Jurnal Teknologi

Full paper

Composite Nonlinear Feedback Control with Multi-objective Particle Swarm Optimization for Active Front Steering System

Liyana Ramli[a,b], Yahaya Md. Sam[a*], Zaharuddin Mohamed[a], M. Khairi Aripin[c], M. Fahezal Ismail[d]

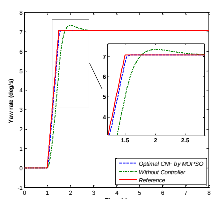
[a]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia
[b]Faculty of Science and Technology, Universiti Sains Islam Malaysia, Bandar Baru Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
[c]Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka, 76100 Durian Tunggal, Melaka, Malaysia
[d]Industrial Automation Section, Universiti Kuala Lumpur Malaysia France Institute, 43650 Bandar Baru Bangi, Selangor, Malaysia

*Corresponding author: yahaya@fke.utm.my

Article history

Received :15 June 2014
Received in revised form :
15 September 2014
Accepted :15 October 2014

Graphical abstract



Abstract

The purpose of controlling the vehicle handling is to ensure that the vehicle is in a safe condition and following its desire path. Vehicle yaw rate is controlled in order to achieve a good vehicle handling. In this paper, the optimal Composite Nonlinear Feedback (CNF) control technique is proposed for an Active Front Steering (AFS) system for improving the vehicle yaw rate response. The model used in order to validate the performance of controller is nonlinear vehicle model with 7 degree-of-freedom (DOF) and a bicycle model is implemented for the purpose of designing the controller. In designing an optimal CNF controller, the parameter estimation of linear and nonlinear gain becomes very important to produce the best output response. An intelligent algorithm is designed to minimize the time consumed to get the best parameter. To design an optimal method, Multi Objective Particle Swarm Optimization (MOPSO) is utilized to optimize the CNF controller performance. As a result, transient performance of the yaw rate has improved with the increased speed of in tracking and searching of the best optimized parameter estimation for the linear and the nonlinear gain of CNF controller.

Keywords: MOPSO; particle swarm optimization; multiple objective; composite nonlinear feedback; active front steering system; optimization; optimal controller

1.0 INTRODUCTION

Vehicle safety system is a major factor in ensuring not only the safety of the passenger but in overall aspects including the vehicle body itself. Hence, an active front steering system (AFS) as implemented in [1-3] is necessary in vehicle handling and stability control because it may control the vehicle movement with the proper direction follows the desired path tracking provided. In order to do that, one of the important vehicle parameters that need to be controlled is a yaw rate of the vehicle. Yaw rate is the rotation about the z-axis located on the centre of gravity of the vehicle. A vehicle without yaw rate control could lose the precision in driving control, especially in cornering manoeuvres. In addition, road condition also plays an important factor which could cause a serious accident if the vehicle handling of the vehicle is neglected. The smaller road adhesion coefficient, the more slippery the road would be. The bicycle model is utilized for the purpose of designing the controller. This model is convenient to use because of the simplicity to integrate with a complex controller and easy to analyse and troubleshoot [4-6]. Nonlinear vehicle model with 7DOF that includes the longitudinal, lateral, yaw motion and rotational motions of the four wheels is sufficient enough to test the effectiveness of vehicle handling with the proposed controller.

A slow response and high overshoot are always being a control tracking problem. Besides, sometimes a quick response also will result a large overshoot in transient performance. Hence, CNF controller could actually solve such problems with its special control methods which will be explained detail in controller design section. The CNF control technique was originally proposed by [7] for a class of second order linear system with input saturation to improve the transient performance of the closed-loop system. Besides, a further improvement of CNF control in multivariable system as reported in [8] and [9] is implemented. Moreover, the CNF control technique is successfully applied to complex control system such as vehicle suspension system [10], helicopter flight control system [11], and many more. In previous work of AFS system in [12], the conventional CNF is successfully applied to improve the transient performance of yaw rate response.

In this paper, the CNF controller with optimization technique is proposed for controlling the yaw rate of the vehicle. The optimal CNF controller must comes with a good optimization method that will result in improving the transient performance in tracking the desired response and this will certainly solve the control tracking problems. In order to achieve the best output response of the vehicle yaw rate, the parameter of linear and nonlinear gain in CNF controller needs to be properly tuned by using a proper method. Based on [13], the authors have used some performance criteria such as the Absolute-Value Of Error (IAE) and the integral of time Multiplied Absolute-Error (ITAE). Besides, Particle Swarm Optimization (PSO) [14], classical root locus theory [8] and Hooke Jeeves method [15] are successfully implemented. In our proposed controller, those parameters are tuned simultaneously and precisely by solving the minimization problems by using Multi Objective Particle Swarm Optimization (MOPSO) which is the main objective of the paper. PSO is a part of swarm intelligence family and well known in solving a very large scale of nonlinear optimization problems.

Kennedy and Eberhart [16] were first established a solution to the complex nonlinear optimization problem by imitating the behavior of bird flocks. They generated the concept of function optimization by means of a particle swarm. In fact, PSO has been extended its ability and seems suitable to solve Multi Objective Optimization Problem (MOOP) such as Multi Objective Particle Swarm Optimization (MOPSO) [17-19]. Thus, MOPSO method is proposed in this paper based on their effectiveness in tuning parameters especially in meeting more than one objective target [17, 20-22]. Those parameters in CNF control law are optimized with three objective functions that are based on the transient performance namely overshoot, settling time and steady state error in finding the minimal error between the actual and the desired response.

