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OPTIMIZING FUZZY LOGIC CONTROL FOR VEHICLE PATH TRACKING WITH PARTICLE SWARM OPTIMIZATION

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ABSTRACT: *This paper presents an optimal path tracking scheme for a vehicle handling dynamics model with eight degrees of freedom. A fuzzy logic controller (FLC) is incorporated to handle nonlinearities using heuristic rules. Particle Swarm Optimization (PSO) is applied to optimize the scaling factors of the FLC outputs, ensuring normalized ranges for controller inputs and outputs. The optimization achieved convergence within 154 iterations. Simulation results under ISO lane change maneuvers at 70-80 kph demonstrate that the optimized fuzzy controller significantly improves trajectory tracking performance, reducing lateral deviation and enhancing control stability compared to the baseline controller.*

KEYWORDS: *Particle Swarm Optimization, Vehicle Handling Dynamics, Fuzzy Control, Driver Model*

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1. INTRODUCTION

Vehicle dynamics simulations have long supported system design and improvement. Numerous research studies can be found in the literature on the development of driver-steering, whole vehicle dynamics and/or sub-system characterization and controller models. Some of these researches have particularly been focused on to improve the provided results by applying the well-known optimization techniques. Optimization and control problems often require analytical models in early design stages [1]. However, complex models frequently demand advanced optimization for effective results. Fuzzy logic methods excel in nonlinear control, using linguistic terms that align with subjective aspects of vehicle handling and stability [2]. This study aims to enhance the performance of a fuzzy logic controller (FLC) for vehicle path tracking by optimizing its output scaling factors using Particle Swarm Optimization (PSO) [3]. Unlike conventional methods that optimize fuzzy membership functions or rules, scaling factors were chosen for simplicity and computational efficiency. The proposed method is evaluated on an eight-degree-of-freedom vehicle dynamics model under ISO lane change maneuvers at 70-80 kph.

Optimization techniques in fuzzy logic controllers (FLCs) are commonly applied to membership functions or scaling factors, integral elements of PID-like fuzzy controllers. Rajeswari and Lakshmi [3] explored an active suspension system controlled by an FLC designed for disturbance rejection. They compared Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for tuning the FLC's scaling factors. Results demonstrated that PSO achieved faster convergence and superior optimization of fitness values compared to GA.

Thanok & Manukid Parnichkun [4] proposed a linear control algorithm for regulating throttle valve angle and brake force in a simplified first-order vehicle model. PSO was employed to optimize the sliding surface and gain parameters of the sliding mode controller. However, optimization was not applied to the FLC responsible for generating the brake force.

Talib and Darus [5] developed a semi-active suspension system with a magnetorheological (MR) damper. They compared FLC-PSO and PID-PSO configurations by optimizing the FLC scaling factors and PID controller gain parameters using PSO. Their simulations revealed that the PSO-optimized FLC achieved the lowest Mean Square Error (MSE) in system response and outperformed both the PSO-tuned PID and the passive suspension system in terms of ride comfort.

Bingul and Karahan [5] applied PSO to tune a Mamdani-type FLC for trajectory planning in a 2DOF robotic system. They optimized both the FLC membership functions and PID controller gain parameters using three cost functions. Results indicated that the FLC tuned with PSO consistently outperformed the PID controller.

Hurel et al. [6] enhanced the performance of an active suspension system using a PD-like fuzzy controller. PSO was used for offline tuning of scaling factors applied to both inputs and outputs of the FLC. The optimized controller demonstrated stable convergence and improved ride comfort metrics.

Hunaini et al. [7] focused on an automatic steering control system employing an FLC for lateral motion and a PID controller for yaw motion control. PSO was utilized to optimize the FLC membership functions and PID coefficients. The online application of PSO yielded superior trajectory-following performance.

Khodayari et al. [8] modelled a double-lane change maneuver using neuro-fuzzy and soft computing techniques. Subtractive clustering was employed to define fuzzy rules, while PSO was applied to refine the initial models, further enhancing their performance.

Chen [9] and Joudaa et al. [10] emphasized the importance of scaling factors in FLC systems. Joudaa highlighted their role in mapping real-world input data to the universe of discourse of fuzzy variables, effectively fine-tuning system performance akin to PID controller optimization.

