Control Strategies to Steer and Drive an Autonomous 4WS4WD Ground Vehicle: A Review of MPC Approaches

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Abstract- The uptake in electric vehicles has led to a keen debate and need for the development of autonomous ground vehicles (AGV). AGVs are equipped with an increasing number of actuators which aid to actively control its lateral and longitudinal dynamics. Amidst the varied road terrains, precision in coordination is of the essence. In that regard, manoeuvrability, accuracy, and controllability are vital aspects to consider in the design of an AGV controller. The four-wheel steer and four-wheel drive (4WS4WD) architecture is one such AGV technology that offers the challenge of over-actuation and nonlinearity. The paper reviews the AGV dynamics and scholarly approaches to handling control task amidst the AGV challenges.

Keywords- Autonomous Ground Vehicle, drive, Model Predictive Control, steer

I. INTRODUCTION

THE imperative nature of vehicle navigation has necessitated the development of Autonomous Ground Vehicles (AGVs) with reliable accuracy, manoeuvrability, and controllability. Usually, an AGV is required to follow a path with a high degree of accuracy under unstructured and uneven terrain conditions, where a significant amount of wheel slip and unpredictable disturbance forces occur at the vehicle's wheels [1]. The four-wheel steer and four-wheel drive (4WS4WD) vehicle, with wheels that can be steered and driven independently, is a revolutionary platform that has great potential to perform high maneuverability and flexibility in harsh environments [2] and [3].

The main challenge in the control of 4WS4WD is the number of control inputs (four steering angles and four drive torques), which results in an over-actuated system [4] and [5], where only three outputs including its degree of freedom (DOF) in the longitudinal, lateral and angular directions of the vehicle are concerned. How to allocate all eight control inputs to achieve high path following performance has not yet been effectively solved [6]. The control allocation should handle the control problems of over-actuated systems.

The aim of this study involves appreciating AGV system dynamics and challenges in the control task by providing an overview of the architectural and control strategies geared to improve the performance of (semi)autonomous vehicles. AGV controls are constrained and uncertain hence Model Predictive Control (MPC) has been designed and established as the promising tool [7]–[14]. The need to synthesize robust and safety constraints with regard to vehicle dynamics is ubiquitous.

The paper reviews control approaches for (semi)autonomous vehicle adopting MPC. Approaches considered are linear MPC, nonlinear MPC, adaptive MPC, and Robust MPC. Decoupling and control allocation approaches are an additional concern when dealing with a control algorithm that handles both lateral and longitudinal vehicle dynamics, hence, forms part of the review.

II. AGV MODEL

A. *CONTROL OVERVIEW*

AGV under consideration has four wheels to be steered and driven independently. The technologies that aid autonomy include sensing, path planning, and control [15]. For that reason, the concept of autonomy requires that the control algorithm depends on sensors and output measurement y in determining reference path trajectory and velocity profile. During motion, a vehicle that veers off the path should be steered back by a control command with a steering angle δ to revert back to its course. In addition, when a vehicle has to be driven consistent with the reference velocity profile set by path/velocity planner, a control command with an equivalent torque input T has to be supplied.

B. *EQUATIONS OF MOTION*

The dynamics of motion for an AGV can be described using the well-developed Newton-Euler formalism. Considering input u and state ψ, the systems can be expressed as;

$$\dot{\psi} = f(\psi, u) \tag{1}$$

The AGV architecture brings together submodules that make up a vehicle which include vehicle body dynamic model, driving unit dynamic model and tire model [16]. The subsystems are integrated together and external disturbances considered in representing vehicle states under eight system inputs; four drive torques and four steering angles.

A vehicles body frame $x, y,$ and z are the longitudinal, lateral and vertical axes (consider Fig. 1). $\dot{x}, \dot{y}$ and $\dot{\theta}$ are the longitudinal, lateral velocities and yaw rate. Considering

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F_x, F_y and M_z are the longitudinal, lateral forces acting on the vehicle CG and the rotating moment about z $axes$.