This paper is organized in 5 sections. Section 1 discussed an overview of the previous work on the CNF controller design and the effectiveness in using MOPSO to solve the optimization problem. In Section 2, the methodology of the study is briefly described comprises the vehicle model and reference model used for the AFS system. Section 3 explains the design of the CNF controller with MOPSO technique. The simulations results are presented and analysed in Section 4 and ended with conclusion and future work recommendation in Section 5.

2.0 VEHICLE DYNAMIC MODELS

There are two types of vehicle model used in this paper. Linear single track vehicle model and nonlinear two track vehicle model are discussed in this section. These two models are established for designing the controller and as a vehicle plant respectively.

2.1 Single Track Vehicle Model

Single track model or typically called as a bicycle model as shown in Figure 1 is implemented in this paper. This type of vehicle model is widely used by many researchers to design the controller. The structure of this model is actually obtained from the combination of two tracks becomes single track based on the vehicle centre line. As a result, the model now becomes simple and easy to integrate with the controller.

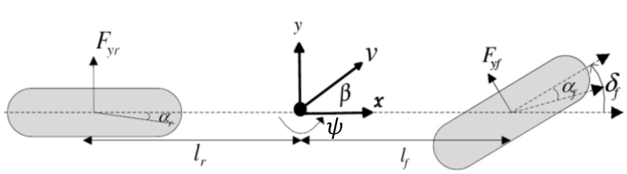


Figure 1 Single track vehicle model

Based on Figure 1 the input of the model is front wheel steer angle δ_f, which is being driven by a driver. Yaw rate $\dot{\psi}$ and side slip β are the control parameters of the vehicle. The other variables are velocity v, l_f and l_r are the distance between front and rear axle to the center of the gravity (COG) given by 1.035m and 1.66m respectively, F_{yr} and F_{yf} are the forces of the wheel in vertical direction (rear and front) and vehicle mass *m*=1700kg. The roll and pitch motion is neglected for planar motion. The other parameters of the vehicle model are road adhesion coefficient μ=1, front tire cornering stiffness $C_f = 105.8$kN and rear tyre cornering stiffness $C_r = 79$kN. The dynamic equation for the lateral and yaw motions are shown respectively as follows

$$mv(\dot{\beta} + \dot{\psi}) = F_{yf} + F_{yr} \tag{1}$$

$$I_z\ddot{\psi} = l_f F_{yf} - l_r F_{yr} \tag{2}$$

Assume that the side slip angle is very small ($\beta \ll 1$), the relationship between cornering stiffness and tire forces are proportional due to the linear tire characteristic and can be described as follows,

$$F_{yf} = -\mu C_f . \alpha_f \tag{3}$$

$$F_{yr} = -\mu C_r . \alpha_r \tag{4}$$

where parameters α_f and α_r indicates the slip angle of the front and left of the wheel respectively. It can be defined as follows

$$\alpha_f = \beta + \frac{l_f . \dot{\psi}}{v} - \delta_f \tag{5}$$

$$\alpha_r = \beta - \frac{l_r . \dot{\psi}}{v} \tag{6}$$

By rearranged Equation (1)-(6), the differential equations of sideslip and a yaw rate variable can be shown as linear state space equation as follows

$$\dot{x} = Ax + Bu \tag{7}$$

$$\begin{bmatrix} \dot{\beta} \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} \dfrac{-(C_f + C_r)}{mv} & \dfrac{l_f C_f - l_r C_r}{mv^2} - 1 \\ \dfrac{l_f C_f - l_r C_r}{I_z} & \dfrac{-({l_f}^2 C_f + {l_r}^2 C_r)}{I_z v} \end{bmatrix} \begin{bmatrix} \beta \\ \dot{\psi} \end{bmatrix} + \begin{bmatrix} \dfrac{C_f}{mv} \\ \dfrac{l_f C_f}{I_z} \end{bmatrix} \delta$$

2.2 Nonlinear Two Track Vehicle Model

The states variables that are essential for vehicle dynamics control are vehicle speed at the center of gravity v, vehicle side slip angle β, yaw rate $\dot{\psi}$ and longitudinal slip for each of tyre λ_i. The validity of the model presented in this section has several assumptions such as the roll motion and suspension dynamics are neglected in the vehicle plane dynamics. The vehicle must be in a low centre of gravity and stiff suspension. As illustrated in Figure 2, the equations for vehicle speed at centre of gravity, sideslip angle and yaw rate dynamics are shown respectively as below

$$\dot{v} = \frac{1}{m}[(F_{x1} + F_{x2})\cos(\beta - \delta) + (F_{x3} + F_{x4})\cos(\beta) + (F_{y1} + F_{y2})\sin(\beta - \delta) + (F_{y3} + F_{y4})\sin(\beta)] \quad (8)$$

$$\dot{\beta} = \frac{1}{mv}[-(F_{x1} + F_{x2})\sin(\beta - \delta) - (F_{x3} + F_{x4})\sin(\beta) + (F_{y1} + F_{y2})\cos(\delta - \beta) + (F_{y3} + F_{y4})\cos(\beta)] - \dot{\psi} \quad (9)$$

$$\dot{\psi} = \frac{1}{J_z}[F_{x1}\left(l_f \sin\delta - \frac{T}{2}\cos\delta\right) + F_{x2}(l_f \sin\delta + \frac{T}{2}\cos\delta) + \frac{T}{2}(F_{x4} - F_{x3}) + F_{y1}\left(\frac{T}{2}\sin\delta - l_f\cos\delta\right) + F_{y2}(l_f \sin\delta - \frac{T}{2}\cos\delta) - l_r(F_{y3} + F_{y4})] \quad (10)$$

