Adaptive Cruise Control by Considering Control Decision as Multistage MPC Constraints

Muhamad Ilfani Miftakhudin
Department of Electrical Engineering
Universitas Indonesia
Depok, 16424 - Indonesia
muhamad.ilfani@ui.ac.id

Aries Subiantoro*
Department of Electrical Engineering
Universitas Indonesia
Depok, 16424 - Indonesia
aries.subiantoro@ui.ac.id

Feri Yusivar
Department of Electrical Engineering
Universitas Indonesia
Depok, 16424 - Indonesia
feri.yusivar@ui

***Abstract*— In designing of original adaptive cruise control (ACC) systems the outer loop is commonly used to control the safe distance between host and lead vehicles, and the inner loop maintains the speed of host vehicle. The aim of this paper is to propose different approach, in which only a single loop is introduced as controller. A decision algorithm for determining a driving mode is designed as part of multistage model predictive control constraints. The nonlinear behavior of vehicle dynamic is represented by a multistage local linear model, which will be identified by using least squares method. The objective of multistage predictive control is to minimized the square of errors between the predicted values of vehicle speed and the safety distance, and their references. The proposed controller demonstrates to more efficient in terms of power computing, it is because the method can keep the optimization control problem as a quadratic programming problem. Some ACC simulation results are given, demonstrating a better performance in terms of distance and speed responses compared to the original ACC system.**

Keywords*— *adaptive cruise control, model predictive control, vehicle modeling, multistage identification

I. INTRODUCTION

Accidents on vehicles often occur including the four-wheeled vehicle. Indonesia is one of the countries with the highest rate of traffic accidents in the world. In the discussion held by United in Diversity (UID) it was stated that WHO estimates that vehicle accidents cause losses of 3 percent of the total Gross Domestic Product [1]. This accident was caused mostly due to the driver's fault. Therefore, it is necessary to apply a cruise control system to avoid accidents that occur in traffic.

By using cruise control systems, four-wheeled vehicles can maintain the desired speed so that this system can reduce a single accident. Cruise control cannot apply to overcome multiple accidents because it cannot detect a vehicle in front. To overcome multiple accidents, Adaptive Cruise Control (ACC) systems have been discovered for maintaining the desired vehicle speed. The ACC systems are also equipped with a proximity sensor to detect the vehicle in front and control the distance between host vehicles with the lead vehicle. If the proximity sensor does not detect the vehicle in front, the system will use speed control. If the speed of lead vehicle is less than the host vehicle, the ACC systems will focus to regulate the distance between host-and-lead vehicles.

In recent years, a number of ACC methods with different approach has been developed and published. Conventional PID controllers have a large overshoot value when applied to cruise controllers compared to fuzzy [2]. Abdullah and colleagues [3] designed the ICC using self-tuning PID with fuzzy supervisor. Wang Jian and colleagues [4] designed Self-learning with Kernel-based Least Square to optimize learning modes. S.G. Kim and colleagues [5] made ACC use the switching method between 2 modes, namely speed control and distance control. Gao Zhenhai and colleagues [6] also designed ACC switching modes using PI controllers and P. Pangwei Wang and colleagues [7] designed switching modes for CACC. Nassare Benalie and colleagues [8] designed ACC using a dual loop controller to maintain speed and distance. Stefan Chamraz and colleagues [9] also designed ACC with dual control loops. Furthermore, G.J.L Naus conducted an ACC experiment using Implicit MPC and multi-parametric quadratic programs for online identification [10]. P.Shakouri [11] designed ACC with PI and LQ Gain Scheduling to control brakes and valves. A. Morand and colleagues [12] designed CC with a CRONE control strategy and compared it to PI. Rocman Schmied and colleagues [13] designed CACC using NMPC controllers with constraints of distance and speed. Dominik Moser and colleagues [14] also designed MPC constraints and Conditional Linear Gauss. Andreas and colleagues [15] designed Energy-Optimal Cruise Control with MPC and used maximum traction force constraints.

However, most ACC methods deal with identical problems i.e. complicated to design and computationally expensive. This is more due to vehicles showing non-linear dynamics and their mathematical models are very difficult to obtain. This kind of ACC systems can cause poor driving comfort. The ACC systems are unable to predict future output precisely, so they cannot anticipate dangerous condition such as sudden brake. With frequent sudden braking, the vehicle requires high fuel consumption and high emissions.