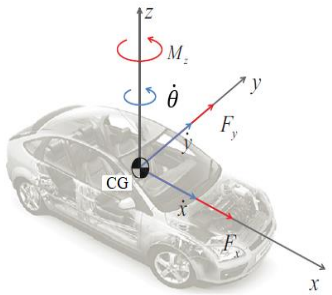

Fig. 1 Vehicle x-y-z orientation

Four-wheel notation for body dynamic in the driving task is governed by,

$$\dot{\psi}(t) = f^{4w}(\psi(t), u(t)) \tag{2}$$

where $\psi(t) \in \mathbb{R}^n$ is the state of the system and $u(t) \in \mathbb{R}^{m_r}$ is the input, $n = 10$ is the number of states and $m_r = 8$ is the number of inputs. The vehicles states are lateral, longitudinal velocities in the inertial frame and angular velocities on the four wheels denoted as:

$$\psi = \left[\dot{y}, \dot{x}, \theta, \dot{\theta}, Y, X, w_{fl}, w_{fr}, w_{rl}, w_{rr}\right]^T \tag{3}$$

Where fl is front left, fr is front right, rl rear left and rr is rear right wheel notations and W. The inputs are steering angle and tractive torque at the four wheels denoted by:

$$u = [\delta_{fl}, \delta_{rl}, \delta_{fr}, \delta_{rr}, T_{fl}, T_{rl}, T_{fr}, T_{rr}]^T \tag{4}$$

where δ is the steering angle and T is the driving torque.

The equation governing motion based on Newtonian formalism [17]–[19] to describe the system are

$$m\ddot{y} = -m\dot{x}\dot{\theta} + F_{yfl} + F_{yfr} + F_{yrl} + F_{yrr} \tag{5}$$

$$m\ddot{x} = m\dot{y}\dot{\theta} + F_{xfl} + F_{xfr} + F_{xrl} + F_{xrr} \tag{6}$$

$$\begin{aligned} I\ddot{\theta} &= x_f\left(F_{yfl} + F_{yfr}\right) - x_r\left(F_{yrl} + F_{yrr}\right) + \ldots \\ &\ldots + c\left(-F_{xfl} + F_{xfr} - F_{xrl} + F_{xrr}\right) \end{aligned} \tag{7}$$

$$\dot{Y} = \left[sin\theta \quad cos\theta\right]\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} \tag{8}$$

$$\dot{X} = \left[cos\theta \quad -sin\theta\right]\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} \tag{9}$$

The x and y components of the tire forces F_x and F_y are computed by

$$F_{yi} = \left[sin\delta_i \quad cos\delta_i\right]\begin{bmatrix} F_{li} \\ F_{ci} \end{bmatrix} \tag{10}$$

$$F_{xi} = \left[cos\delta_i \quad -sin\delta_i\right]\begin{bmatrix} F_{li} \\ F_{ci} \end{bmatrix} \tag{11}$$

Lateral and longitudinal tire forces F_{li} and F_{ci} are governed by

$$F_{ci} = f_c\left(\alpha_i, s_i, \mu, F_{zi}\right) \tag{12}$$

$$F_{li} = f_l\left(\alpha_i, s_i, \mu, F_{zi}\right) \tag{13}$$

where α represents the slip angle of the tire, s is the slip ratio, μ is the friction coefficient and F_z is the normal force. In addition, $F_{ci}$and F_{li} indicate lateral (cornering) and longitudinal tire forces in the tire frame. F_{yi} and $F_{xi}$are the components of tire forces along the lateral and longitudinal vehicle axes. α_i are the wheel slip angles.

Two-wheel notation equation is better used in the design of the steer dynamics as Fig. 2 below.

