

Integrated Stability Control System for Electric Vehicles with In-wheel Motors using Soft Computing Techniques

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ABSTRACT

An electric vehicle model has been developed with four direct-drive in-wheel motors. A high-level vehicle stability controller is proposed, which uses the principles of fuzzy logic to determine the corrective yaw moment required to minimize the vehicle sideslip and yaw rate errors. A genetic algorithm has been used to optimize the parameters of the fuzzy controller. The performance of the controller is evaluated as the vehicle is driven through a double-lane-change maneuver. Preliminary results indicate that the proposed control system has the ability to improve the performance of the vehicle considerably.

INTRODUCTION

In the last two decades, advances in electronics have revolutionized many aspects of the automobile. Of particular focus have been the areas of engine management and vehicle dynamics safety systems such as anti-lock braking systems (ABS), traction control systems (TCS), electronic stability programs (ESP), and active steering (AS) systems. These safety systems involve the use of electronic control units to adjust the brake, accelerator, and/or steering inputs provided by the driver in order to control the slip of individual tires during emergency braking (ABS) or maneuvering (TCS), or to control the vehicle yaw rate and sideslip angle either by braking individual wheels (ESP) or by manipulating the steering angle of the wheels (AS). For further information on different strategies for influencing the yaw dynamics of a vehicle using differential braking and active steering systems, see [1-3].

According to a recent study conducted by the Insurance Institute for Highway Safety, ESP systems have the potential to reduce the risk of fatal single-vehicle crashes by 56%, the risk of fatal multi-vehicle crashes by 17%, and the risk for all fatal vehicle crashes by 34% [4]. A similar investigation performed by the Institute for Traffic Accident Research and Data Analysis in Japan suggests that ESP can reduce single-vehicle accidents by 35%, head-on collisions with other vehicles by 30%, and the number of casualties per year resulting from single-vehicle crashes and head-on collisions by 35% [5]. As a result, the U.S. National Highway Traffic Safety Administration has mandated that ESP be implemented on all passenger cars and light trucks by 2012 [6].

Another recent development in the automotive industry is the electric vehicle (EV), which has attracted a great deal of interest as an environmentally- and energy-conscious means of providing personal transportation. Thanks to substantial improvements in electric motor and battery technologies, EVs now have driving performance metrics that make them viable alternatives to traditional internal combustion engine vehicles in some markets. Furthermore, EVs are more versatile platforms on which to apply advanced motion control techniques, since the motor torque and speed can be generated and controlled quickly and precisely. In fact, the torque response of an electric motor is on the order of a few milliseconds and, therefore, responds 10 to 100 times faster than the internal combustion engines and hydraulic braking systems in use today [7]. The use of small but powerful direct-drive in-wheel motors allows for the implementation of the most advanced torque vectoring system possible, in which any desired torque distribution between the four wheels can be realized. Such a platform also represents the most advanced all-

wheel-drive (AWD) system, generating the optimal amount of traction on each tire by controlling the speed of the motors. The Hy-wire concept car developed by General Motors represents such a platform [8].

As part of an ongoing AUTO21 research project, a full vehicle model with four direct-drive in-wheel motors has been developed in the ADAMS/View environment in order to investigate advanced vehicle stability and traction control strategies [9-10]. This platform (Figure 1) represents a two-passenger electric all-wheel-drive urban vehicle (AUTO21EV) that has a similar configuration to the commercially-available Smart *fortwo*. Table 1 lists relevant parameters used in the AUTO21EV model.

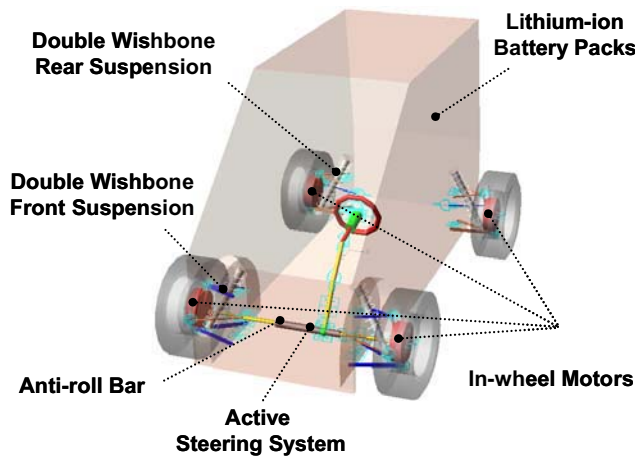


Figure 1: AUTO21EV concept vehicle

Parameter	Value	Unit
Vehicle mass (M)	1075	kg
Vehicle yaw moment of inertia (I_{zz})	1171	kg m ²
Distance from CG to front axle (a)	0.82	m
Distance from CG to rear axle (b)	0.98	m
Front track width (t_f)	1.275	m
Rear track width (t_r)	1.350	m
Front tire cornering stiffness ($C\alpha_f$)	45 570	N/rad
Rear tire cornering stiffness ($C\alpha_r$)	45 570	N/rad
Tire size	175/55 R15	—
Tire unloaded radius (r)	0.2905	m