In this paper, the authors propose adaptive cruise control (ACC) system using the multistage MPC published in our works [16]. The main contribution of this work lies on utilizing a multistage linear model for maintaining MPC problem as a quadratic programming problem, and also describing the decision algorithm as MPC constraints instead of using switching strategy in inner loop of original ACC. In order to show the ability of proposed controller, some simulation results compared to the original ACC are also provided.

II. DYNAMIC SYSTEMS AND IDENTIFICATION MODELS

A. Nonlinear Dynamic

The model used in the design of the control system is a longitudinal vehicle model with regarding to longitudinal stability. The model used is a quarter-vehicle model by considering one axis of freedom that is located at the midpoint of the vehicle. Longitudinal vehicle models can be represented as below and will be identified by a multistage least square method.

*Corresponding author: aries.subiantoro@ui.ac.id

$$\dot{v}_x(t) = \frac{1}{r}\frac{(T_w - T_b)}{m}$$
$$\dot{d}\,(t) = v_r$$
$$\dot{v}_r = \dot{v}_{xh} - a_{xl} \quad (1)$$
$$\Delta\dot{\psi} = \left(\frac{d_y^2}{d^2}\right)\left(\frac{v_{ry}\, d_x - v_{rx}\, d_y}{d_x^2}\right) - \dot{\psi}_h$$

where

$$\dot{\psi}_h = \frac{v_{xh}\cos(\beta)}{l_f + l_r}\left(tan(\delta_f) - tan(\delta_r)\right) \quad (2)$$

The input variable of this system is the throttle control signal (u_t) and the brake control signal (u_b). Where to produce wheel torque and braking torque can be formulated as follows.

$$Tw = R_f R_{tr} C_{tr}(T_e(u_t, N_e) - I_{ei}\alpha_e \quad (3)$$
$$Tb = K_b \,. u_b \quad (4)$$

B. Multistage Least Square Identification

Referring to [3], identification of multistage least square can represent a nonlinear model into 2 linear models. This second level model serves to compensate for errors so that the results of identification are closer to the actual model. Multilevel linear models can be represented in the form of 2 linear model equations as follows

First level equation

$$\mathbf{x}_1(k+1) = \mathbf{A}_1\mathrm{x}_1(k) + \mathbf{B}_1\mathbf{u}(k) + \mathbf{k}_{x1} \quad (5)$$
$$\mathbf{y}_1(k) = \mathbf{C}_1\mathbf{x}_1(k) + \mathbf{D}_1\mathbf{u}(k) + \mathbf{k}_{y1} \quad (6)$$

Second level equation

$$\mathbf{x}_2(k+1) = \mathbf{A}_2\mathbf{x}_2(k) + \mathbf{B}_2\mathbf{u}(k) + \mathbf{k}_{x2} \quad (7)$$
$$\mathbf{y}_2(k) = \mathbf{C}_2\mathbf{x}_2(k) + \mathbf{D}_2\mathbf{u}(k) + \mathbf{K}_{y1}\mathbf{e} \quad (8)$$

From the above equation, the least square method will get the parameters $\mathbf{A}_1$, $\mathbf{B}_1$, $\mathbf{C}_1$, $\mathbf{D}_1$, $\mathbf{A}_2$, $\mathbf{B}_2$, $\mathbf{C}_2$, $\mathbf{D}_2$, $\mathbf{k}_{x1}$, $\mathbf{k}_{y1}$, $\mathbf{k}_{x2}$, and $\mathbf{K}_{y2}$ which will be used in the prediction control model.

