Heliyon 5 (2019) e03056

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Optimization of steering control to improve the energy consumption of internal combustion engine vehicles

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ARTICLE INFO

Keywords:
Energy
Mechanical engineering
Energy storage technology
Energy economics
Energy conservation
Urban energy consumption
Fuel technology
Internal combustion engine
Dynamic control
Steering sensitivity
Global search algorithm (GSA)

ABSTRACT

This study aims at developing a vehicle dynamic simulator using combined CarSim and MATLAB/Simulink software packages loaded with the performance curves and characteristics of an internal combustion engine to optimize the effects of steering control on the energy consumption of an internal combustion engine vehicle. The simulator consists of modules for the engine, transmission, vehicle dynamic load, energy management strategy, and driving patterns. The goal of this research is to develop an advanced Steer By Wire (SBW) system. As the vehicle is turning, the repeatable turning or oversteer might occur due to several factors: 1. The path is narrow or the road curvature is high; 2. The insufficient designs of turning radius; 3. The driver's choice for turning paths; 4. Human operation factor (slow or fast operating steering wheel that the vehicle is unable to follow the route). Hence, under various steering sensitivity, vehicle speed, and turning radius, we searched the optimal operation parameters globally that the vehicle might save the maximal energy under the safety concerns. The results will be provided as the reference for the drivers or directly be integrated for the SBW under the semi-automatic driving mode. The results of optimal steering control show that: as the turning radius is 40m and vehicle speed is 70 km/h, the maximal energy consumption improvement is 42.72%. If the optimal vehicle speed is considered, the improvement can be even larger. The vehicle model was built based on the real vehicle parameters which can further be employed for the real transportation system.

1. Introduction

The automobile emission standards have become more stringent due to energy crisis and environmental problems in the past few years [1]. Many researches focused on the optimal energy management of internal combustion engine vehicles including conventional diesel/gasoline vehicles and hybrid electric vehicles were undertaken and documented [2, 3]. The energy efficiency performances of vehicles are closely correlated to either driving patterns or steering behaviors. For the effects of the former, several optimization algorithms have been proposed and applied for designing the control strategy of the powertrain of vehicle. Dynamic programming (DP) is a widely-used method of energy management since a truly optimal state with respect to the designated control variables for a given and predictable driving cycle can be attained [4, 5]. However, for a real vehicle driving on real roads, DP is impractical due to unknown road conditions. To counter this drawback, stochastic dynamic programming (SDP) can further implement DP for real-time control of uncertain road loads [6]. However, the high computational load and complicated mathematical derivation required restrict the usage to a vehicle control unit (VCU). In addition to DP and SDP, genetic algorithms constitute a practical approach for highly nonlinear vehicle systems [7]. Nevertheless, the lack of analytical solutions means modifying the control laws is problematic. Contrarily, problems of prediction control, linear regulation, and robust control all have analytical solutions [8]. To accommodate computational efficiency alongside accurate control, rule-based control combined with equivalent consumption minimization strategies can be used to search for the optimal solution or the lowest-cost path [9, 10].

Replacing internal combustion engine vehicles by electric vehicles has also been recognized by industry and car market as a feasible solution of green transportation. The fuel efficiency and exhaust emission for electric vehicles have been proven to be significantly lower than those for conventional internal combustion engine vehicles [11]. Nowadays, to increase the energy efficiency and extend the driving range of vehicles, utilizing tires with reduced rolling resistance has become more popular (a delta of 4% in rolling resistance can affect fuel consumption by 0.4 L per 100 km) [12]. The resulting less cornering stiffness compared with conventional tires inevitably lowers the handling performance and safety. An effective control strategy of torque distribution for avoiding

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https://doi.org/10.1016/j.heliyon.2019.e03056
Received 6 September 2019; Received in revised form 14 November 2019; Accepted 12 December 2019

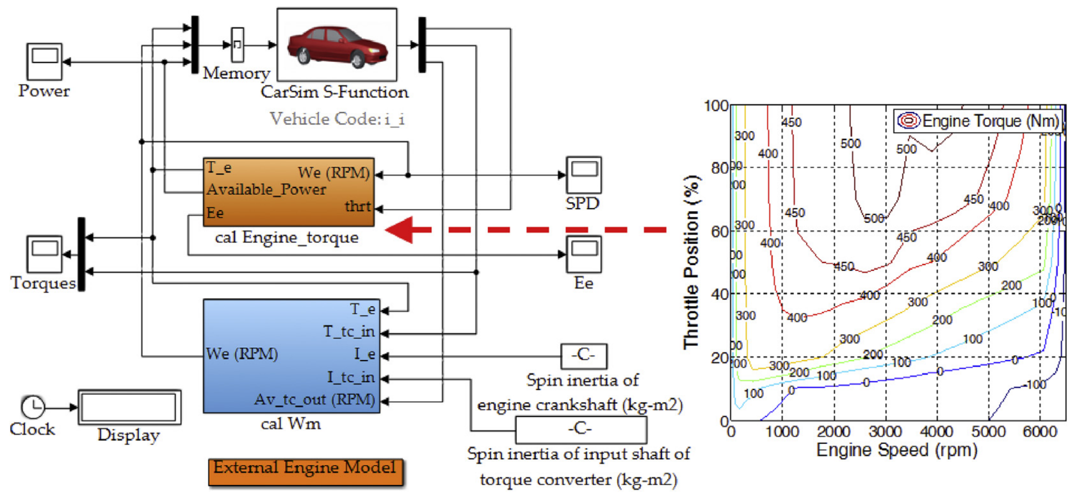


Figure 1. Configuration of the internal combustion engine vehicle.