Table 1: AUTO21EV model parameters

Since a simulation model was desired that is fast enough to allow for the testing of different control strategies, an alternative 14-degree-of-freedom vehicle model with independent suspensions and four direct-drive in-wheel motors was developed using DynaFlexPro, a Maple package that uses a symbolic formulation procedure and linear graph theory to generate computationally efficient simulation code [11]. Numerical formulation techniques, such as those employed in MSC.ADAMS, produce system matrices that are only valid for a given instant of time and, thus,

must be reformulated at every time step of a simulation. Symbolic formulation techniques, on the other hand, combine the system parameters and modelling variables to create sets of equations that describe the system for all time. Since the governing dynamic equations must only be generated once if formulated symbolically, such approaches are ideal for real-time applications, including hardware- and operator-in-the-loop scenarios.

The model developed with DynaFlexPro has been used to design a high-level vehicle dynamic controller based on the theory of fuzzy logic. The objective of the controller is to determine the corrective yaw moment required to minimize the vehicle yaw rate and sideslip errors, comparing the actual vehicle states to those calculated using a reference model. Fuzzy controllers are generally well-suited for complex nonlinear dynamic control problems, and can act as high-level supervisory modules that assign tasks to lower-level subsystems and controllers. These features make the fuzzy control system an ideal candidate for handling the complexities of integrated chassis control management, and allow the lower-level control systems, such as the in-wheel motor controllers and the active steering system, to be designed simply as tracking controllers using the reference signals generated by the supervisory controller. Since fuzzy systems have no inherent learning capabilities, the fuzzy rules governing the behaviour of the controller have been designed using expert knowledge, and a genetic algorithm has been used to tune the membership functions and optimize the parameters of the fuzzy control system.

VEHICLE MODEL WITH IN-WHEEL MOTORS

The AUTO21EV was modelled by Vogt *et al.* [12] with independent suspensions and four hub motors, as shown in Figure 2. The topology of the system was defined in block diagram form using ModelBuilder, a graphical user interface companion for DynaFlexPro. This model is imported into the MATLAB/Simulink environment as a 14-degree-of-freedom multi-body vehicle model.

A relatively simple multi-body dynamic model was used in order to limit the complexity of the full mechatronic system. The topology shown in Figure 2 was recommended by Sayers [13] for simulating the handling and braking behaviour of a vehicle, and has been adopted by several commercial software packages [14]. The sprung mass of the vehicle is considered to be a single rigid body, which will be referred to herein as the chassis. The position and orientation of the vehicle chassis, measured with respect to a global reference frame, together comprise six degrees-of-freedom. The chassis is connected to the four unsprung masses with prismatic joints, each of which is associated with a linear spring and damper, representing the suspension compliance. Together, these components add four degrees-of-freedom to the vehicle model. The components of the suspension and steering systems

are considered to belong to the unsprung mass, including the stator of the in-wheel motors, are lumped into these four masses. Each wheel consists of a tire, a rim, and the rotor component of the in-wheel motor, and is connected to its corresponding lumped mass with a horizontally-oriented revolute joint that allows the wheel to spin, thereby adding four additional degrees-of-freedom into the model. In order to realize Ackermann steering, the steering system is modelled with two independent motion drivers on the front axle, which are used to steer the vehicle on a prescribed trajectory and, as such, do not add any degrees-of-freedom to the system.