The equation of the identification model with the bias matrix is

$$\mathbf{x}(k+1) = \mathbf{Ax}(k) + \mathbf{Bu}(k) + \mathbf{k}_x \quad (9)$$
$$\mathbf{y}(k) = \mathbf{Cx}(k) + \mathbf{Du}(k) + \mathbf{k}_\mathrm{y} \quad (10)$$

So that for the first level it can be represented as follows

$$\mathbf{x}^T(k+1) = [\mathbf{x}^T(k) \quad \mathbf{u}^T(k) \quad 1]\begin{bmatrix}\mathbf{A}^T\\ \mathbf{B}^T\\ \mathbf{k}_x{}^T\end{bmatrix} \quad (11)$$

$$\mathbf{y}^T(k) = [\mathbf{x}^T(k) \quad \mathbf{u}^T(k) \quad 1]\begin{bmatrix}\mathbf{C}^T\\ \mathbf{D}^T\\ \mathbf{k}_y{}^T\end{bmatrix} \quad (12)$$

$$\mathbf{X}_1 = \mathbf{\Phi_1\theta_1} \quad (13)$$
$$\mathbf{X}_2 = \mathbf{\Phi_2\theta_2} \quad (14)$$

where

$$\mathbf{X}_1 = \begin{bmatrix}\mathbf{x}^T(0)\\ \mathbf{x}^T(1)\\ \vdots\\ \mathbf{x}^T(N-2)\end{bmatrix} \quad (15)$$

$$\mathbf{\Phi_1}\begin{bmatrix}\mathbf{x}^T(0) & \mathbf{u}^T(0) & 1\\ \mathbf{x}^T(1) & \mathbf{u}^T(1) & 1\\ \vdots & \vdots & \vdots\\ \mathbf{x}^T(N-2) & \mathbf{u}^T(N-2) & 1\end{bmatrix} \quad (16)$$

Parameters of the first level model can be obtained from

$$\mathbf{\theta}_1 = \begin{bmatrix}\mathbf{A}^T\\ \mathbf{B}^T\\ \mathbf{k}_x{}^T\end{bmatrix} = (\mathbf{\Phi_1}^T.\,\mathbf{\Phi_1})^{-1}\mathbf{\Phi_1}^T\mathbf{X}_1 \quad (16)$$

$$\mathbf{\theta}_2 = \begin{bmatrix}\mathbf{C}^T\\ \mathbf{D}^T\\ \mathbf{k}_y{}^T\end{bmatrix} = (\mathbf{\Phi_2}^T.\,\mathbf{\Phi_2})^{-1}\mathbf{\Phi_2}^T\mathbf{X}_2 \quad (17)$$

The estimation error of first stage $\mathbf{e}_1$ is used at the second level, so that the equation at the second level is obtained

$$\mathbf{x}^T(k+1) = [\mathbf{x}^T(k) \quad \mathbf{u}^T(k) \quad 1]\begin{bmatrix}\mathbf{A}^T\\ \mathbf{B}^T\\ \mathbf{k}_x{}^T\end{bmatrix} \quad (18)$$

$$\mathbf{y}^T(k) = [\mathbf{x}^T(k) \quad \mathbf{u}^T(k) \quad \mathbf{e}_1{}^T]\begin{bmatrix}\mathbf{C}^T\\ \mathbf{D}^T\\ \mathbf{K}_y{}^T\end{bmatrix} \quad (19)$$

So parameters at the second level can be formulated as

$$\mathbf{\theta}_3 = \begin{bmatrix}\mathbf{A}^T\\ \mathbf{B}^T\\ \mathbf{k}_x{}^T\end{bmatrix} = (\mathbf{\Phi}_3{}^T.\,\mathbf{\Phi}_3)^{-1}\mathbf{\Phi}_3{}^T\mathbf{X}_3 \quad (20)$$

$$\mathbf{\theta}_4 = \begin{bmatrix}\mathbf{C}^T\\ \mathbf{D}^T\\ \mathbf{k}_y{}^T\end{bmatrix} = (\mathbf{\Phi}_4{}^T.\,\mathbf{\Phi}_4)^{-1}\mathbf{\Phi}_4{}^T\mathbf{X}_4 \quad (21)$$

III. PREDICTIVE CONTROL DESIGN

A. Predictive Control Model

After conducting the identification process and obtaining the identification matrix value, a multistage prediction model can be arranged. The purpose of this controller is to optimize the criteria function [17]

$$\mathbf{V}(k) = \sum_{j=1}^{q}\sum_{i=1}^{H_p}||\hat{\mathbf{y}}_j(k+i) - \mathbf{w}_j(k+i)||_{\mathbf{Q}}^2 + \cdots + \sum_{j=1}^{p}\sum_{i=0}^{H_u-1}||\Delta\hat{\mathbf{u}}(k+i)||_{\mathbf{R}}^2$$