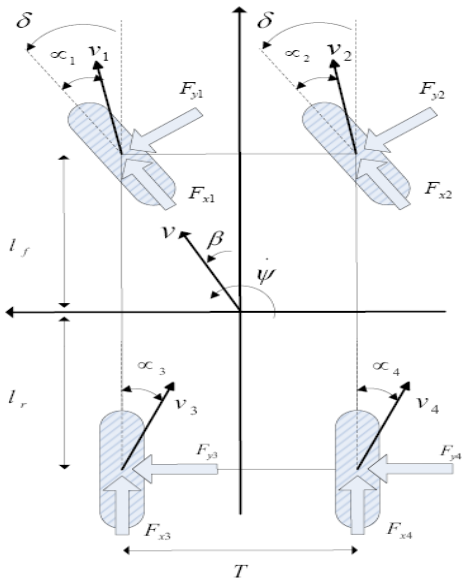


Figure 2 Nonlinear two track model

The forces on x-axis F_{xi} are pointing along the heading while the forces on y-axis F_{yi} are pointing at the left side of the vehicle and z-axis F_{zi} forces are pointing out to the top of the vehicle. Basically, the Equation (8)-(10) are derived based on a coordinate frame at the vehicle's centre of gravity. The nonlinear longitudinal tire forces F_{xi} and the lateral tire forces F_{yi} are derived by using the Pacejka tire model.

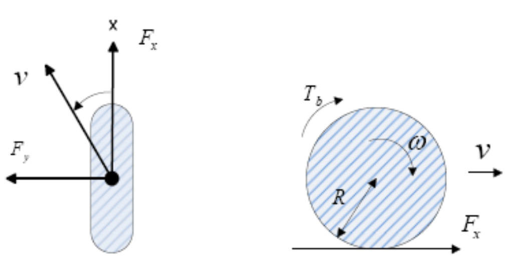


Figure 3 Wheel rotation motion on top and side view

As shown in Figure 3 ω_i indicates i^{th} wheel rotational speed, meanwhile v_i indicates i^{th} wheel vehicle's velocity. Hence, the tyre longitudinal slip λ_i during braking condition can be derived as below

$$\lambda_i = \frac{v_i - R\omega_i}{v_i} \quad (11)$$

Where v_i for each wheel are given as follows

$$v_1 \cong v - \dot{\psi}\left(\frac{T}{2} - l_f\beta\right) \quad (12)$$

$$v_2 \cong v - \dot{\psi}\left(\frac{T}{2} + l_f\beta\right) \quad (13)$$

$$v_3 \cong v - \dot{\psi}\left(\frac{T}{2} - l_r\beta\right) \quad (14)$$

$$v_4 \cong v - \dot{\psi}\left(\frac{T}{2} - l_r\beta\right) \quad (15)$$

The drive torque T_{drive_i} of the driveline is also called as an accelerating torque. Meanwhile, the decelerating effects from vehicle comes from the braking torque T_{Br} and tyre longitudinal force F_{xi} multiplied by the tire radius R. Along with the presence of moment of inertia of the wheel J_w, the wheel rotational speed is given as below

$$J_w\dot{\omega} = T_{drive_i} - T_{Br_i} - RF_{xi} \quad (16)$$

2.3 Reference Model

The reference model determines the desired value that the vehicle should comply and serves the best for the driver and the vehicle to achieve the safe or optimum condition. As mentioned in [23], the desired value of the side slip angle in a steady state condition is always zero whereas the desired yaw rate is determined by the following equation,

$$\dot{\psi}_d = \frac{v}{(l_f + l_r) + k_{us}v^2}\delta_f \quad (17)$$

where k_{us} is under steer parameter and can be expressed by,

$$k_{us} = \frac{m(l_r C_r - l_f C_f)}{(l_r + l_f)C_f C_r} \quad (18)$$

■3.0 THE OPTIMAL CNF DESIGN

Composite Nonlinear Feedback consists of the composition between two laws, which are linear and nonlinear feedback law without any switching element. By referring to control system diagram in Figure 4, δ_d is a steer angle commanded by driver, δ_c is a corrected steer angle by the CNF controller and δ_f is a front steer angle which is a sum of δ_d and δ_c. The aim of the system is to minimize an error of yaw rate which is the difference between the yaw rate reference, $\dot{\psi}_d$ and the yaw rate of the vehicle model $\dot{\psi}$.

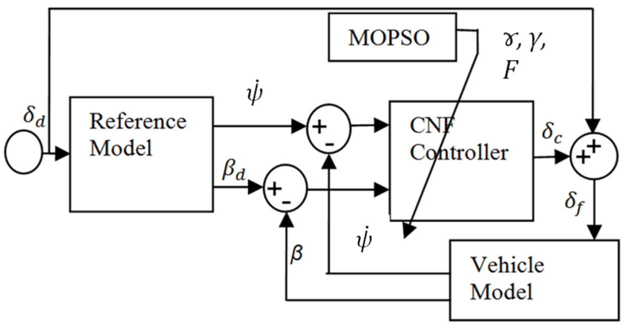


Figure 4 Control system diagram

In CNF control, the linear feedback law is commanding the small damping ratio to get the fast response but it will cause some overshoot that needs to be controlled as well. Hence, the nonlinear feedback law will act simultaneously to overcome this problem by tuning down the value of damping ratio and as a result, it will improve the overshoot while the signal is approaching the target reference. The general state space form of linear time-invariant continuous system with input saturation is characterized by

$$\dot{x} = Ax + Bsat(u), \;\; x(0) = x_0 \tag{19}$$

$$y = Cx \tag{20}$$

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}$, $y \in \mathbb{R}^p$ are the state vector, control input and controlled output vector respectively. A, B and C, are constant system matrices, and sat: $\mathbb{R} \rightarrow \mathbb{R}$ represents actuator saturation which can be expressed by,

$$sat(u) = sgn(u)min\,\{u_{max}, |u|\} \tag{21}$$

where u_{max} is a saturation level of an actuator input. In order to apply this in CNF control law, the following assumptions of system matrices are considered as follows