slip has become imperative to enhance the handling characteristics for electric vehicles [13]. Furthermore, some researchers aimed at developing optimized control algorithms to solve the interrelated problems between handling performance and energy efficiency [14, 15]. These researchers developed coordinated control algorithms simulated with a CarSim vehicle model that can provide comprehensive optimization of a vehicle's dynamics performance and energy consumption. The simulation results were in the form of multidimensional tables that could be downloaded to a VCU. Hence, this research defined a cost function, which was the minimized cost for the global search algorithm (GSA). Another penalty term was added to avoid searches for unreachable solutions.

The ensuing problems of handling performance and safety of vehicles aroused by consistently boosting energy efficiency have long been received much attention. This brings about high interests in developing a variety of active-safety technologies for vehicles. The vehicle dynamic control is one of the key technologies and has gained significant advancement. A related analysis software of vehicle dynamics with industrial standard called CarSim® has been recognized as a powerful simulation tool capable of integrating some other softwares to simulate the complicated behavior of vehicle dynamics. A simulation study of an electric vehicle with in-wheel motors using combined MATLAB/Simulink® and CarSim® was carried out. The results show that the proposed algorithm for the control strategy can improve both driving stability and energy consumption [16]. One simulation research of vehicle dynamics on an electric vehicle equipped with four independent in-wheel motors is performed to evaluate the feasibility of the proposed new control method for rollover prevention. The dynamic analysis software CarSim® loaded with the experimental data of vehicle parameter and performance, and coupled with a real-time system called dSPACE MicroAutoBox® has been proven to possess capability of simulating rollover conditions [17]. Furthermore, a proposed strategy of wheel torque distribution based on multi-objective optimization is implemented into a simulation program of vehicle dynamics combining both MATLAB® and CarSim® for four-wheel-drive electric vehicles. The results reveal that the developed strategy can simultaneously improve handling performance as well as energy efficiency [18]. Zhao et al. [19] proposed integrated electric/hydraulic steering system that can simultaneously improve the energy consumption and control performance of steering. This system is optimized using an objective function defined as the error between steering road feeling and steering wheel return. A method of improved multi-objective Particle Swarm was proposed to optimize the relationships between the energy consumption and the steering characteristics of the test vehicle in an intelligent transportation environment. Results show that the energy consumption reductions of 34% and 14% are achieved at high speed and low speed, respectively. The 15km on-road test also reveals that an energy consumption improvement of 51.7% along with a reduction of average steering wheel return error of 11.5% is achieved. Moreover, Chatzikomis et al. [20] developed a new torque control algorithm to include in a simulation model for a vehicle with in-wheel motor. The simulated results with verification by experiments indicate an energy reduction of 4% at the constant-speed straight line operation, and an average power reduction of greater than 5% coupled with the lateral acceleration of greater than 3.5 m/s^2 at the static steering. In addition, the yaw rate and sideslip angle oscillations are effectively compensated under extreme transient test. Chen et al. [21] proposed a controller based on the hybrid model predictive control for the nonlinear dynamics model. It is implemented in a simulation program for the yaw stability control of an electric vehicle. Some required signals are to be tracked and used for control so that the in-wheel motors of the vehicle can be maintained in high-performance operations. The simulation results under the proposed MPC control compared with those of the open-loop control were compared show that the former can rapidly track the target and stabilize the vehicle.

In the present study, a vehicle dynamic simulator using combined CarSim® and MATLAB/Simulink® software packages loaded with the experimental performance curves and characteristics of an internal combustion engine is utilized to perform the optimization of steering control on the energy consumption of an internal combustion engine vehicle. The goal of this research is to develop an advanced SBW system. The CarSim software package provided the vehicle automatic maneuver and the real vehicle parameters. This research established the global optimal search program on the Matlab platform. By CarSim, the convincible and commercialized software package, and the self-developed optimal search algorithm, the research results are valuable for real transportation applications in the future.