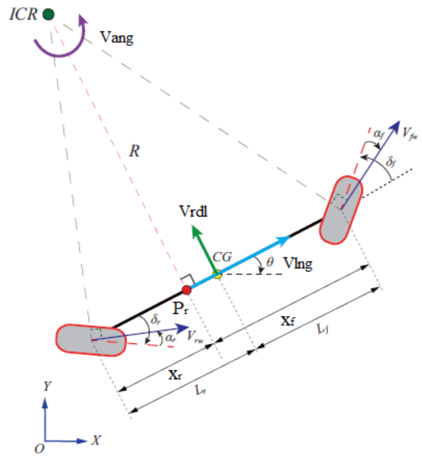

Fig. 2 Two wheel steer model

By considering angular and radial velocity as shown in the Fig. 2 above, the kinematic equations of the vehicle defined through the global coordinate system $(X - O - Y)$ is summarized as

$$\dot{X} = V_{lng}cos\theta - V_{rdl}sin\theta \tag{14}$$

$$\dot{Y} = V_{lng}sin\theta + V_{rdl}cos\theta \tag{15}$$

$$\dot{\theta} = \frac{V_{lng}\left(\tan\left(\delta_f + \alpha_f\right) - \tan\left(\delta_r + \alpha_r\right)\right)}{L_f + L_r} \tag{16}$$

where V_{lng} is the longitudinal velocity, V_{rdl} is the radial velocity, δ_f front steering input, δ_r is the rear steering input, α_f is front slip angle, $\alpha_r$is the rear slip angle. The system states can be expressed as a model based on the dynamic and kinematic equation as

$$Pos = \begin{bmatrix} x & y & \theta \end{bmatrix}^T \tag{17}$$

$$Vel = \begin{bmatrix} V_{lng} & V_{rdl} & V_{ang} \end{bmatrix}^T \tag{18}$$

$$Acc = \begin{bmatrix} a_{lng} & a_{rdl} & a_{ang} \end{bmatrix}^T \tag{19}$$

where a_{lng}, a_{rdl} and a_{ang} are longitudinal, radial and angular acceleration respectively.

III. CONTROL STRATEGIES

This section reviews MPC formulation and approaches applied to steering and/or drive functions of a (semi)autonomous system.

A. *GENERAL MPC FORMULATION*

Design makes use of a model of a process in the computation of the control signal by performing a minimization of the objective function [9]. In that regard, the design of the objective function relates the future plant behaviour. A dynamic model according to [7] is of essence which yield the *predictive model* concept and make use of a design interval time known as *prediction horizon*.

The control algorithms consistent with model prediction differ based on the process model, objective function, noise, and application of constraints [12]. Predictive model is a mathematical representation that describes or approximates behaviour of the real system. The computation is done and applied in a receding horizon technique [20]. Due to use of modern computer systems in computation, a discrete model is a convenient approach for computation of the control command. The prediction model thus contains

$$x_{k+1} = f(x_k, u_k) \tag{20}$$

where $x_k \epsilon \mathbb{R}^n$ represents the system state while $u_k \in \mathbb{R}^m$ represents the instantaneous control action at time k. In addition, an objective cost function is used as the criteria for optimizing the computation of control command. The function is used to compute control trajectory along the prediction horizon N [9]. The form of the equation is

$$J_N(x_k, \bar{u}(k)) = \sum_{i=0}^{N-1} L^{Stage}(x(k+i \mid k)) + V^{Term}(x(k+N \mid k)) \tag{21}$$

where $L^{stage}(.)$ represents the stage cost while $V^{Term}(.)$ represents the terminal cost and $\bar{u}(k)$ represents future instantaneous control that evolves along the prediction horizon at instant k.

The computation of the control command to ensure the system state evolves along a desire trajectory has to satisfy a set of constraint imposed as expressed by [12] due to system limits and design desirables. Constraints can be formulated as (in)equality and system model on the terminal cost [11].

B. *LINEAR MPC CONTROL*

A feedback linearized model based on feedback linearization following the equations (5-7) and (14-16) and linear MPC were studied by [16]. The reference profile was used to define an offset model used in the evaluation of the AGV performance under varied terrains and winding curvatures. The offset model inferred from

$$\tilde{\theta} = \theta - \theta_{ref} \tag{22}$$

$$Vel = \begin{bmatrix} V_{lng} - V_{lngref} \\ V_{rdl} - V_{rdl} ref \\ V_{ang} - V_{angref} \end{bmatrix} \tag{23}$$

$$\tilde{a} = \begin{bmatrix} a_{\ln g} - a_{lngref} \\ a_{rdl} - a_{rdlref} \\ a_{ang} - a_{angref} \end{bmatrix} \tag{24}$$