1. (A, B) is stabilizable,
2. (A, C) is detectable, and
3. (A, B, C) is invertible and has no zeros at $s = 0$.

3.1 The CNF Control Laws

There are three steps taken for designing CNF law by using state feedback method [8]. The steps are described as follows,

Step 1: Design a linear feedback law.

$$u_L = Fx + Gr \tag{22}$$

where r is a step command input and F is a 1 by 2 matrix $[f_1, f_2]$ and so-called linear feedback gain which is chosen such that $A + BF$ is asymptotically stable and the closed loop system $C(sI - A - BF)^{-1}B$ has certain desired properties such as a low damping ratio. Beside, matrix G is a scalar and given by $G = -[C(A + BF)^{-1}B]^{-1}$

Step 2: Design a nonlinear feedback law

$$u_N = \rho(y, r)B^T P(x - x_e) \tag{23}$$

where $\rho(y, r)$ is any non-positive function locally Lipchitz in y, which is used to change the system closed loop damping ratio as the system output y in Equation (20) approaches the step command input r. Matrix $P > 0$ exists since $A + BF$ is asymptotically stable and can be obtained from the following Lyapunov equation,

$$(A + BF)^T P + (A + BF)P = -W \tag{24}$$

for some given value of $W > 0$ which is positive definite matrix and an equilibrium point x_e is given by,

$$x_e = G_e r \tag{25}$$

where,

$$G_e = -(A + BF)^{-1}BG \tag{26}$$

In order to adapt the variation of tracking target, the nonlinear function $\rho(r, y)$ based on [13] in Equation (23) is used as follows

$$\rho(r, y) = \gamma e^{-\Upsilon\Upsilon_0|y-r|} \tag{27}$$

where,

$$\Upsilon_0 \begin{cases} \dfrac{1}{|y_0 - r|}, & y_0 \neq r \\ 1, & y_0 = r \end{cases}$$

Step 3: Combining both feedback laws to obtain CNF control law

$$u_{CNF} = u_L + u_N = Fx + Gr + \rho(r, y)B^T P(x - x_e) \tag{28}$$

3.2 The CNF with MOPSO Algorithm

As introduced by [16], originally the PSO method is considered in single objective problem only. Thus, to enhance the implementation of original PSO, a multi-objective strategy is introduced in this paper by using linear weight summation (LWS) approach as described in Figure 5 [17]. The main objective to optimize the CNF controller is to achieve the best output response especially in transient response to ensure that the system is fast in tracking the desired response. Thus, a fast settling time (Ts), zero steady state error (SSE) and overshoot (OS) at a permissible level must be achieved. These three criteria have been selected to be the objective functions in finding the minimal value as the best optimal tuning gain parameters for CNF controller.

The summation of these three objective functions is shown as follows,

$$Fitness_i = w_{SSE}(SSE)_i + w_{OS}(OS)_i + w_{Ts}(Ts)_i \tag{29}$$

where,
w_{SSE} = weight value for the steady state error
w_{OS} = weight value for the overshoot
w_{Ts} = weight value for the settling time

Table 1 Parameters involved in MOPSO

Parameter	CNF with MOPSO
$\boldsymbol{D}$	Maximum number of iteration set by the user
$\boldsymbol{v_{ij}^{t+1}}$	Velocity vector of particle *i* in dimension *j* at time *t*
$\boldsymbol{x_{ij}^{t}}$	Position vector of particle *i* in dimension *j* at time *t*
$\boldsymbol{Fitness_{ij}^{t}}$	Fitness value of particle *i* in dimension *j* at time *t*
$\boldsymbol{P_{best,i}^{t}}$	Personal best position of particle *i* in dimension *j* found from initialization through time *t*
$\boldsymbol{G_{best}}$	Global best position of particle *i* in dimension *j* found from initialization through time *t*
$\boldsymbol{c_1}$ & $\boldsymbol{c_2}$	Positive acceleration constants
$\boldsymbol{r_{1j}^{t}}$ & $\boldsymbol{r_{2j}^{t}}$	Random numbers *U*(0,1) at time *t*.
$\boldsymbol{\varepsilon}$	Different between min and max fitness value in the iteration
$\boldsymbol{\omega}$	Inertia weight