2. Design of the ICEV

2.1. System configuration

A commercialized software called CarSim is used as the simulation platform for analyzing the vehicle dynamic behavior. Some control variables for steering sensitive to energy consumption at various vehicle speed are tuned using GSA to search for an optimal turning radius with maximal traveling mileage and improved energy-saving from engine. The performance maps imported from test data of real vehicles are utilized. As a result, multi-dimensional tables can be constructed and easily installed in the vehicle control unit in favor of future commercialization of the controller. First, the steering dynamics of the vehicle models were developed in CarSim, where they were characterized as follows:

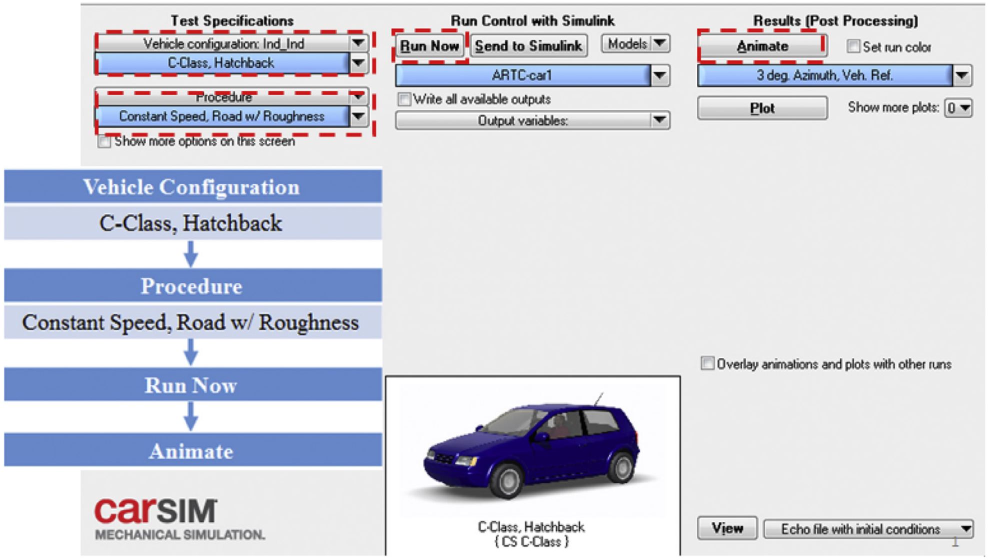


Figure 2. CarSim model selection.

1. Precise mathematical models for vehicle dynamics minimized the research period for developing the vehicle system.
2. A complete graphical user interface provided a user-friendly environment for vehicle designs and a setting for test scenarios.
3. Support of various development platforms allowed for integration with platforms such as MATLAB/Simulink and LabVIEW for research.
4. A real-time simulation system with hardware-in-the-loop supported integration with real-time simulation environments such as RT-LAB and LabVIEW-RT.

2.2. Detailed process for CarSim simulation

In this research, the test vehicle is modeled with a hatchback car in the design case of Carsim. The independent engine and transmission programs are chosen from the Simulink examples of CarSim. The single reduction ratio is set for the transmission as depicted in Figure 1. A 200kW engine is selected with the functional expressions of engine torque, engine power, and BSFC shown in Eqs. (1), (2), and (3). The operation range of engine is designated by the constraint of engine output torque. Meanwhile, the situation of oversteering or incomplete vehicle turning should be considered and attributed to four factors: 1. Narrow road width or small road curvature; 2. Insufficient designed turning radius; 3. The selection of turning paths; 4. Human maneuver (slow or fast steering that lose the route track) The engine torque output with respect to the throttle position and the engine speed is as follows:

$$T_e = f(TP,\ N_e) \tag{1}$$

Where T_e is the engine output torque (Nm); TP is the throttle position (%); and N_e is the engine speed (rpm). Therefore, the output engine power is as follows:

$$P_e = \frac{2\pi}{60} T_e N_e \tag{2}$$

where P_e is the engine output power (W). Furthermore, the instant brake-specific fuel consumption (BSFC) of the engine is normally tabulated by T_e and N_e. Along with Eq. (1), BSFC can be determined as follows:

$$\mathrm{BSFC} = f(TP,\ N_e) \tag{3}$$

1. From CarSim software package, the real vehicle maneuver is

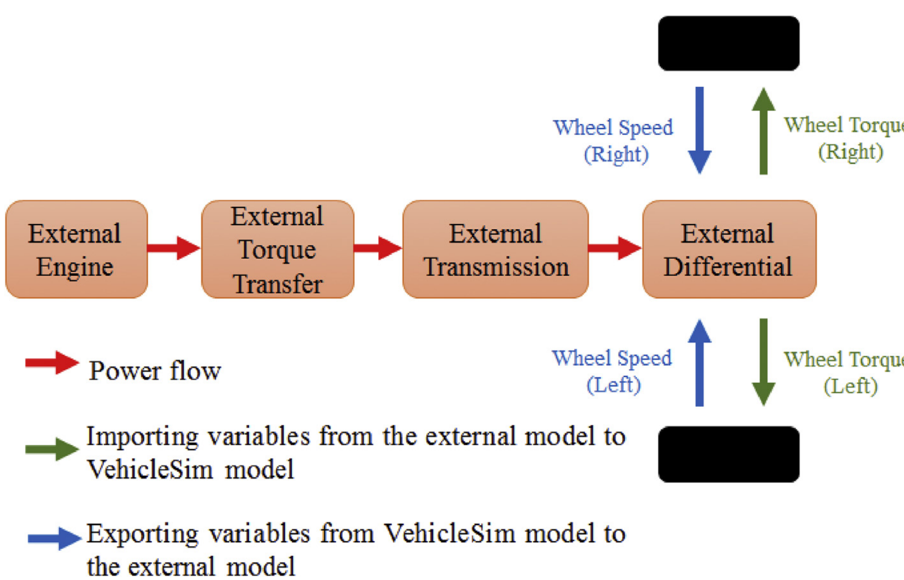


Figure 3. Modifying the setting inputs of vehicle structure from Simulink.