Is used in the design formulation of the MPC. The author used a sequential quadratic programming solver where the offset model based on the linearized system is expressed as;

$$\dot{x} = A.x + v(x,t) \tag{25}$$

where

$$A = \begin{matrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{matrix}$$

is the system state matrix. The system the output is determined by

$$y_c = C_c x \tag{26}$$

where

$$C_c = \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{matrix}$$

is the output matrix. The system (25) is discretized so as to form discrete state-vector defined by

$$\mathrm{x_d}(\mathrm{k}+1) = \mathrm{A_d x_d}(\mathrm{k}) + \mathrm{B_d u_d}(\mathrm{k}) \tag{27}$$

$$\mathrm{y_d}(\mathrm{k}) = \mathrm{C_d x_d}(\mathrm{k}) \tag{28}$$

Matrices A_d, B_d, C_d of the system are updated after discretization. The system represented by (27) portrays oscillation hence solved through definition of new control input presented by [12] as (27) and the system augmentation to yield

$$\begin{bmatrix} x_{k+1} \\ x_{k+1}^u \end{bmatrix} = \begin{bmatrix} A & B \\ 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ x_k^u \end{bmatrix} + \begin{bmatrix} B \\ I \end{bmatrix} \Delta u_k \tag{29}$$

and, $$y_k = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x_k \\ x_k^u \end{bmatrix} \tag{30}$$

where, $$\Delta u_k = u_k - u_{k-1} \tag{31}$$

The optimal control problem is then formulated as

$$\min \sum_{i=0}^{Hp} (z_i - z_{ref,i})^T Q (z_i - z_{ref,i}) + \sum_{i=0}^{Hp-1} [(u_i - u_{i-1})^T R (u_i - u_{i-1})] \tag{32}$$

The system performance was investigated based on data presented in the table 1 shown below.

Table 1 Data used in simulation [1]

Para	Value	Unit	Para	Value	Unit
Vehicle Model					
M	200	Kg	m_d	15	kg
L_f	0.85	m	L_r	0.85	m
L_h	0.5	m	R_w	0.25	m
J_z	45	$Kg.m^2$	J_w	0.8	$Kg.m^2$
System constraints					
F_{dmax}	250	N	δ_{max}	40	^{0}
F_{dmin}	-250	N	δ_{min}	-40	^{0}
ΔF_{dmax}	0.8	N	$\Delta\delta_{max}$	0.35	^{0}

The linear MPC controller based on a linearized system of equation posted an offset error of 3.2 cm and subsequent heading error of less than 2^0 at speeds of less than 3 m/s.

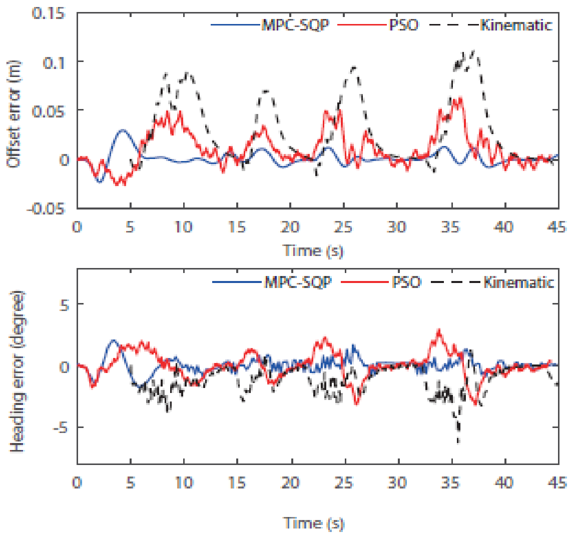

Fig. 3 Performance simulation [1]

The linear MPC performance were impressive yet still suffered due to model errors as a result of approximations made by linearization of the process. For that reason, performance of the strategy deteriorates in cases where aggressive manoeuvres are required.