In this study, a previously developed path following vehicle control model [11] was taken into consideration from the optimization point of view. The simulation was performed in the Matlab© environment, utilizing a Simulink© vehicle model controlled by a fuzzy logic system designed to track a predefined trajectory. Particle Swarm Optimization method was chosen to improve the outputs of the rule-based FLC using the scaling factors. Instead of optimizing fuzzy membership functions or rules, output scaling factors were optimized using PSO for simplicity and effectiveness. Unlike traditional approaches that optimize fuzzy membership functions or rule bases, this study optimizes the output scaling factors of the FLC. This method offers significant advantages for complex FIS structures, such as the one used in this study, which consists of 5 inputs, 3 outputs, and over 200 fuzzy rules. By focusing on scaling factors, the optimization process becomes computationally efficient while maintaining the integrity of the rule base.

2. METHODOLOGY

2.1. Vehicle Model

The vehicle model used in this study is based on the research done by Uzunsoy and Erkilic [11]. The model incorporates eight degrees of freedom, including lateral, yaw, longitudinal, and roll motions, while accounting for traction and braking forces during handling maneuvers, as well as the dynamics of individual wheels. Equations (1)-(4) can be derived by Newton-Euler approach, representing the four rigid body degree of freedom, according to the longitudinal, lateral forces and roll and yaw moments applied onto the vehicle system such as longitudinal force, F_x, lateral force, F_y, roll moment, M_x, and yaw moment, M_z. Further details on the model can be found in the same study [11].

$$\sum F_x = m(\dot{U} - rV) = \left[F_{xrL} + F_{xrR} + \left(F_{xfL} + F_{xfR} \right)\cos\delta - F_{brL} - F_{brR} - \left(F_{bfL} + F_{bfR} \right)\cos\delta - \left(F_{yfL} + F_{yfR} \right)\sin(\delta) \right] \quad (1)$$

$$\sum F_y = m(\dot{V} + rU) = \left[F_{yrL} + F_{yrR} + \left(F_{yfL} + F_{yfR} \right)\cos\delta + \left(F_{xfL} + F_{xfR} \right)\sin\delta - \left(F_{bfL} + F_{bfR} \right)\sin\delta \right] \quad (2)$$

$$\sum M_x = I_{xx}\dot{p} = \left[m_s \cdot \left(\dot{V} + r \cdot U \right)\left(h_{cg} - h_{rc} \right) + m_s g \left(h_{cg} - h_{rc} \right)\varphi - C_\varphi \dot{\varphi} - K_\varphi \varphi \right] \quad (3)$$

$$\sum M_z = I_{zz}\dot{r} = \begin{bmatrix} a\left(F_{yfL} + F_{yfR} \right)\cos\delta + \frac{t_f}{2}\left(F_{yfL} - F_{yfR} \right)\sin\delta + a\left(F_{xfL} + F_{xfR} \right)\sin\delta + \frac{t_r}{2}\left(F_{brL} - F_{brR} - F_{xrL} + F_{xrR} \right) - \ldots \\ \ldots - b\left(F_{yrL} + F_{yrR} \right) - \frac{t_f}{2}\left(F_{xfL} + F_{bfR} - F_{xfR} - F_{bfL} \right)\cos\delta - a\left(F_{bfR} + F_{bfL} \right)\sin\delta \end{bmatrix} \quad (4)$$

In conjunction with the vehicle model, a semi-analytical tire model representing both longitudinal and lateral forces was used [11]. The model is originated by the studies of Allen et al [12, 13].

2.2. Fuzzy Logic Controller (FLC)

Human experience can be introduced to a controller by fuzzy logic much better than conventional control approaches and satisfactorily accurate results can be provided [14]. Besides, the FLC can be used as a multi-input nonlinear state feedback controller [11]. In this study, a well-known Mamdani-type fuzzy inference system (FIS) was used to mimic some basic human driver behaviors in following a defined trajectory.