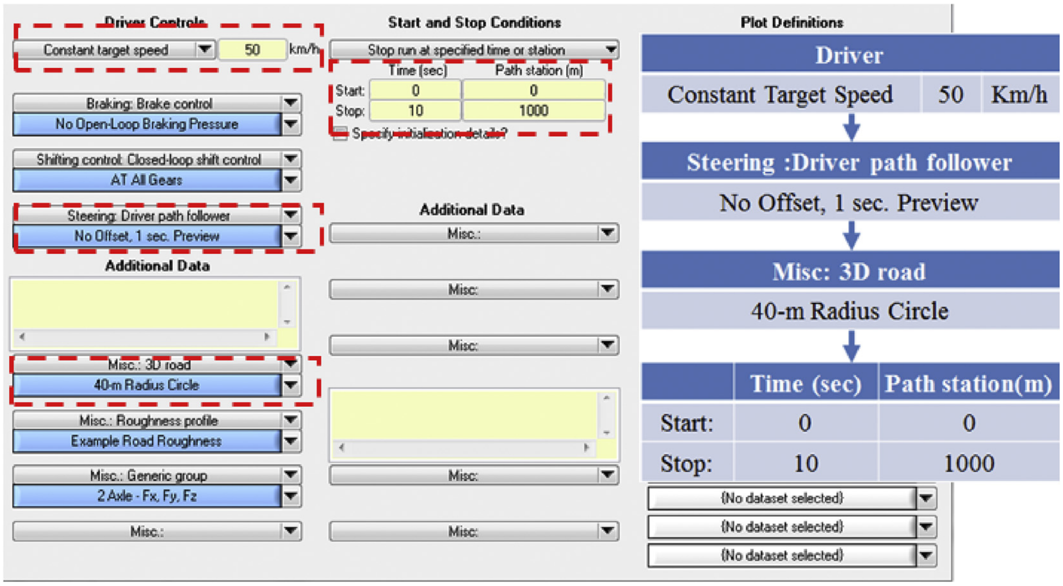


Figure 4. Setting the simulation parameters.

provided. By various control parameters for vehicle turning, the optimal energy saving combination under different control parameters, turning radius and vehicle speed will be searched. It leads to enhancing the traveling mileage and improving the energy consumption of the engine. For establishing the self-driving vehicle model using CarSim, MATLAB/Simulink was integrated with CarSim and the testing parameters were then set including the vehicle structure and the simulation environment as illustrated in Figure 2. Although this research aimed to minimize the consumed energy (fuel) of the vehicle, safety problems were also considered. Hence, by setting the geometric parameters of the vehicle, road conditions, and the testing scenarios, CarSim simulated and evaluated vehicle dynamics. Because of this simulation, no real vehicle was exposed to danger and damage; moreover, the testing time, testing field, human resources, and cost were reduced. Figure 2 displays the included settings, which were vehicle configuration, procedures, driver controls, and constant target speed. Virtual vehicle dynamics were thus investigated using CarSim.