C. NONLINEAR MPC CONTROL

Nonlinear MPC has been implemented for bicycle and tire model in Fig. 2, system (5-7) and (14-16) by [22]. Kong et al. [22], investigated discretization time and the vehicle model; kinematic and bicycle model to design a controller.

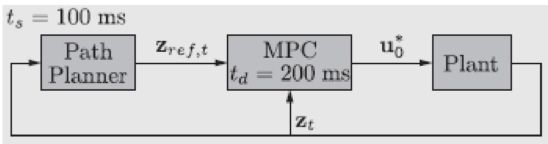

Fig. 4 Controller and planner

The setup used a nonlinear system of equations to design a Model predictive controller (MPC). In that regard, with optimal control formulation as (32). The input and prediction horizon at 8 steps and thus looks ahead 1.6 s. The sampling time, $t_s = 100\ ms$, discretization time $t_d = 200\ ms$ was used and limits to the system were considered as shown in table 2.

Table 2 System limits

	θ	a	$\dot{\theta}$	$\dot{a}$
minimum	-37^0	$-1.5\ m/s^2$	$-10^0/s$	$-3\ m/s^3$
maximum	37^0	$1\ m/s^2$	$10^0/s$	$1.5 m/s^3$

The investigation was performed for low-speed tracking, and results show an impressive performance when a kinematic model (14-16) is used for lateral control.

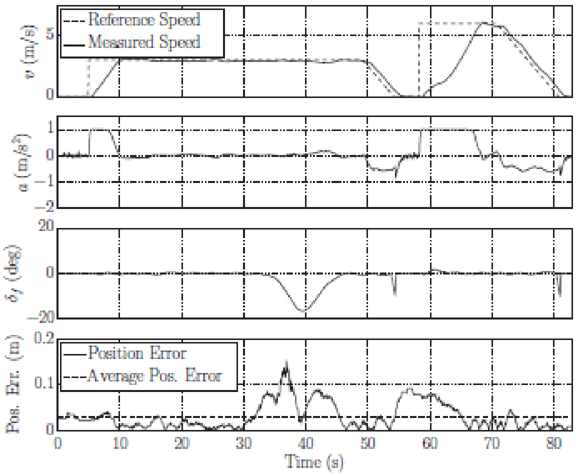

Fig. 5 Kinematic performance on a low-speed right turn tracking

The controller is capable of operating in the go and stop scenario where reference velocity ranged from $0\ to\ 6\ m/s$. Moreover, the standard deviation of distance error compared to the reference path was $0.03\ m$ with a single maximum value of $0.15\ m$ occurring at the turning point.

Nonlinear MPC have the advantage as the model used represents the true process scenario hence computation of the control command yields a better tracking performance [13]. On the contrary, the computational load and discretization offer a challenge for system that require fast response and during uncertainty.

D. ADAPTIVE MPC CONTROL

A real-time adaptation of the control command is a vital feature when uncertainty and errors in a model are present [23]. Adaptation allows a recursive and refined vehicle model estimate which ultimately offer comfort and safety. Considering the nonlinear system expressed by (5-7) and (14-16), steering control was considered by Bujarbaruah et al. [23] where a steering offset estimation was defined. The steady-state trajectory error model as

$$\Delta x_t = A\Delta x_t + B\Delta\delta_t + E\theta_a + w_t \qquad (33)$$

Where

$$\Theta_t = \left\{\theta_t \in \mathrm{R}^p : \Delta x_t - A\Delta x_{t-1} - B\Delta\delta_{t-1} - E\theta_t \in \mathrm{W},\ t \geq 0\right\} \quad (34)$$

where $\Delta x, t \geq 0$ represents the realized trajectory for a closed loop. Knowledge of steering offset θ_a is defined by the domain Θ regarded as the *feasible parameter set*, and is estimated from other previous vehicle data. At every time step data gathered on the input-output state is used to update the *feasible parameter set* at time t. The expression reveals the ability to progressively update the knowledge of Θ with consideration of all other previous time instants.