The first step in designing predictive controllers is to make predictive models based on multilevel linear models. Obtained prediction function from state is

$$\begin{bmatrix}\hat{\mathbf{x}}_2(k+1)\\ \hat{\mathbf{x}}_2(k+2)\\ \vdots\\ \hat{\mathbf{x}}_2(k+H_p)\end{bmatrix} = \begin{bmatrix}\mathbf{A}_2\\ \mathbf{A}_2{}^2\\ \vdots\\ \mathbf{A}_2{}^{H_p}\end{bmatrix}\mathbf{x}_2(k) + \begin{bmatrix}\mathbf{B}_2\\ \mathbf{A}_2\mathbf{B}_2\\ \vdots\\ \sum_{i=0}^{H_p-1}\mathbf{A}_2{}^i\mathbf{B}_2\end{bmatrix}\mathbf{u}(k-1) + \cdots$$

$$+\begin{bmatrix} \mathbf{B}_2 & \cdots & 0 \\ \mathbf{A}_2\mathbf{B}_2+\mathbf{B}_2 & & 0 \\ \vdots & \ddots & \vdots \\ \sum_{i=0}^{H_p-1}\mathbf{A}_2{}^i\mathbf{B}_2 & \cdots & \sum_{i=0}^{H_p-H_u}\mathbf{A}_2{}^i\mathbf{B}_2 \end{bmatrix}\begin{bmatrix} \Delta\mathbf{u}(k) \\ \vdots \\ \Delta\mathbf{u}(k+H_u-1) \end{bmatrix}+\cdots$$

$$+\begin{bmatrix} \mathbf{I} \\ \mathbf{I}+\mathbf{A}_2 \\ \vdots \\ \sum_{i=0}^{H_p-1}\mathbf{A}_2{}^i \end{bmatrix}\begin{bmatrix} \mathbf{k}_{x2} \\ \mathbf{k}_{x2} \\ \vdots \\ \mathbf{k}_{x2} \end{bmatrix} \tag{22}$$

So that the output prediction function is obtained as follows

$$\underbrace{\begin{bmatrix} \hat{\mathbf{y}}_2(k+1) \\ \hat{\mathbf{y}}_2(k+2) \\ \vdots \\ \hat{\mathbf{y}}_2(k+H_p) \end{bmatrix}}_{\mathbf{Y}} = \mathbf{C}_2\underbrace{\begin{bmatrix} \mathbf{A}_2 \\ \mathbf{A}_2{}^2 \\ \vdots \\ \mathbf{A}_2{}^{H_p} \end{bmatrix}}_{\boldsymbol{\psi}}\mathbf{x}_2(k)+\mathbf{C}_2\underbrace{\begin{bmatrix} \mathbf{B}_2 \\ \mathbf{A}_2\mathbf{B}_2 \\ \vdots \\ \sum_{i=0}^{H_p-1}\mathbf{A}_2{}^i\mathbf{B}_2 \end{bmatrix}}_{\boldsymbol{\Gamma}}\mathbf{u}(k-1)\ldots$$

$$+\mathbf{C}_2\underbrace{\begin{bmatrix} \mathbf{I} \\ \mathbf{I}+\mathbf{A}_2 \\ \vdots \\ \sum_{i=0}^{H_p-1}\mathbf{A}_2{}^i \end{bmatrix}}_{\boldsymbol{\Phi}}\mathbf{k}_{x2}+\cdots$$

$$+\mathbf{C}_2\underbrace{\begin{bmatrix} \mathbf{B}_2 & \cdots & 0 \\ \mathbf{A}_2\mathbf{B}_2+\mathbf{B}_2 & & 0 \\ \vdots & \ddots & \vdots \\ \sum_{i=0}^{H_p-1}\mathbf{A}_2{}^i\mathbf{B}_2 & \cdots & \sum_{i=0}^{H_p-H_u}\mathbf{A}_2{}^i\mathbf{B}_2 \end{bmatrix}}_{\boldsymbol{\Theta}}\underbrace{\begin{bmatrix} \Delta\mathbf{u}(k) \\ \vdots \\ \Delta\mathbf{u}(k+H_u-1) \end{bmatrix}}_{\Delta\mathbf{U}}+\cdots$$