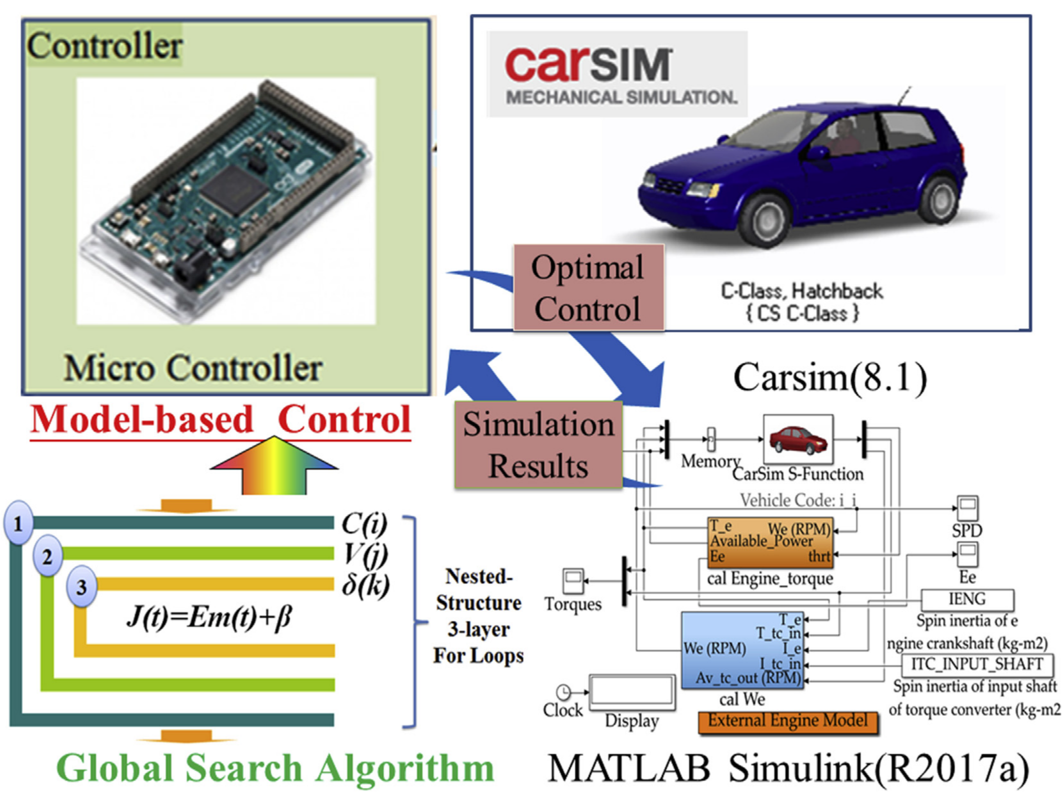


Figure 5. Simulator of the MATLAB/CarSim integrated platform.

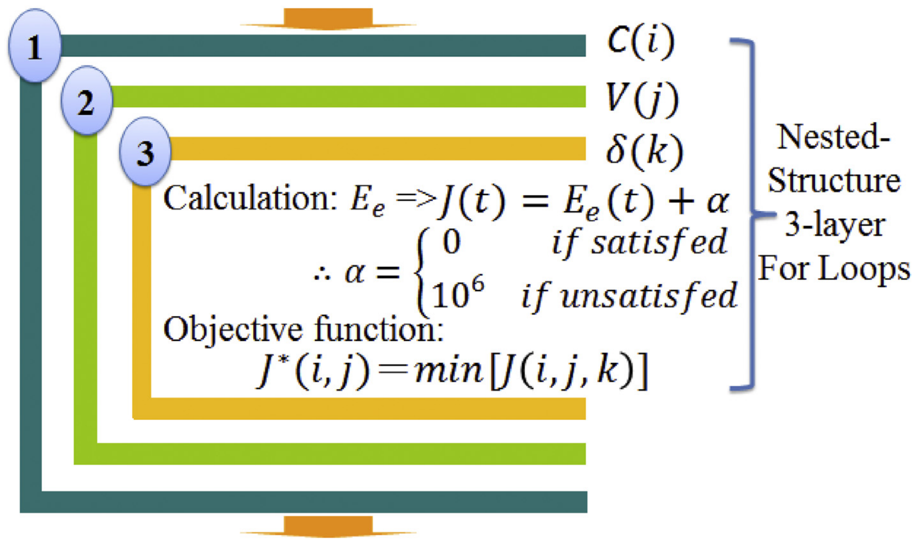


Figure 6. Schematic diagram of software configuration of the global search algorithm.

2. For modifying the vehicle structure setting inputs, the parameters for the engine and the transmission were first input from Simulink. As such, Simulink determined the powertrain performance and CarSim determined the vehicle dynamics as demonstrated in Figure 3. By setting the vehicle powertrain system externally to CarSim (i.e., from Simulink), the engine, transmission, and the differential were modeled and interconnected.

3. Regarding the simulation parameters, the simulation time, driving distance, vehicle steering control parameters, vehicle speed, and rotation radius were determined as shown in Figure 4. The process of constructing the steady-state circling test procedure included setting the driver controls and constant target speed. By looking at the "driver path follower," the circle test environment, simulation time, and traveling distance, the driving control settings were determined.

4. For modifying the steering control parameters, the steering sensitivity was determined based on the range of several factors, such as the steering angle, steering rate, and steering delay.

2.3. Platform establishment

CarSim was used to construct the vehicle steering dynamics with the selected vehicle parameters. Simulink was used for delivering the output performance and parameters of the engine and the transmission. Using the GSA, the total energy consumption was made the optimal target for minimization; the process is illustrated in Figure 5. From Figure 5, the process can be divided into three sections. First, the MATLAB m-file was coded to construct the optimization search using the GSA. Second, the vehicle system, testing environment, and road condition were set and constructed using CarSim. Third, the Simulink platform was used to construct the models of the engine, transmission, and differential.