The design considered an affine feedback policy $\pi(.)$ for control approximation.

$$\pi_t(.) : \Delta\delta_t(\Delta x_t) = -K\Delta x_t + v_t \qquad (35)$$

where $K \in \mathbb{R}^{m\times n}$ is the fixed stabilizing state feedback gain chosen by Bujarbaruah et al. [23] as optimal LQR while the auxiliary control is depicted by v_t. Constraints are then imposed in the form and the control objective is to keep Δx_t small.

$$C\Delta x_t + D\Delta\delta_t \leq b \qquad (36)$$

Bujarbaruah et al. [23] showed how an MPC is able to achieve a recursively feasible control policy. The adaptive control algorithm considered is

1. **While** $\theta_a = constant$ **do**
2. Obtain road curvature $C(s)$. Compute corresponding steady state trajectory $x_{ss}(s)$and steering angle input $\delta_{ss}(s)$. Set $t = 0$; initialize feasible parameter set Θ_0
3. **While** $C(s)$unchanged w.r.t step 2 **do**
4. Compute the terminal invariant set X_t^N. Compute v_t^* from (35) and apply steering command

$$\delta_t = \delta_{ss}(s) - K\left(x_t - x_{ss}(s)\right) + v_t^* \quad (37)$$

5. Update $\Theta_{(t+1)}$ using (34). Set $t = t + 1$
6. Estimate $C(s)$
7. **End while**
8. Set $\Theta_0 = \Theta_t$. return to step 2
9. **End while**

The adaptive robust design was tested based on the data in table 3, longitudinal speed of $V_x = 30\ m/s$ and the reference lane chosen to be a circular arc of curvature $C(s) = 1\ m$.

Table 3 Vehicle data used by [23]

Parameter	Value
M	$1830\ kg$
J_z	$3477\ kgm^2$
L_f	$1.152\ m$
L_r	$1.693\ m$
C_f	$40703\ N/rad$
C_r	$64495\ N/rad$

The test involved a comparison between adaptive and robust control as illustrated in the simulation results in Fig. 6. An adaptive model of the system (5-7) and control obtained through (35) has great potential to steer a vehicle with minimal offset error.

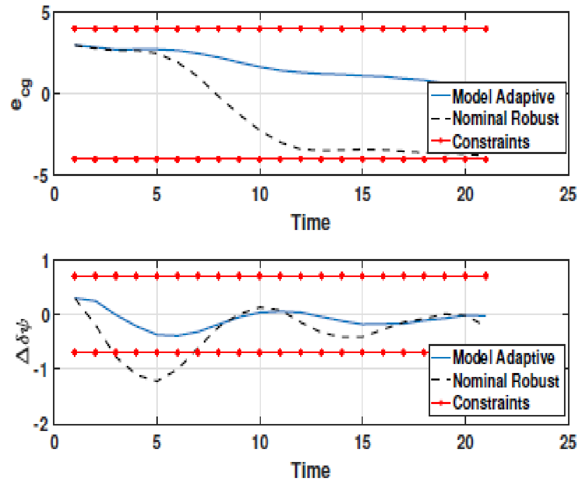

Fig. 6 Adaptive versus robust MPC

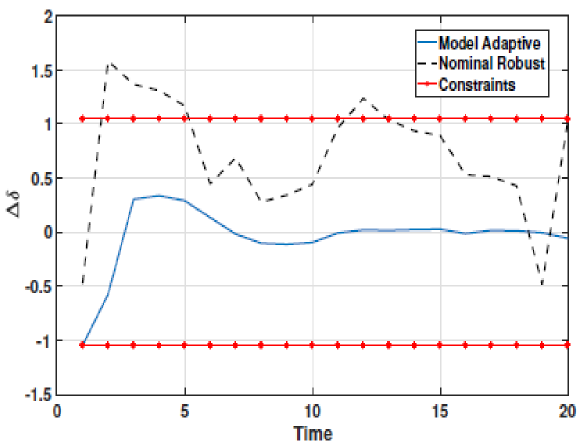

Fig. 7 Adaptive versus robust MPC operating outside constraints

Adaptive MPC is limited by model errors due to approximations by linearization [23]. In view of the adaptive nature of computation of the control command, the adaptive MPC bear greater potential in handling uncertain scenarios and the demand needs of aggressive manoeuvres. It offers an intuitive approach to the design consideration focusing on the challenges through which the AGV undergoes as they operate through with need for apt controllability, versatile manoeuvres and accurate tracking performance.