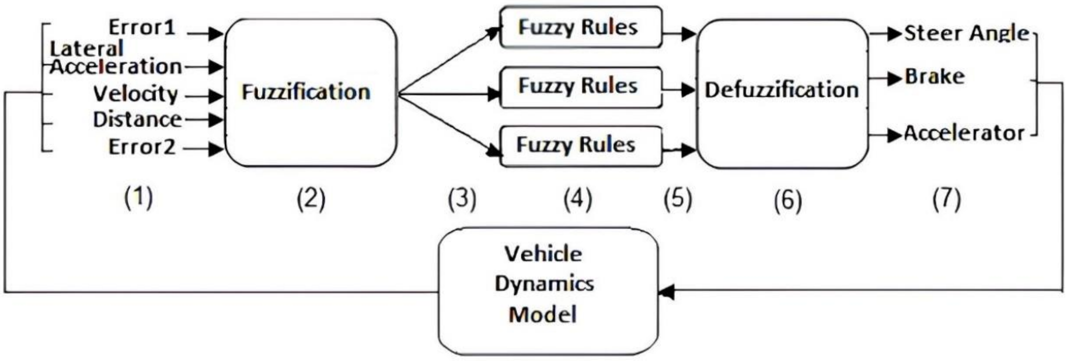
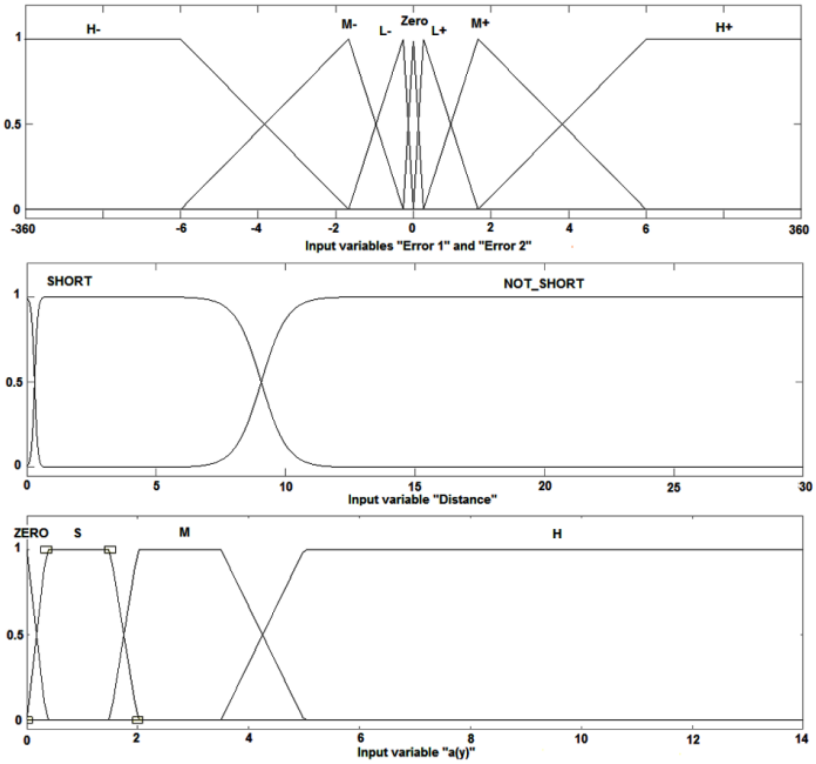
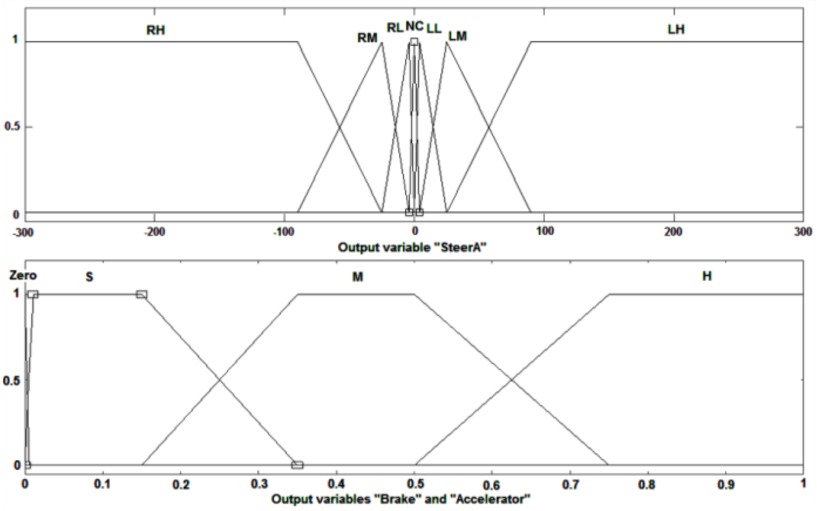


Figure 1. *Details of FIS structure integrated into the vehicle dynamics model* [11]

The used FIS and the controller strategy can be summarized as in Figure 1. Depending on the experience, Gaussian, triangular or trapezoidal membership functions were used in the inputs and outputs of the FIS structure (see Figure 2). Error 1 and 2 are measures of the vehicle orientation from the driver point of view, while the rest is related to the distance left to the first target, lateral acceleration and longitudinal velocity of the vehicle. Then, three main control parameters such as steering angle, brake and gas pedals, those can be provided by a driver, were the outputs.



(a)



(b)

Figure 2. *Input (a) and output (b) membership functions of the FIS [11]*

Meanwhile, the model does not claim to cover all the aspects of a human driver and the performance of the FIS depends on the experience. Exhaustive details of the FLC model can be found in Uzunsoy's research [11]. However, at this point, an optimization study can further improve the previously accepted reliability and accuracy of the model outputs.