3. Optimal steering control in ICEV

GSA has been proven useful and effective in the situation of the offline global search for the optimal target as presented in the documentary works of Hung et al. [22] and Wu et al. [23]. Hereby, GSA is further applied in this study by constructing a three-for-loop structure corresponding to the three parameters, i.e. rotational radius C, vehicle speed V, and steering sensitivity δ. Consequently, a three-dimensional table can be derived for comparison and practical implementation. The simulation is incorporated with an engine performance for test bench to search for the optimal operating points using GSA with the cost function based on the energy consumption minimization strategy. The structure of the program comprises three For Loops of the discretized vehicle parameters, i.e. C, V, and δ, to perform the global minimization search. The engine output power P_e is calculated under the required driving condition at each instant, and, thereby, integrated with respect to time to obtain the accumulated engine output energy E_e. The optimization process is carried out using GSA with the objective function defined by minimal E_e. The resulting optimal solutions can be constructed as multidimensional tables and directly implemented in vehicle control units for optimal energy management.

Steering sensitivity can be determined by two key factors: (1) the steering delay (the response time from the driver to keep the vehicle on the target route); (2) the steering speed (after receiving the actual/demanded error, the steering affects the vehicle dynamics). Hence, three sets of high, middle, and low sensitivity were determined as follows: [steering delay, steering speed]: [0, 1400], [0.15, 1200], and [0.3, 1000]. For a high steering sensitivity, the steering delay was ignored, and the steering speed was the fastest of the three cases. The nominal steering sensitivity setting in CarSim was the middle steering sensitivity, and the low steering sensitivity was [0.3, 1000] where the steering delay time was the longest and the steering speed was the lowest. To search for the optimal steering control, the GSA was employed with the following steps:

(1) Parameter discretization—for the three control parameters, we first set three rotational radius (40, 50, 60 m) C, six vehicle speeds (20, 30, 40, 50, 60, 70 km/h) V and three ranges of steering sensitivity δ ([0.3 s, 1000 deg/s], [0.15 s, 1200 deg/s], [0 s, 1400 deg/s]) for our simulation.
(2) Cost function determination—before the global search, the cost function was set to be the energy consumption of the engine and minimized:

$$J(t) = E_e(t) + \alpha \tag{4}$$

Where E_e is the engine energy consumption and α is the penalty value. This was set to avoid searching for solutions that would have violated physical constraints (e.g., exceeding the maximal values of engine torque or engine speed), creating safety issues, or causing functional failure of the vehicle. When the vehicle operates by following a circle, it may deviate from its course or the tires might slip due to the vehicle inertia force. Hence, if the aforementioned conditions occurred under a specific radius and vehicle speed, a large value of α would be given and the

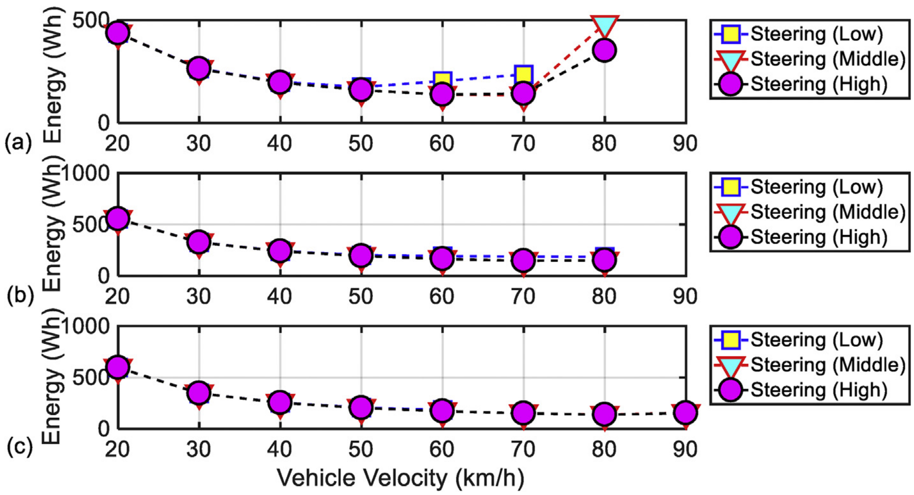


Figure 7. Simulation results under different constant velocities at fixed rotational radii of (a) 40 m, (b) 50 m, and (c) 60 m.

Table 1. Comparison of three steering control sensitivities at different constant vehicle speeds (40 m radius).

Constant Velocity (km/h)	Energy Consumption for Lower Steering (Wh)	Energy Consumption for Middle Steering (Wh)	Energy Consumption for Higher Steering (Wh)
20	437.3854	437.2495	**437.0415**
30	264.7079	263.7135	**263.5959**
40	199.5733	196.7028	**196.6381**
50	174.6501	160.0129	**159.9667**
60	204.1229	138.2511	**138.1298**
70	236.0922	**135.235**	142.8352
80	**N/A**	482.2588	**352.153**
90	**N/A**	**N/A**	**N/A**
100	**N/A**	**N/A**	**N/A**

The significance of bold is minimize energy consumption at constant vehicle speed, the significance of underline is minimize energy consumption at different constant vehicle speeds.

simulation would stop. Due to the low energy component of the cost function, the penalty was required to be a large value so that unreasonable searches were avoided. The value was defined as:

$$\alpha = \begin{cases} 0 & \textit{if satisfed} \\ 10^6 & \textit{if unsatisfed} \end{cases} \tag{5}$$

(3) For-loop data search—the engine output power was calculated and then the cost function defined by minimal energy consumption of engine was searched using GSA at a nested for-loop of the specific vehicle parameters, as illustrated in Figure 6. With a given fixed radius and driving conditions, factors such as the steering angle, throttle position, and brake pedal position were evaluated and recorded in form of an optimal two-dimensional table as shown below:

$$J^*(i,j) = \min[J(i,j,k)] \tag{6}$$

(4) Optimization results—using Eq. (6) the optimal results were derived from the database. Under a fixed radius and a fixed vehicle speed, the optimal steering case was determined.