The weight value is set based on probability. Weight value for the highest priority is set to 0.7, second priority is 0.2 and lowest priority is 0.1. OS will be the highest priority and then followed by Ts as a second priority and SSE as a lowest priority. The fitness value in Equation (29) is determined first before the selection of personal best P_{best} and global best G_{best} are done. All the parameter involved in MOPSO is given by Table 1. The control variables for MOPSO algorithm are Υ and γ in Equation (27) and $F = [f_1\ f_2]$ in Equation (22) indicates the position vector of particle *i* in the multidimensional search space at time step *t*, then the position of each particle is updated in the search space as follow

$$x_{ij}^{t} = \begin{cases} \Upsilon_i^t = \Upsilon_i^t + v_i^{t+1} \\ \gamma_i^t = \gamma_i^t + v_i^{t+1} \\ {f_1}_i^t = {f_1}_i^t + v_i^{t+1} \\ {f_2}_i^t = {f_2}_i^t + v_i^{t+1} \end{cases} \tag{30}$$

where, v_i^t is the velocity vector of particle *i* that runs the optimization based on both own experience knowledge and the social experience knowledge from all particles. The velocity of particle *i* is determined by

$$v_{ij}^{t+1} = \omega v_{ij}^t + c_1 r_{1j}^t \left[P_{best,i}^t - x_{ij}^t\right] + c_2 r_{2j}^t \left[G_{best} - x_{ij}^t\right] \tag{31}$$

Inertia weight ω is a weight that controls the momentum of the particle. This can be done by multiplied it with the previous velocity v_{ij}^t as indicated in Equation (31). By adjusting the value of inertia weight, particles can be converged accurately and control the capability in terms of exploration and exploitation. In order to obtain a quick convergence at the optimum point, inertia weight will be decreased linearly with the iteration number as given by the following equation

$$\omega^{t+1} = \omega_{max} - \left(\frac{\omega_{max} - \omega_{min}}{D}\right) j \tag{32}$$

where,
ω_{max} and ω_{min} are the minimum and maximum values of inertia weight respectively.
D is the maximum iteration number.
j is the current iteration number.

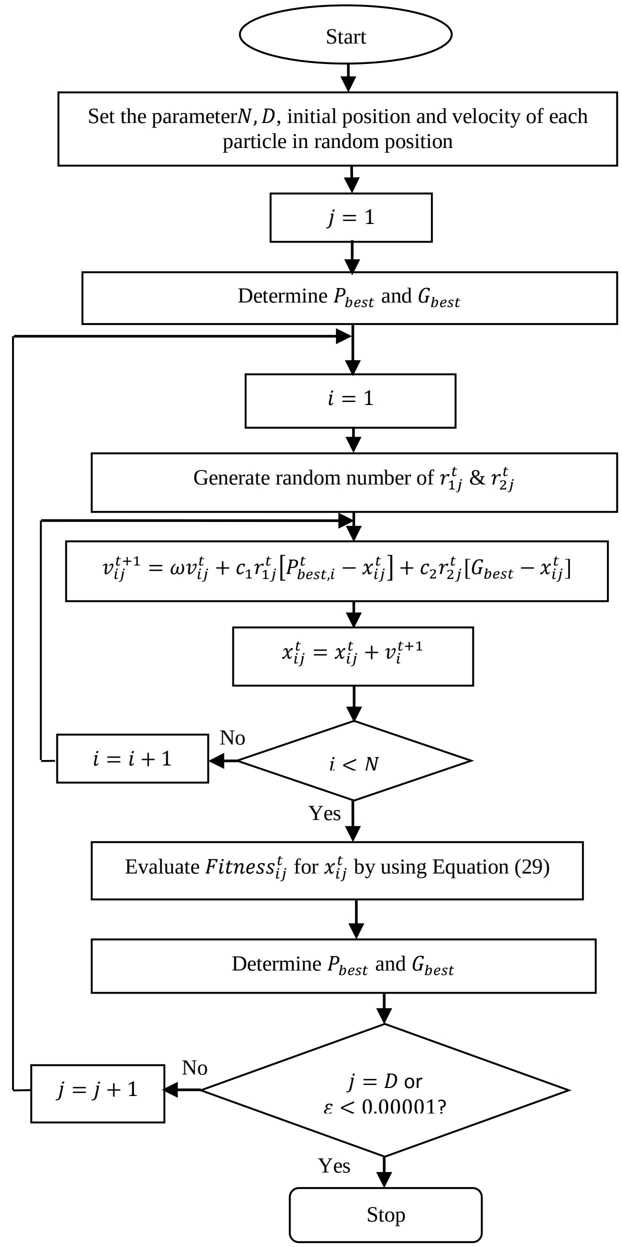


Figure 5 Process of MOPSO algorithm flowchart

By considering a minimization problem, all the particles are evaluated based on $Fitness$ value, together with finding the personal best and global best (best value of particle in the overall swarm). The personal best position $P_{best,i}$ at $t+1$ where $t \in \{0, \ldots, N\}$, is defined as

$$P_{best,i}^{t+1} = \begin{cases} P_{best,i}^t, & Fitness(x_i^{t+1}) > Fitness(x_i^t) \\ x_i^{t+1}, & Fitness(x_i^{t+1}) \le Fitness(x_i^t) \end{cases} \tag{33}$$

Meanwhile, to calculate the global best position G_{best} at time step t is given as follows

$$G_{best} = \min\{P_{best,i}^t\} \tag{34}$$

Each particle position is updated by the current velocity until it ended with a stopping criterion, either the value of $\varepsilon < 0.00001$

or MOPSO algorithm has reached the maximum iteration that is set by user.

4.0 RESULTS AND DISCUSSIONS

The result is carried out through simulation work by using matlab software. This result is significant in order to find the effectiveness of the controller with MOPSO algorithm. The steering angle input signal used in the system is called J-turn maneuver as shown in Figure 6.