2.3. Particle Swarm Optimization (PSO)

As it was discussed in the Introduction part, PSO method was chosen to improve the FLC model results. Swarm Intelligence is a part of artificial intelligence based on collective and decentralized behavior of individuals those interact with each other and the environment. PSO, on the other hand, is a stochastic evolutionary algorithm, based on swarm intelligence that searches for the solution of optimization problems to predict the behavior of individuals according to the particular objectives of the problem [15]. It was first developed by Dr. Kennedy and Dr. Eberhart in 1995. It is proposed as an alternative for evolutionary techniques such as genetic algorithms, especially from the points of computational effectiveness and easy implementation capability [16]. The main approach of the PSO algorithm is to search through a *j*-dimensional problem to optimize an objective function. Furthermore, it has the ability to reach the global optimum while avoiding local optima [17].

In PSO, each individual is called particle, and the population is called a swarm. A swarm can travel in many directions over the search space in order to satisfy the limits of the objective function for a system. A swarm of particles can be replaced on a *j*-dimensional search space for an *i*-variabled problem. PSO is initialized by random velocities and the positions to search for an optimum solution [18]. Every particle is updated to find the two best values in each iteration. The best position (solution) found in the j-dimensional space during the iteration is "*Pbest*" and the best value provided so far by any particle in the population is the global best (*Gbest*). The velocities of each particle are adjusted accordingly to its own flying experience and the other particles flying experience. Then, the velocity of the particle is determined by the expression given in Equation (5).

$$v_{ij}^{t+1} = wv_{ij}^{t} + c_1 r_{1j}^{t}\left[P_{best,i}^{t} - x_{ij}^{t}\right] + c_2 r_{2j}^{t}\left[G_{best} - x_{ij}^{t}\right] \quad (5)$$

where, *w* is the inertia coefficient, and the first term of the equation is the inertia component which is responsible for keeping the particle in the same direction as it was before. v_{ij}^{t} represents the velocity of the i_{th} particle in dimension *j*, at time *t*. In a similar manner, x_{ij}^{t} is the position vector of the current particle, c_1 and c_2 are acceleration constants or learning factors of the algorithm (cognitive and social scaling factors, respectively), while r_1 and r_2 are the random numbers from the uniform distribution of (0,1). x_i^t in the Equation (6) on the other hand, denotes the position vector of particle *i* in a multidimensional search space at time step t and the position of each particle is updated in the search space by using the expression of x_i^{t+1}.

$$x_i^{t+1} = x_i^{t} + v_i^{t+1} \quad (6)$$

2. FINDINGS AND DISCUSSION

The mathematical model was applied in Matlab/Simulink environment with the inclusion of FLC and PSO algorithm. The basic model diagram is shown in Figure 3. The PSO algorithm written in Matlab environment optimized the scaling factors KA, KB, and KC, which were applied to the FLC outputs.

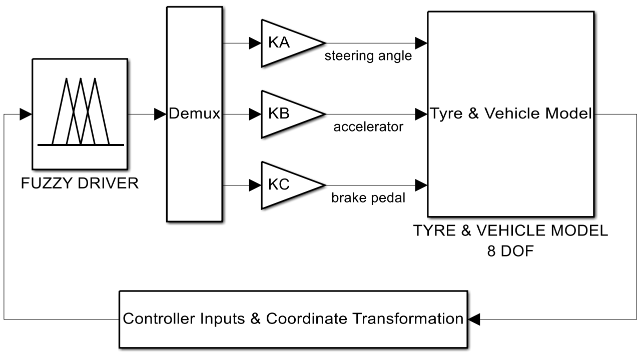


Figure 3. *Simulink model of vehicle and fuzzy driver*

ITAE of Objective function was calculated by the expression given in Equation (7):

$$ITAE = \int [\omega_1(t).t|e_1(t)| + \omega_2(t).t|e_2(t)| + \omega_3(t).t|e_3(t)|] \quad (7)$$

In the equation, ω_1, ω_2, ω_3 are the weighting factors, e_1, e_2 and e_3 are *Error1*, (*Error1-Steer Angle*) and *d(Error1-Steer Angle)/dt*, respectively. PSO parameters used to improve the controller outputs are shown in Table 1. The parameters of the PSO algorithm were chosen based on well-established initial estimates commonly used in the literature. The swarm size was set to 50, a value frequently used in PSO applications as it balances computational efficiency and optimization performance. This choice aligns with recommendations in the literature (Kennedy and Eberhart, 1995), ensuring adequate exploration of the solution space for moderately complex problems like the one presented in this study.