E. ROBUST MPC CONTROL

Due to disturbances and model errors, using a robust MPC helps to tighten the system state and input constraints satisfactorily. Gao et al. [14] used a force-input nonlinear bicycle model and formulated a robust invariant set based on Lipchitz constants for a nonlinear system. Using the system (5-7) and the depicted slip angles that affect rear tire forces in (12-13) is approximated by

$$\alpha_f = \frac{\dot{y} + a\dot{\theta}}{\dot{x}} - \delta \quad (38)$$

$$\alpha_r = \frac{\dot{y} - b\dot{\theta}}{\dot{x}} \quad (39)$$

And the system description includes an external disturbance and constraints;

$$x_k = Ax_k + g\left(x_k\right) + Bu_k + w_k \quad (40)$$

s.t

$$x_k \in \Xi \quad (41)$$

$$u_k \in \boldsymbol{u} \quad (42)$$

where $g(.) : \mathcal{R}^n \to \mathcal{R}^n$ a nonlinear Lipschitz function and which $w_k \in W \subset \mathcal{R}^n$ is a disturbance of additive nature. The control design of the system (40-42) involve a feedforward control input referred to as a nominal system [23], [21] and a feedback controller acting on the error occurring from the nominal system. The control input consistent with $u_k = \bar{u}_k + \hat{u}(e_k)$ and an error dynamic equation

$$e_{k+1} = Ae_k + Bu\left(e_k\right) + \left(g\left(x_k\right) - g\left(\overline{x_k}\right)\right) + w_k \quad (43)$$

with the nonlinear term $(g(x) - g(\bar{x}))$ is bounded using Lipschitz constant $g(.)$ whereby it is treated to be part of the disturbance.

Matrix pair (A, B) of (43) being controllable means there exists a stabilizing feedback gain K and such that $(A + BK)$ is Hurwitz. In that regard, a robust positively invariant set associated with the gain K is computed following through algorithm below

1: 1: $\Omega_0 \leftarrow \{0\}$
2: $W \leftarrow W$
3: $i \leftarrow 0$;
4: $\boldsymbol{repeat}$
5: $i = i + 1$
6: $W = W \oplus B(\Omega_i)$;
7: $\Omega_i = Reach_{fa}(\Omega_{i-1}, W) \cup \Omega_{i-1}$.
8: $\boldsymbol{until}\ \Omega_i == \Omega_{i-1}$
9: $Z \leftarrow \Omega_i$

Upon which a stabilizing state feedback gain K with an infinite horizon LQR solution for the system matrix pair (A, B) to yield a new controller becomes

$$u_k = u_k + K_{LQR}^{\infty}(x_k - \overline{(x_k)}) \quad (44)$$

The optimal formulation with Q, R, S *and* λ as weighting matrices for state tracking error, control action and change rate action and violation of soft constraints respectively.

$$\min_{u} \sum_{k=0}^{H_{p-1}} \left\| x_{t+k,t} - x_{ref} \right\|^2 Q + ...$$

$$\left\| u_{t+k,t} \right\|^2 R + \left\| \Delta u_{t+k,t} \right\|^2 + \lambda\varepsilon \qquad (45)$$

Tests were performed using mass 2050 kg, 3344 kg/m^2 utilizing an electric motor for drive torque.

Table 4 Data used by Gao et al. [14]

Para	Value	Units	Para	Value	Units
u_{max}	[0,0.5,0]	[−]	$[H_p]$	12	-
$u_{\min}$	−[0.5,0.5,0]	[−]	H_c	8	-
$\Delta u_{\max}$	[20,20,20]	[−] /sec	H_i	2	-
$\Delta u_{\min}$	−[20,20,20]	[−] /sec	T_s	100	ms
Q	(1,20,5,10)	-	R	(1,1,1	-
S	(1,1,1)	-			

The controller was tested through a track whereby a vehicle performs obstacle avoidance at 80 kph.