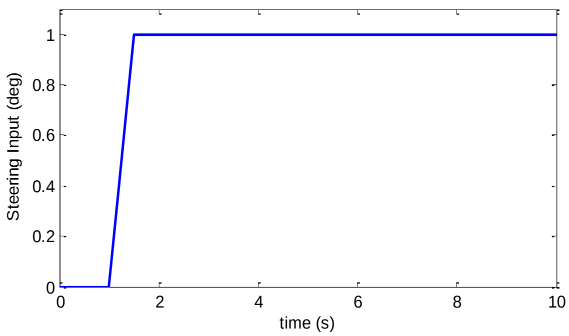


Figure 6 J-turn steer input

It is tested with dry road condition of road adhesion coefficient (μ=1) with constant velocity $v = 100\, {}^{km}/_{h}$. The 2 DOF linearized single track model (bicycle model) with $x = [\beta\ \dot{\psi}]^T$ is given by

$$\dot{x} = Ax + Bsat(u), \qquad x(0) = x_0 \qquad (35)$$
$$y = Cx$$

where,

$$A = \begin{bmatrix} -3.9026 & -0.9839 \\ 6.9689 & -3.8942 \end{bmatrix},\ B = \begin{bmatrix} 2.2343 \\ 35.9250 \end{bmatrix},\ C = [0\ \ 1]$$

whereby, the yaw reference generator [23] is as follows

$$\dot{\psi}_d = 7.0654\delta_d \qquad (36)$$

In MOPSO algorithm, the parameter initialization has been set with the following values: the number of particles N involved in swarm searching is set to 20, the maximum iteration D for the particles to repeat is set to 150 iterations and the acceleration coefficients c_1 and c_2 are both set to 1.4. While for maximum and minimum weight value ω are set to 0.9 and 0.4 respectively. The optimal CNF control law by MOPSO algorithm is given as follows

$$u^*_{CNF} = F^* + Gr + \rho^*(r,y)B^TP(x - x_e) \qquad (37)$$

with P satisfies $(A + BF)^TP + (A + BF)P = -I$ and the control variables optimized by MOPSO are as follow,

$\Upsilon^* = 0.0305$, $\gamma^* = 0.1656$ and $F^* = [0.4844\ \ -0.0086]$
hence, the nonlinear function in Equation (27) yields,

$$\rho^*(r,y) = 0.1656e^{-0.0305\Upsilon_0|y-r|} \qquad (38)$$

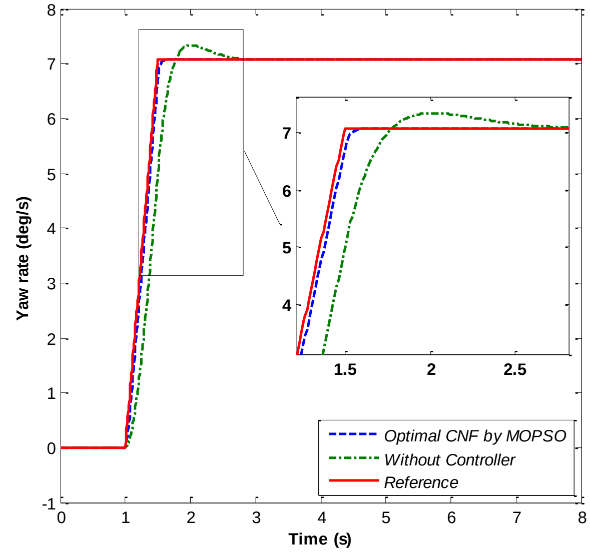


Figure 7 Yaw Rate Output Response optimized by MOPSO

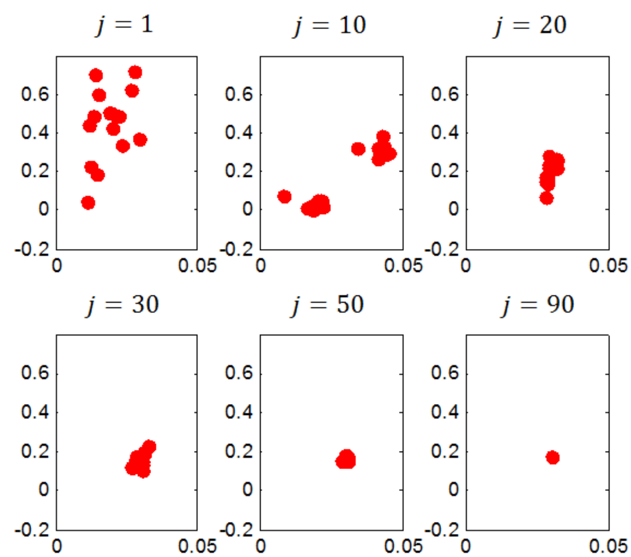


Figure 8 Convergence of particles at different iteration *j*

Figure 7 shows the output response of the yaw rate performance which is the optimal CNF by MOPSO has improved the overall performance and able to track the reference that is obtained from Equation (17). Besides, MOPSO algorithm has successfully optimized the CNF control performance which able to minimize the fitness functions of the system as the number of iterations increasing as shown in Figure 9 where an overshoot becomes a highest priority to be selected first in the optimal selection and followed by Ts and SSE shown in Figure 10 and Figure 11 respectively. Table 2 shows the performance results of the system. Thus, based on the results, the output response controlled by CNF controller that is optimized by MOPSO has produced a fast response with approximately 0% of overshoot and zero steady state error value.