Using the aforementioned GSA process, the optimal control and optimal results were derived for the engine vehicle steering at a fixed radius.

4. Results and discussion

Combining mechatronics technologies with advanced steering systems is likely to be a future direction for the automobile industry. Safety and stability are two of the most crucial factors that consumers will demand in such vehicles. Secondary concerns are likely to be comfort, convenience, and appearance. By simulating driving scenarios and various driving conditions, the derived steering system will be expected to provide optimal drivability along with the lowest energy consumption.

Simulation results are exhibited in Figure 7. At a fixed radius of 40 m, when the vehicle speed exceeded 80 km/h and, as shown in Figure 7(a), the three cases of steering sensitivity ([0.3 s, 1000 deg/s], [0.15 s, 1200 deg/s], and [0 s, 1400 deg/s]) were unable to satisfy the driving

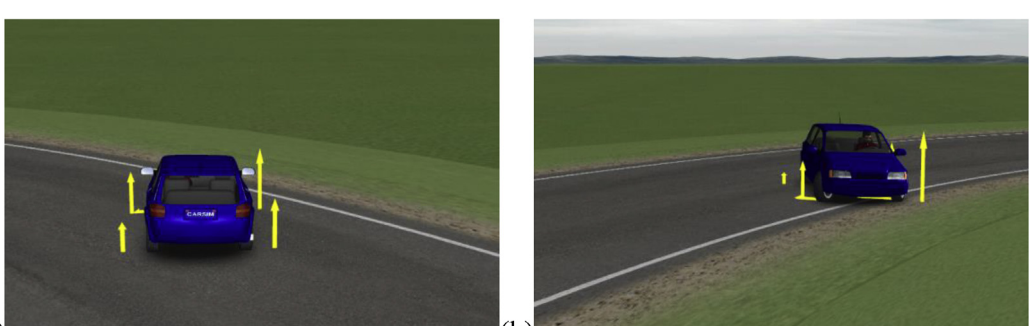
(a)

(b)

Figure 8. Unqualified tests (a) outside caused by understeering and (b) outside caused by oversteering.

Table 2. Comparison of three steering control sensitivities at different constant vehicle speeds (50 m radius).

Constant Velocity (km/h)	Energy Consumption for Lower Steering (Wh)	Energy Consumption for Middle Steering (Wh)	Energy Consumption for Higher Steering (Wh)
20	555.1682	555.0470	**554.8597**
30	327.0496	326.4448	**326.3822**
40	242.2269	241.0305	**240.9672**
50	201.2320	194.4617	**194.4065**
60	192.7240	165.3627	**165.3009**
70	N/A	147.4051	**147.1065**
80	185.9524	**150.3686**	152.0752
90	N/A	N/A	N/A
100	N/A	N/A	N/A

The significance of bold is minimize energy consumption at constant vehicle speed, the significance of underline is minimize energy consumption at different constant vehicle speeds.

Table 3. Comparison of three steering control sensitivities at different constant vehicle speeds (60 m radius).

Constant Velocity (km/h)	Energy Consumption for Lower Steering (Wh)	Energy Consumption for Middle Steering (Wh)	Energy Consumption for Higher Steering (Wh)
20	596.1547	595.9955	**595.9383**
30	346.3581	346.1096	**346.0520**
40	254.5087	254.1016	**254.0559**
50	207.4126	204.1172	**204.0660**
60	183.4568	172.3745	**172.3411**
70	N/A	151.2344	**151.1662**
80	N/A	138.9843	**138.3545**
90	N/A	155.1611	**154.1372**
100	N/A	N/A	N/A

The significance of bold is minimize energy consumption at constant vehicle speed, the significance of underline is minimize energy consumption at different constant vehicle speeds.

conditions. Consequently, the study only listed the results for vehicle speeds between 20 to 80 km/h as in Table 1. After comparing the results, the lowest energy consumption occurred at a vehicle speed of 70 km/h. The highest energy improvement for this optimal condition compared with the case of low steering sensitivity was 42.72% [(236.0922 Wh − 135.235 Wh) ÷ 236.0922Wh]. Any uncontrollable or dangerous status including understeering or oversteering was set to be N/A, as shown in Figure 8. As the vehicle is operating with high speed, the wind resistance rises as well. As the vehicle is at the circular motion, if the turning speed of steering wheel is too fast or too slow, the driving path will be increased as well as the safe concern is required. These two conditions will increase the traveling mileage and the vehicle energy usage.