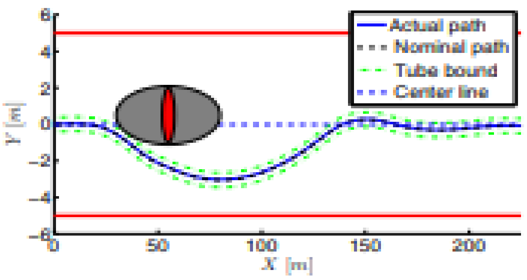

Fig. 8 Nominal system obstacle avoidance

Where it's braking and steering input for the nominal system was as shown

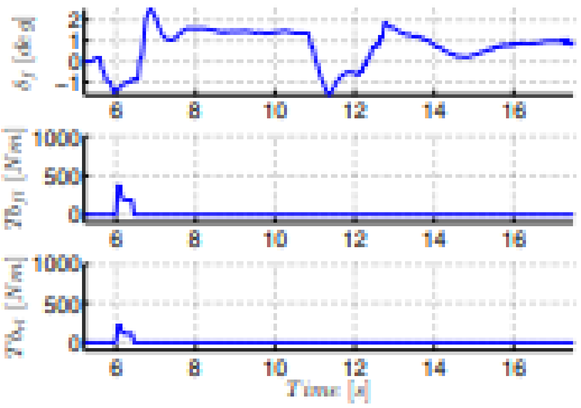

Fig. 9 Nominal system inputs

For robust design tests, the friction coefficient was set to 0.1, and the controller is set up for a nominal $\mu = 0.3$ to represent a snow track. The vehicle was tested at 35 kph as shown below

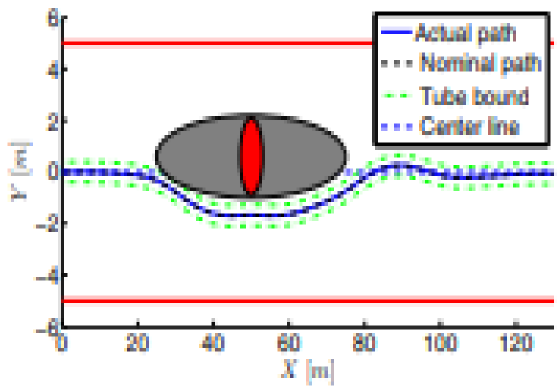

Fig. 10 Robust system obstacle avoidance

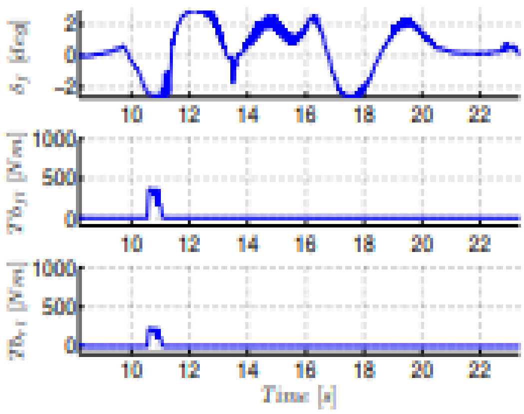

Fig. 11 Robust system inputs

The robust controller posted effective system behaviour under uncertain environment. The unmeasured disturbance are best handled by robust MPC [8], [10], [24]. The strategy leans towards MPC stability while the challenge is in incorporating the uncertainties in the optimal problem solution.

IV. CONCLUSION

The survey has shown the MPC approaches and design consideration for (semi)autonomous vehicles to enhance performance. The control strategies presented reveal the strength of the Model Predictive Control technique. Individual solutions portray advantages over each other. On the other hand, the limitations of a strategy are well covered by another. Handling MPC application design requires consolidation of advantages to satisfy design objective. This is achieved with consideration of constraints and penalties that are associated. The review is a foundation for further research and design to be carried out by the authors under the adaptive model predictive control.

V. REFERENCES

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