal traffic systems. Based on literature review each class may be divided into several classes. The related works to all classes and subclasses are explained in this section.

1) ENERGY-OPTIMAL TRAFFIC SYSTEMS

The relevant literature to this study considering fuel-saving methods can be divided into two classes: 1- energy-optimal algorithms and 2- speed harmonization. Energy optimal algorithms consider direct fuel optimization, whereas speed harmonization considers indirect fuel consumption optimization.

a: SPEED HARMONIZATION

In congested traffic flow, drivers cannot travel at a fuel-efficient speed and achieve optimal fuel consumption. To address this problem, speed harmonization is proposed [72]. This approach can be used in changing speed limits for roadway segments [52], [72], [73], [74] and providing guidance work zone [75]. Congestion reduction of speed harmonization techniques leads to other types of fuel saving that we call indirect fuel saving. There is a limited number of studies on decentralized speed harmonization (i.e., without a centralized roadside unit) [76], [77].

Yang et al. proposed a decentralized speed advisory system for manual-driven vehicles with V2V communication and radar data, named green vehicles [76]. In this system, the green vehicles share their location and speed data, but each vehicle makes its calculations and decisions. They

TABLE 3. Feature and objectives of ECO-ACC algorithms.

Authors/ References	Objective	Features
Bae et al., 2022/ [69]	energy consumption	• This work proposes a mathematical framework for an online ECO-ACC for a plug-in hybrid electric vehicle. • This work suggests ECO-ACC, which includes other human drivers and uncertain traffic signals in Southern California.
Ma et al.,2021/[70]	energy consumption	• This work combines both advantages of eco-driving and platooning. • Connected autonomous vehicles platoon can pass the continuous signalized intersections without separation. • An improvement in calculation speed using a modified dynamic programming algorithm.
Tajeddin et al., 2019/[32]	fuel consumption	• They optimize fuel consumption, variation from defined speed, and soft safety constrain. • The model receives information on surrounding vehicles through V2V communication and performs lane-changing if needed.
Weißmann et al., 2018, 2017 /[71], [72]	fuel consumption	• They developed a two-stage (offline and online) fuel optimization ACC. The model first estimates fuel-efficient trajectory for the whole road based on topographic data. Then, online optimization is performed to minimize variation from that optimum trajectory. Fuel consumption is estimated based on the physical model.
Lim et al., 2017 /[67]	fuel consumption	• The model has two optimization stages (i.e., online and offline). The offline stage optimizes fuel consumption for the whole path at the beginning. Then, the online stage optimizes fuel consumption and variation from a speed limit or the leading vehicle's speed. They used an engine deterministic model with gear change cost to estimate fuel consumption.
Lin et al., 2016 /[28]	fuel consumption	• They minimized electric and gas consumption, considering MPC for the leading vehicle and topography of the roadway. • They used a deterministic engine model to estimate fuel consumption.
Vajedi and Azad, 2016 /[37]	energy cost	• Their objective function was to optimize fuel cost (i.e., gas and electric) with a soft safety constraint. The model considers road topography and MPC for the leading vehicle. An engine deterministic model is used to estimate fuel consumption.
Sakhdari et al., 2016 /[5]	fuel consumption	• The ACC uses topographical information, V2I to an intersection, and a physical energy model to optimize fuel consumption for the vehicle. They predicted the leading vehicle's acceleration, assuming drivers keep the same acceleration rate which gradually decreases.
Wang et al., 2014 /[29]	fuel consumption	• They developed one energy-efficient and one travel-efficient model. The energy-efficient model optimizes CO2,