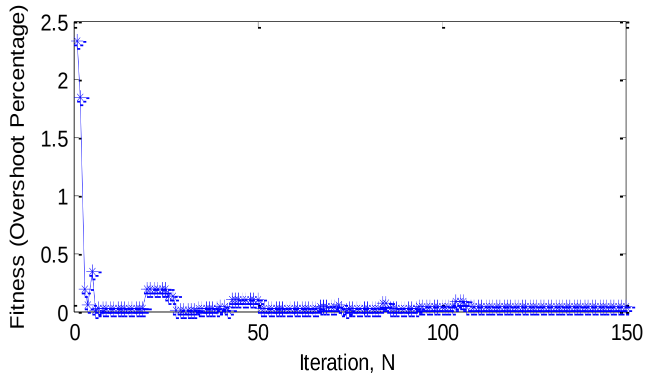


Figure 9 Iteration versus Fitness of overshoot percentage

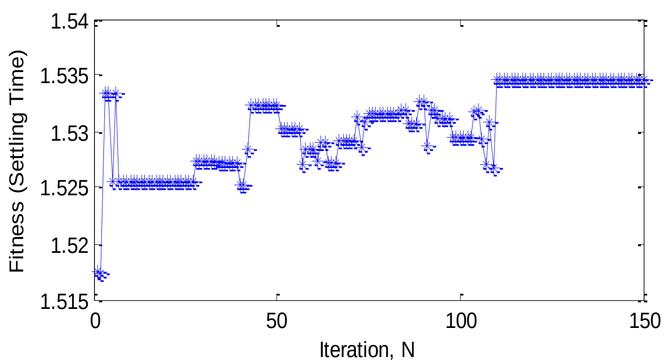


Figure 10 Iteration versus Fitness of settling time

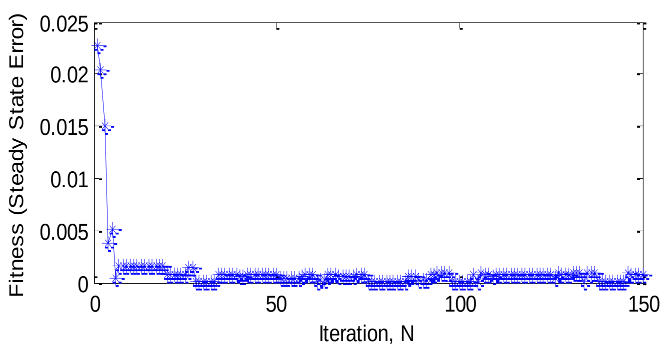


Figure 11 Iteration versus Fitness of steady state error

Furthermore, MOPSO has an advantage and solution to avoid the premature convergence problem. This is due to the inertia weight ω in Equation (32) which it provides the balance between global and local exploitation and exploration. MOPSO has converged fast without experience the premature convergence and therefore, it can find the optimal solution with less number of iterations as shown in Figure 8 where all the particles have converged at the optimal point at iteration of 90 without need to wait until it stops at the maximum iteration that is set by user.

Table 2 Summary of the overall performance by MOPSO

Performance of Response	CNF with MOPSO
Settling Time (s)	1.5346
Steady State Error	0.0008
Overshoot (%)	0.01699

Moreover, MOPSO does not require any extra generation of new population per iteration which could lead to time consuming. MOPSO generates only one population for the rest of the operation where all the particles from the same population will search until they found the better solution and this certainly will decrease the time complexity. Besides that, the acceleration constant in MOPSO algorithm must be selected properly. The similar value set on c_1 and c_1 seems to result in the most effective way to search the optimal point without experience the premature convergence or highly attracted to either P_{best} or G_{best} only. The optimal value of control variables are shown in Table 3 as below,

Table 3 Optimal control variables by MOPSO

Performance of Response	CNF with MOPSO
Alpha ɤ	0.0305
Beta ɣ	0.1656
Linear feedback gain $[\boldsymbol{f_1}\ \boldsymbol{f_2}]$	[0.4844 -0.0086]

■5.0 CONCLUSIONS

By using MOPSO in CNF controller, a better result can be obtained by focusing on the improvement of transient performance (Ts, OS and SSE) which are based on the multi objective optimization problem solving. Based on the result, CNF control has shown its capability in order to achieve fast response of vehicle yaw rate which capable in tracking the desired response. It eliminates overshoot and able to achieve fast settling time after being optimized by MOPSO. Hence, by applying this algorithm to the CNF control law, the tracking control problem of transient response is successfully solved and the vehicle handling is improved by using AFS system. As a conclusion, the vehicle can move safely without any dangerous accident like over steering, under steering, spinning or skidding. For the future work, the optimal CNF with the combination of any other robust controller could enhance the vehicle handling performance for AFS system especially in other extreme cornering maneuver such as sine and fish hook maneuvers.

Acknowledgement

The authors would like to express deep appreciations to the Ministry of Higher Education, Malaysia, through Research Management Centre (RMC), Universiti Teknologi Malaysia (UTM) and UTM for providing a research grant (Vot 05H02), opportunity and necessary facilities to support this research work.

References

[1] Kanghyun, N., Fujimoto, H. and Hori,Y. 2014. Advanced Motion Control of Electric Vehicles Based on Robust Lateral Tire Force Control via Active Front Steering. *IEEE/ASME Transactions on Mechatronics*. 19(1): 289–299.

[2] Qiang, L., Guobiao, S., Jie, W. and Yi, L. 2014. Yaw Stability Control of Active Front Steering with Fractional-Order PID Controller. *Information Engineering and Computer Science ICIECS 2009. International Conference on*. 1–4

[3] Zhang, J. Y., Kim, J. W., Lee, K. B. and Kim, Y. B. 2008. Development of an Active Front Steering (AFS) System with QFT Control. *International Journal of Automotive Technology*. 9(6): 695–702.