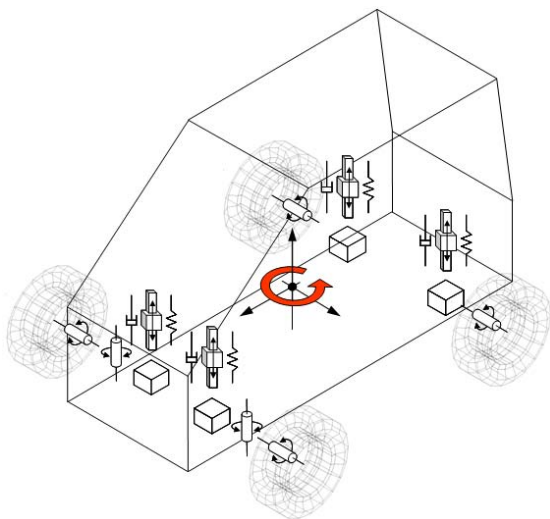


Figure 2: DynaFlexPro model of AUTO21EV

The Pacejka2002 Magic Formula [15] was used as the tire model, as it can effectively represent the nonlinearities that are present in the actual vehicle and, thus, is recommended for studies on vehicle handling and stability. To simplify the design of the fuzzy controller, a torque driver was added to the DynaFlexPro model at the center of mass of the vehicle, acting about the vertical axis. This torque must ultimately be applied as individual traction forces at the contact patches of the tires. Strategies for distributing this torque among the in-wheel motors and active steering system are under development.

INTEGRATION OF IN-WHEEL MOTORS WITH VEHICLE MODEL - In-wheel motors currently on the market are generally designed as direct-drive permanent magnet synchronous machines (PMSM). This implies that no gear reduction is used between the motor and the wheel drive shaft, which can reduce the weight and size of the system, but also requires that the speed-torque characteristics of the motor meet the requirements of the vehicle. These motors generally contain rare-earth permanent magnets in the rotor, which provide a high power density and employ electric commutation through the use of inverters, allowing the design of a robust and reliable brushless, variable-speed PMSM motor with a high power-to-weight ratio [16]. PMSM motors are designed upside-down, meaning that

the rotor is the rotating external part, which can also be attached to the rim, and the stator is attached to the wheel shaft. This approach is primarily used to reduce the moment of inertia of the rotating parts, thereby reducing the amount of energy required to stop or accelerate the wheels. In addition, PMSMs have the ability to increase performance and efficiency by eliminating the magnetization loss in the field of the motors. The flux-weakening characteristic of the PMSM not only improves the efficiency of the motors, but also prevents overheating of the tires by the rotor [17]. Details on the modelling, simulation, and analysis of inverter-fed PMSM-type motors can be found in [16-20].

The in-wheel motors used in this model are assumed to be PMSMs consisting of a cage-less surface permanent magnet rotor and a stator with three-phase windings and a sinusoidal back electromotive force. Balanced sinusoidal three-phase current is enforced in the stator to achieve synchronous operation and a smooth torque profile [18]. In total, five parameters and two state variables are identified for the motor model. The three-phase voltages are the inputs to the motor model and the motor torque is the output; the mechanical angle and angular velocity, which are state variables in the vehicle model, are treated as external parameters. Further details about the motor model and motor controller units used in this work can be found in [12, 17]. To address the multidisciplinary nature of the whole system, it is desirable to obtain one model rather than separate mechanical and electrical models [21]. This multi-domain approach has been accomplished through the use of linear graph theory, on which the fundamentals of the DynaFlexPro software package have been built. A component template for the PMSM-type motor was developed [11] and added to the existing vehicle model. Table 2 lists the specifications of the in-wheel motors used in this work.

Specification	Value	Unit
Maximum power	25	kW
Peak torque	300	Nm
Maximum speed (no load)	3200	rpm
Maximum voltage	315	V
Maximum current	300	A
Total mass	30	kg
Rotor mass	11.2	kg
Magnetic flux (B)	0.4	V/rad/s
Phase inductance (L_s)	6	mH
Phase resistance (R_s)	1.653	Ω
Number of pole pairs	10	–

Table 2: In-wheel motor specifications

FUZZY LOGIC AND GENETIC ALGORITHMS

Fuzzy logic and genetic algorithms have both been applied to a wide variety of problems. Still an active area of research, however, is the fusion of these techniques