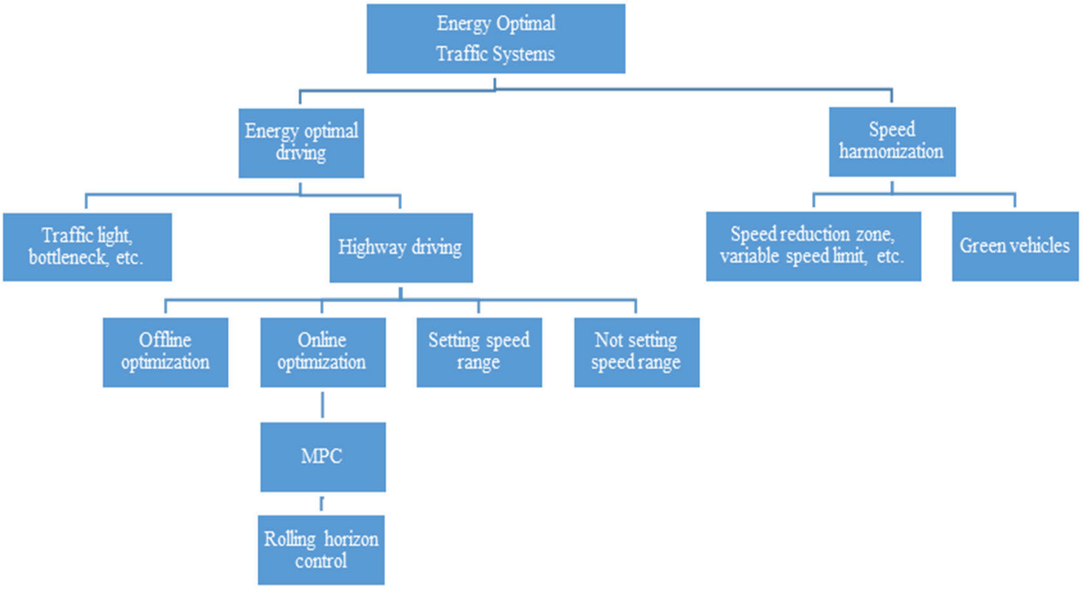

FIGURE 3. Main research areas in energy-efficient traffic systems.

TABLE 3. *(Continued.)* Feature and objectives of ECO-ACC algorithms.

		comfort (acceleration rate), safety constraints, and driving at the desired speed and gap. The travel-efficient model optimizes driving at the desired speed, gap, and comfort costs. • They used a discrete finite speed and optimum speed through the simulation (i.e., no optimization, just a lookup table). CO2 emission is estimated based on a simple model based on travel. Speed
Saerens et al., 2013 /[30]	fuel consumption	• They optimized the amount of fuel consumption by travel time. • They used an engine deterministic model to estimate fuel consumption.
Ahn et al., 2013/[31]	fuel consumption	• The model receives a speed range from the driver and uses topographic data to minimize fuel consumption for the vehicle. • They used an engine deterministic model to estimate fuel consumption. They simulated their model in a 26-mile section of I-81 between Roanoke and Blacksburg, Virginia.

calculated fuel consumption by CMEM model and conducted a traffic simulation. They reported a 15% to 35% reduction in fuel consumption and emissions. The savings are higher in stop-and-go conditions and single-lane ring road simulation. They found that a 5% MPR could significantly influence traffic flow. A field test found that this algorithm reduced fuel consumption by 20% and 30%, respectively, under the slow and fast-moving trafic conditions [77].

b: ENERGY OPTIMAL DRIVING

Most energy-optimal algorithms attempt to optimize fuel consumption in specific traffic conditions, like in signalized intersections or road closures [43], [78], [79], [80]. A limited number of studies have developed energy-optimal systems for normal highway travel [31], [42], [53], [67]. These systems can be offline (i.e., considering all road characteristics known in advance for the system) or online (i.e., real-time prediction of unknown characteristics, like road slope and surrounding vehicles' behavior). In online optimization, model predictive control (MPC) is used to predict the environment status (e.g., average traffic speed or the preceding vehicle's acceleration). MPCs vary from simple linear models (e.g., predicting the preceding vehicle's acceleration while assuming a fixed acceleration rate for the preceding vehicle [81]) to complex non-linear algorithms. However, computation time is the main limitation of online MPC algorithms, especially when the number of control inputs is too large. Rolling horizon control is an approach to solving the computation time problem. In rolling horizon control, the control period is limited to a short planning period, and the optimization focuses on than planning horizon. The number of parameters to optimize is small, and the optimization process is fast. Some energy-optimal systems request the driver to set a comfortable speed or a range of speed, but other algorithms can find the most optimum speed to travel.

Every energy-optimal algorithm with an optimization function needs to estimate fuel consumption for potential solutions. There are two main classes of instantaneous fuel consumption modeling in the literature: 1) data-driven approaches and 2) physical modeling approaches [82]. Data-driven approaches rely on field data to estimate fuel consumption and emissions, but physical models formulate engine and vehicular motions to calculate fuel consumption and corresponding emissions. Lookup tables are a data-driven approach, which are massive databases of fuel and emission data from field tests. It provides the amount of fuel consumption and emissions for a given velocity, acceleration, and slope from the field data. Although this method is easy to use, the available databases are usually sparse due to measurement difficulties. The regression models fit a non-linear regression approximator to the field test dataset and provide coefficients and weights to estimate fuel consumption and emission for a given vehicle. Ahn energy and emission model is an example of a regression-based model [83].