[4] Hamzah, N., Sam, Y. M., Selamat, H., Aripin, M. K. and Ismail, M. F. 2012. Yaw Stability Improvement for Four-Wheel Active Steering Vehicle Using Sliding Mode Control. *Signal Processing and its Applications (CSPA), IEEE 8th International Colloquium*. 127–132.

[5] Qiang, L., Guobiao, S., Yi, L. and Jie, W. 2010. Yaw Rate Control of Active Front Steering Based on Fuzzy-logic Controller. *Education Technology and Computer Science (ETCS). Second International Workshop*. 125–128.

[6] Wu, Y., Song, D., Hou, Z. and Yuan, X. 2007. A Fuzzy Control Method to Improve Vehicle Yaw Stability Based on Integrated Yaw Moment Control and Active Front Steering. In *Mechatronics and Automation, 2007. ICMA 2007. International Conference*. 1508–1512.

[7] Lin, Z., M. Pachter, and S. Banda. 1998. Toward Improvement of Tracking Performance Nonlinear Feedback for Linear Systems. *International Journal of Control*. 70(1): 1–11.

[8] Chen, B. M., Lee, T. H., Kemao, P. and Venkataramanan, V. 2003. Composite Nonlinear Feedback Control for Linear Systems with Input Saturation: Theory and An Application. *Automatic Control, IEEE Transactions on*. 48(3): 427–439.

[9] Lan, W., Chen, B. M. and He, Y. 2006. On Improvement of Transient Performance in Tracking Control for a Class of Nonlinear Systems with Input Saturation. *Systems & Control Letters*. 55(2): 132–138.

[10] Ismail, M. F., Sam, Y. M., Peng, K., Aripin, M. K. and Hamzah, N. 2012. A Control Performance of Linear Model and the Macpherson Model for Active Suspension System Using Composite Nonlinear Feedback. In *Control System, Computing and Engineering (ICCSCE), 2012 IEEE International Conference*. 227–233.

[11] Guoyang, C. and P. Kemao. 2007. Robust Composite Nonlinear Feedback Control With Application to a Servo Positioning System. *Industrial Electronics, IEEE Transactions on*. 54(2): 1132–1140.

[12] Aripin, M. K., Sam, Y. M., Kumeresan, A. D., Peng, K., Hasan, M. and Ismail, M. F. 2013. A Yaw Rate Tracking Control of Active Front Steering System Using Composite Nonlinear Feedback. In *AsiaSim 2013*. Springer Berlin Heidelberg. 231–242.

[13] Weiyao, L. and Chen, B. M. 2007. On Selection of Nonlinear Gain in Composite Nonlinear Feedback Control for a Class Of Linear Systems. In *Decision and Control, 2007 46th IEEE Conference*. 1198–1203.

[14] Ramli, L., Sam, Y. M., Aripin, Z. Mohamed, M. K. Aripin and Ismail, M. F. 2013. Optimal Composite Nonlinear Feedback Controller for an Active Front Steering System. *Applied Mechanics and Materials, 2014.* 554: 526–530.

[15] Weiyao, L., Thum, C. K. and Chen, B.M. 2010. A Hard-Disk-Drive Servo System Design Using Composite Nonlinear-Feedback Control With Optimal Nonlinear Gain Tuning Methods. *Industrial Electronics, IEEE Transactions*. 57(5): 1735–1745.

[16] Kennedy, J. and R. Eberhart. Particle Swarm Optimization. *Neural Networks, 1995. Proceedings., IEEE International Conference*. 1942–1948.

[17] Jaafar, H. I., Sulaima, M. F., Mohamed, Z. and Jamian, J. J. 2013. Optimal PID Controller Parameters for Nonlinear Gantry Crane System via MOPSO Technique. *Sustainable Utilization and Development in Engineering and Technology (CSUDET), 2013 IEEE Conference*. 86–91.

[18] Mahmoodabadi, M. J., Taherkhorsandi, M. and Bagheri, A. 2014. Optimal Robust Sliding Mode Tracking Control of a Biped Robot Based on Ingenious Multi-objective PSO. *Neurocomputing*. 124(0): 194–209.

[19] Domínguez, M., Fernández-Cardador, A., Cucala, A. P., Gonsalves, T. and Fernández, A.. 2014. Multi Objective Particle Swarm Optimization Algorithm for the Design of Efficient ATO Speed Profiles in Metro Lines. *Engineering Applications of Artificial Intelligence*. 29: 43–53.

[20] Li, J. Z., L., Zeng, J. T, Xia, J. W.i, Li, M. H. and Liu, C. X. 2009. Research on Grid Workflow Scheduling Based on MOPSO Algorithm. *Intelligent Systems. GCIS '09. WRI Global Congress*. 199–203.

[21] Kitamura, S., Mori, K., Shindo, S., Izui, Y. and Ozaki, Y. 2005. Multiobjective Energy Management System Using Modified MOPSO. *Systems, Man and Cybernetics, 2005 IEEE International Conference*. 3497–3503.

[22] Sharaf, A. M. and El-Gammal, A. A. A. 2009. A novel Discrete Multi-Objective Particle Swarm Optimization (MOPSO) of Optimal Shunt Power Filter. *Power Systems Conference and Exposition, 2009. PSCE '09. IEEE/PES*. 1–7.

[23] Mirzaei, M. 2010. A New Strategy for Minimum Usage of External Yaw Moment in Vehicle Dynamic Control System. *Transportation Research Part C: Emerging Technologies.* 18(2): 213–224.