As exhibited in Figure 7(b), at a fixed radius of 50m, as the vehicle speed exceeded 80 km/h, the driving conditions were once again unsatisfied. Therefore, Table 2 lists the results from vehicle speeds varying from 20 to 80 km/h; the lowest energy consumption occurred at a vehicle speed of 70 km/h. The highest energy improvement was 0.2% for this optimal case when compared with the middle steering sensitivity. Due to a driving length of 200 m being uncompleted at low steering sensitivity, the results were not considered.

As exhibited in Figure 7(c), at a fixed radius of 60 m, the driving conditions for all three steering sensitivities could not successfully be achieved when the vehicle speed was over 90 km/h. As such, Table 3 lists the results with vehicle speed ranging from 20 to 90 km/h. At 80 km/h, the lowest energy consumption occurred. Comparing the optimal results with middle steering sensitivity, the highest energy improvement was 0.45%. Low steering sensitivity was not considered once again due to being unable to complete 200 m driving. Results indicated that with an increased radius, safe vehicle speed can be increased when appropriate.

To summarize the results in Figure 7, we replotted the optimal energy consumption of the engine under various vehicle speeds and rotational radii as demonstrated in Figure 9. Because the steering sensitivity was a function of the steering delay time and the steering acceleration, according to the results, with increased vehicle speed, higher steering sensitivity was required to satisfy the driving conditions as well as to lower the energy consumption. Conversely, with increased rotational radius, at the same traveling distance, the energy consumption was increased; however, the highest speed was also increased. Therefore, optimization should search at different radii, vehicle speeds, and steering sensitivities to minimize energy consumption. As the speed exceeds 80 km/h, under various turning radius, the vehicle might be unable to normally operate due to the physical constraints. Hence, a large value is given representing the penalty for physical constraints. Please refer to Tables 1, 2, and 3.

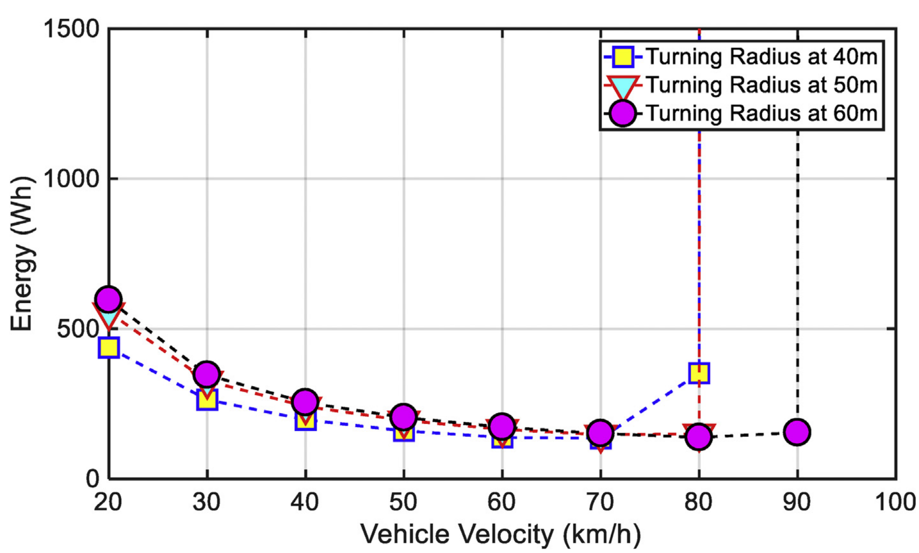


Figure 9. Simulation results under optimal steering control in different constant vehicle speeds.

5. Conclusion

This study conducted an integrated MATLAB/CarSim vehicle dynamic simulator loaded with the performance curves and characteristics of an internal combustion engine to optimize the effects of steering control on the energy consumption of an internal combustion engine vehicle under various driving conditions. Through the vehicle steering dynamics established in CarSim, we fixed the rotational radius and altered the vehicle speeds and steering sensitivities. An algorithm for optimized energy consumption was used to enable optimal driving operation. Results compared the three steering sensitivities from 20 to 90 km/h. The greatest improvement in energy consumption demonstrated was 42.72% at a turning radius of 40 m. The developed platform is able to provide valuable information for vehicle performance with pure simulation prior to on-road testing of a real vehicle; consequently, R&D costs, human resources, and development cycles can be significantly reduced. Since Carsim is a commercialized software package with complicated 3-D vehicle system governing equations built based on intensive theories associated sufficient calibrations from experiments, the simulation results possess satisfactorily high accuracy with respect to real driving and, thus, are useful for further development in the intelligent transportation field.

Declarations

Author contribution statement

Chien-Hsun Wu: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This work was supported by the Ministry of Science and Technology of the Republic of China, Taiwan, for financial support for this research under Contract No. MOST 107-2221-E-150-036 and 108-2221-E-150-012.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

The author would like to thank the Industrial Technology Research Institute (ITRI) and project for advanced vehicle control.

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