2) OBJECTIVE FUNCTIONS

This part will review the most related studies in energy optimization and speed harmonization, considering mathematical formulations. This section is organized into five subsections to study different variations of mathematical approaches to proposed energy optimal solutions. Subsections a, c, and d focus on hilly roads, lane-changing ability, and harmonization issues in designing ACC algorithms. Subsections b, and d, focus on online and two-stage approaches to designing ACC algorithms.

a: ENERGY OPTIMAL ALGORITHM CONSIDERING HILLY ROADS

Saerens et al. proposed an energy-optimal algorithm for hilly roads [30]. Their algorithm optimizes fuel consumption rate (i.e., fuel consumed per mile travel). The objective function is defined in (1), (2), (3), and (4).

$$\min_{v(.),s(.),p(.)} \int_0^{s_e} L.d_s \tag{1}$$

$$L = \frac{\dot{m}_f}{v} \tag{2}$$

$$\dot{m}_f = \begin{cases} \alpha_0 + \alpha_1 P + \alpha_2 P^2 & if\ P \geq 0 \\ \alpha_0 & if\ P < 0 \end{cases} \tag{3}$$

$$P = v.\left(I\frac{d_v}{dt} + c_0(\theta) + c_1(\theta).v + c_2.v^2\right) \tag{4}$$

where L is the fuel consumption rate through the rolling horizon $\dot{m}_f$ is fuel consumption, v is velocity, α is the coefficients captured from the VT-CPFM model, and P is the needed engine power. I is inertia, c is road friction and driveline fiction, and θ is road slop. More information is available from [30]. A numerical simulation showed that the algorithm could save 5% more fuel than conventional cruise control systems.

b: ENERGY OPTIMAL ALGORITHM CONSIDERING TWO-STAGE OPTIMIZATION TECHNIQUE

Lim et al. proposed a two-stage energy optimal algorithm that minimizes fuel consumption [67]. In the first stage, the algorithm performs an offline fuel optimization for the whole road with longer rolling horizons and fewer details. Then, it performs online fuel optimization with short rolling horizons and minimizing velocity variation from the target velocity, estimated in the first stage. They used the Willans line approximation to estimate fuel consumption, which defines a linear relationship between torque and fuel consumption rate based on a regression analysis. The objective function in the second stage is given in (5).

$$J_{opt} = w_1 \sum_{k=0}^{n-1} \dot{m}_f(k)\,\Delta t_k + w_2 \sum_{k=0}^{n-1} \left(v(k+1)^2 - V_{target}(k+1)^2\right)^2 \tag{5}$$

$$\dot{m}_f = \left(\beta_1 \frac{f_r g_r(n)}{r_w} v + \beta_2\right) T_e + \gamma_1 \frac{f_r g_r(n)}{r_w} v + \gamma_2 \tag{6}$$

where J_{opt} is the objective function, $\dot{m}_f$ is the fuel consumption rate, k is the time, n is the rolling horizon, v is the velocity, V_{target} is target velocity, T_e is the engine torque, $g_r(n)$ is gear ratio, r_w is wheel radius, β and γ are constant, which are captured from autonomie simulation software, and w is weight.

c: ENERGY OPTIMAL ALGORITHM CONSIDERING LANE CHANGING ABILITY

Kamal et al. developed an energy-optimal algorithm based on MPC with a lane-changing ability [42]. The objective function is given in (7).

$$\min L_a + L_b + L_c \tag{7}$$

$$L_a = \sum_{r=t}^{t+T} \left(w_v(v_h(\tau) - v_d)^2 + w_u u_h^2(\tau)\right) \tag{8}$$

$$L_b = w_b \sum_{\tau=t}^{t+T} \frac{1 - l_h(\tau)}{1 + e^{-\alpha_b(t_h(\tau) - t_r)}} \tag{9}$$

$$L_c = w_c \sum_{\tau=t}^{t+T} \sum_{j=q_1}^{qm} l_h(\tau)\, e^{-\alpha_c\left(x_h(\tau) - \bar{x}_j(\tau)\right)^2} \tag{10}$$

L_α is the penalty due to variation from pre-defined speed v_d and a penalty for acceleration u_h. L_b is the safety penalty due to following the preceding vehicle with short time headway t_h (i.e., a soft safety constraint), while the safe time headway is t_r. L_c is the lane-changing penalty, l_h is a binary lane-changing status, x_h is the location of the subject vehicle, t is the planning start time, T is the rolling horizon, w and α are weights. This energy-optimal algorithm reduced mean velocity by 6% and improved fuel economy by 7% in a traffic simulation.