into a hybrid system that exploits their strengths while reducing the effects of their weaknesses. In the 1990s, despite the previous success of fuzzy logic systems, their inability to adapt was found to severely limit their potential applications; genetic-fuzzy systems address this limitation. A genetic-fuzzy system is essentially a fuzzy system augmented by a learning process based on a genetic algorithm. The most popular type of genetic-fuzzy system is the genetic-fuzzy rule-based system, where an evolutionary algorithm is employed as a design method to learn or tune different components of a fuzzy knowledge base. The knowledge base of a descriptive Mamdani-type fuzzy inference system is comprised of a database, which contains the definitions of the scaling factors and membership functions, and the rule base, which is the collection of linguistic fuzzy rules. In order to use a genetic algorithm for optimizing a fuzzy knowledge base, the rules or membership functions must first be represented as a set of tunable parameters. It is also necessary to define an appropriate performance index, based on the optimization criterion, with which to evaluate the proposed knowledge bases. Finally, the knowledge base parameters must be transformed from the optimization space (phenotype space) into a suitable genetic representation (genotype space) [22]. A genetic process can evaluate, select, and evolve the genetically encoded candidate solutions. At this point, it is important to differentiate between tuning and learning problems. Tuning is concerned with the optimization of an existing fuzzy inference system having a predefined rule base. Learning, on the other hand, constitutes an automated design method for fuzzy rule sets that starts from scratch [23] – that is, learning processes do not require a predefined set of rules. The objective in the case of tuning is to find the best possible set of parameters for the database of the fuzzy inference system. For example, tuning can be applied to the scaling functions that normalize the universe of discourse of the input and output variables. Linear scaling functions can be parameterized by either a single scaling factor [24] or by two parameters [25]; three and four parameters have been used for nonlinear scaling functions [26]. Tuning can also be applied to the fuzzy membership functions. In this case, each chromosome encodes the parameterized membership functions associated with all the rules in the rule base [22]. The rule base of a fuzzy inference system can also be tuned using a genetic algorithm [27-31].

FUZZY LOGIC CONTROLLER DESIGN

Fuzzy control systems are nonlinear control methods that can tackle complicated nonlinear dynamic control problems. As such, they are ideally-suited for controlling the highly nonlinear behaviour inherent in vehicular dynamics. Fuzzy controllers are described in vague linguistic terms, which suit the subjective nature of vehicle stability and handling, and allow one to implement expert knowledge directly in the rule base of the fuzzy controller [32]. In addition, the idea of using a fuzzy logic controller as a high-level supervisory module

that assigns tasks to the low-level actuators appears to be an ideal method of addressing the complexities of integrated chassis control management. This approach allows the lower-level controllers to be designed simply as tracking controllers, designed to track the reference signals generated by the supervisory controller. In this application, the AUTO21EV fuzzy logic controller acts as a high-level supervisory module that determines the required corrective yaw moment that must be applied to the vehicle to minimize the sideslip and yaw rate errors, comparing the actual values to those obtained using a reference model in order to follow the trajectory desired by the driver.

The proposed controller requires two vehicle states, yaw rate and vehicle sideslip angle, to determine the required corrective yaw moment. To date, yaw rate tracking algorithms have been used to improve stability near the limit of handling during normal driving. A recurring problem found throughout the literature, however, is how to define the limits of handling and distinguish between emergency and normal driving situations. The studies of yaw rate stability are dominated by the use of reference model feedback control, where the controller attempts to match the nonlinear behaviour of the vehicle with that of a reference bicycle model. As the vehicle approaches its performance limits, the actuation power required to reduce the tracking error becomes large and may exceed the capability of any active chassis subsystem. In general, information about the yaw rate alone is not always sufficient because, for instance, a vehicle may be undergoing an acceptable yaw rate while skidding sideways. Many researchers claim that significantly more comprehensive control can be achieved given vehicle sideslip angle information [31]. The vehicle sideslip angle is defined as the angle between the forward orientation of the vehicle and the direction of its velocity. The driver is particularly sensitive to the sideslip motion of the vehicle and tends to prefer small sideslip angles [33]. This preference arises from the sensation of instability at larger angles, which is perhaps rooted in the real potential for loss of control when the vehicle sideslip angle and tire slip angles become too large. Thus, both sideslip and yaw rate are extremely important factors influencing the driver's perception of handling behaviour and, as a result, the quality of the driving experience depends strongly on the quality of the feedback signals of these two states. Together, the yaw rate and sideslip angle are able to completely describe the motion of a vehicle on a horizontal plane. Yaw rate can be directly measured by a yaw rate sensor (gyroscope), whereas the sideslip angle must be estimated [34, 35].

Using a bicycle model as the reference model, the desired yaw rate can be determined as a function of the front axle steering angle (δ_w) and the vehicle forward velocity (v_x) as follows [1]:

$$\dot{\psi}_{desired} = \frac{v_x}{L + K_{us} \times v_x^2} \times \tan(\delta_w) \quad (1)$$