Table 1. *Parameters used for particle swarm optimization*

Number of Iterations	154
Inertia weight, *w(min, max)*	(0.4, 0.9)
Learning factors: (c_1, c_2)	(2, 2)
Swarm size	50

The convergence of PSO was achieved at 154 iterations, as shown in Figure 4, demonstrating the stability and effectiveness of the optimization process. The optimized scaling factors obtained through PSO were found to be KA =892.67, KB =565.19, and KC = 874.06. These values ensure that the fuzzy controller outputs (steering angle, accelerator pedal, and brake pedal) are appropriately scaled for optimal vehicle path tracking performance.

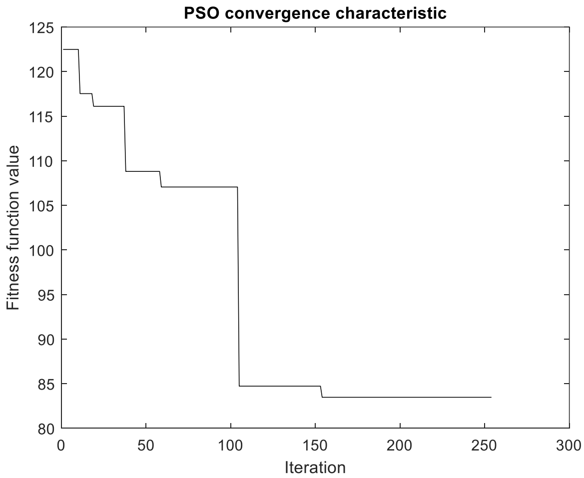


Figure 4. *PSO convergence characteristics*

The optimized fuzzy driver significantly improved the vehicle's trajectory tracking performance under the ISO lane change maneuver at 70-80 kph, as depicted in Figure 5. The optimized trajectory closely follows the desired path, minimizing lateral deviation compared to the original fuzzy controller. Specifically, the lateral deviation peak was reduced from 5.25 meters to 5.09 meters at 70 kph (approximately 3.05% improvement) and from 4.38 meters to 3.97 meters at 80 kph (approximately 9.36% improvement).

These results highlight the effectiveness of the optimized scaling factors in enhancing the performance of a complex FIS structure with over 200 rules, demonstrating the practicality of this approach for high-dimensional fuzzy systems. This method circumvents the need for direct rule or membership function modification, significantly reducing computational complexity while maintaining robust trajectory tracking, particularly at higher speeds where improvements are more pronounced.

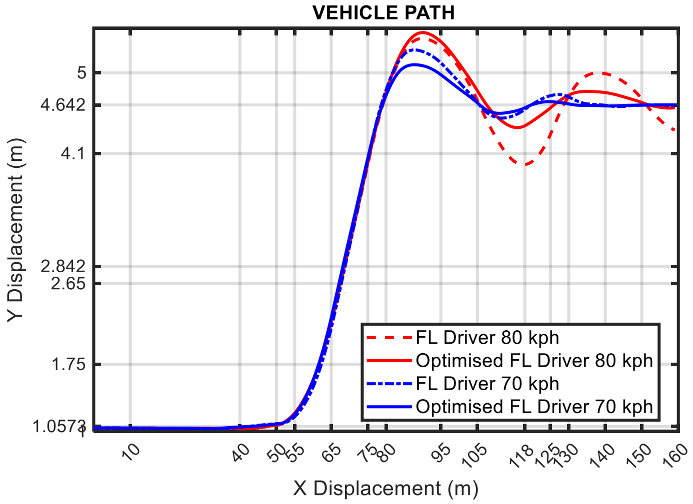


Figure 5. *Vehicle trajectory comparison for normal and optimized fuzzy driver at 70 and 80 kph vehicle longitudinal velocity 3,97*4,38 5,09-5,25*

3. CONCLUSION

This study developed an optimal path tracking scheme for a vehicle handling dynamics model using a fuzzy logic controller (FLC) optimized with Particle Swarm Optimization (PSO). The optimization focused on output scaling factors, ensuring computational simplicity and effectiveness. PSO demonstrated stable convergence within 154 iterations. Under ISO lane change maneuvers at 70-80 kph, the optimized FLC achieved reduced lateral deviation and improved control stability compared to the baseline fuzzy controller.

These findings confirm that scaling factor optimization is a viable approach for enhancing FLC performance in vehicle handling systems. Future work can focus on real-time implementation of adaptive PSO methods and testing the controller under varying road conditions to ensure robustness and practicality.

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