d: ONLINE ENERGY OPTIMAL ALGORITHM

Park et al. introduced an online energy optimal algorithm using topographic information [53]. Their optimization function, denoted by (11), reduces fuel consumption and variation from reference velocity, which the driver sets.

$$cost = w_1 * FC_{(v_0,v_1)} + w_2 * |v_1 - v_{ref}| * FC_{(v_{ref})} + w_3 * |g_1 - g_0| * FC_{(v_{ref})} \quad (11)$$

$$FC(t) = \beta_0 \omega(t) + \beta_1 P(t) + \beta_2 P(t)^2 \quad (12)$$

where cost is minimized, FC. is the fuel consumption through driving at reference velocity v_{ref} or changing speed from v_0 to v_1, g is the gear number, P(t) is the instantaneous total power, w_t is the engine speed, w is weight, β is coefficients which are captured from VT-CPFM. A traffic simulation showed a 30% to 60% fuel-saving possibility in different scenarios. They estimated that this energy-optimal algorithm could save up to 14 billion gallons of gas annually in the U.S.

e: ENERGY OPTIMAL ALGORITHM BASED ON SPEED HARMONIZATION TECHNIQUES

Some studies used optimization for speed harmonization and increasing traffic network throughput [52], [72], [73], [84], [85]. Tajalli et al. developed a speed harmonization algorithm for connected vehicles [72]. In this algorithm, a central unit calculates optimum speeds and sends them to each connected vehicle at different roadway segments. They used an optimization function to 1) maximize traffic density in each road segment, aiming to maximize throughput, and 2) minimize speed variation between two subsequent segments. The objective function was defined as:

$$Max \left[\sum_{t \in T} \sum_{i \in c_s} x_i^t - \gamma \sum_{t \in T} \sum_{i \in C\{c_s\}} \sum_{j \in \{i, \Gamma_i\}} \left| v_i^t - v_j^{t+1} \right| \right] \quad (13)$$

where x_i^t is the number of vehicles in segment i at time t, γ is a weight factor, and v_i^t is the average speed of vehicles in segment i at time t. The goal of this objective function is not to reach maximum traffic density, which could cause congestion and lower speed travel. The authors defined a constraint based on the fundamental diagram to maintain x_i^t at an optimum level. For more information, please see [72]. A traffic simulation showed that the algorithm could reduce travel time by up to 5%, speed variation by up to 29%, and increase average speed by up to 6%.

V. DISCUSSION

The study section of this paper focuses on features, objectives, and solutions to highlight the research trends. According to this study, our findings can be summarized as follows;

- The recently reported ACC algorithms appear to have taken into account objective aspects such as safety, comfortability, and robustness, as well as optimizing energy consumption. A growing number of objective functions have made finding appropriate solutions more challenging.
- From a solution perspective, most solutions are based on quadratic programming and dynamic programming. Some of the recently reported solutions are based on artificial intelligence [86]. A number of intelligent tuning methods to adjust different controller structures have been described in terms of ant lion optimization algorithms [20], atom search optimization algorithms [87], differential evolution algorithms [88], genetic algorithms [89], arithmetic optimization algorithms [90] and Harris hawk optimization algorithms [91], as well as particle swarm and teaching learning-based optimization algorithms [92].
- Some actions executed in each vehicle may lead to hurtful consequences on the life of humans. Therefore, the ACC algorithms should be examined from different angles; one of the most important is safety. Unfortunately, most recently reported algorithms are examined in a simulated environment with synthetic data and scenarios. Therefore, the safety concerns may not be resolved easily by the existing simulation-based scenarios.

Other issues pointed out by most ACC algorithms are how we can deploy large-scale data processing techniques and secure communications among entities in ACC algorithms. The issue arises because of the increasing data about vehicles, traffic, and communications among entities (V2V and V2I). This issue will be challenging in designing real-time solutions because of the time limitation that we have to provide an appropriate solution.

VI. CONCLUSION

In this paper, we conducted a holistic literature review on ACC algorithms that can result in significant fuel savings (i.e., CACC, ECO-ACC). About 90 publications from well-eminent journals and conferences were studied. For each literature review, the objectives and features were summarized. A classification of energy-optimal traffic systems was also proposed. Since the number of objectives and features of solutions has increased, the proposed literature review focused on the existing and future trends in research and developments of ACC algorithms. The existing trends in designing new versions of ACC algorithms have a high potential to use novel technologies such as blockchain. Therefore, as future work, we may invest in the applications of this technology to different aspects of designing ACC algorithms.

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