$$+\underbrace{\begin{bmatrix} \mathbf{D}_2 \\ \mathbf{D}_2 \\ \vdots \\ \mathbf{D}_2 \end{bmatrix}}_{\boldsymbol{\Lambda}}\mathbf{u}(k-1)+\underbrace{\begin{bmatrix} \mathbf{D}_2 & \mathbf{D}_2 & 0 & 0 \\ \mathbf{D}_2 & \mathbf{D}_2 & \mathbf{D}_2 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{D}_2 & \mathbf{D}_2 & \mathbf{D}_2 & \mathbf{D}_2 \end{bmatrix}}_{\boldsymbol{\Omega}}\begin{bmatrix} \Delta\mathbf{u}(k) \\ \vdots \\ \Delta\mathbf{u}(k+H_u-1) \end{bmatrix}+\cdots$$

$$+\underbrace{\begin{bmatrix} \mathbf{k}_{y2} \\ \mathbf{k}_{y2} \\ \vdots \\ \mathbf{k}_{y2} \end{bmatrix}}_{\boldsymbol{\Xi}}\hat{\mathbf{e}}_1 \tag{23}$$

The prediction function above can be represented in the matrix notation as follows

$$\mathbf{Y}=\boldsymbol{\psi}\mathbf{x}(k)+(\boldsymbol{\Gamma}+\boldsymbol{\Lambda})\mathbf{u}(k-1)+\boldsymbol{\Xi}\mathbf{e}_1(k|k)+(\boldsymbol{\Theta}+\boldsymbol{\Omega})\Delta\boldsymbol{\mu}(k)+\boldsymbol{\Phi}$$

where the error prediction value (e_1) is obtained from the calculation

$$\hat{\mathbf{e}}_1(k|k)=\mathbf{y}(k)-\hat{\mathbf{y}}(k|k-1) \tag{24}$$

After finding prediction model, the next step is to formulate the criterion function $V(k)$ as a function of the prediction model. By defining $\mathbf{Y}$ (k), $\mathbf{W}$ (k), and $\Delta\boldsymbol{\mu}$ (k) as predictions of output, set point, and changing control signals in sequence. Thus, the criterion function $V(k)$ can be represented in the matrix notation as follows

$$\begin{aligned} V(k) &= ||\boldsymbol{\zeta}(k)-(\boldsymbol{\Theta}+\boldsymbol{\Omega})\Delta\boldsymbol{\mu}(k)||_{\mathbf{Q}}^2+||\Delta\boldsymbol{\mu}(k)||_{\mathbf{R}}^2 \\ &= \boldsymbol{\zeta}^T(k)\mathbf{Q}\boldsymbol{\zeta}(k)-2\Delta\boldsymbol{\mu}^T(k)(\boldsymbol{\Theta}^T+\boldsymbol{\Omega}^T)\mathbf{Q}\boldsymbol{\zeta}(k)+\cdots \\ &\quad +\Delta\boldsymbol{\mu}^T(k)\big((\boldsymbol{\Theta}^T+\boldsymbol{\Omega}^T)\mathbf{Q}(\boldsymbol{\Theta}+\boldsymbol{\Omega})\big)\Delta\boldsymbol{\mu}(k)++\Delta\boldsymbol{\mu}^T\mathbf{R}\Delta\boldsymbol{\mu}(k) \end{aligned}$$

where ζ(k) is a valuable free response

$$\boldsymbol{\zeta}(k)=\mathbf{W}(k)-\boldsymbol{\psi}\mathbf{x}(k)-(\boldsymbol{\Gamma}+\boldsymbol{\Lambda})\mathbf{u}(k-1)-\boldsymbol{\Xi}\mathbf{e}_1(k|k)-\boldsymbol{\Phi}$$

The next step is to design constraints for MPC. The constraint used is

$$\begin{aligned} &\Delta\mathbf{U}_{\min}\le\Delta\mathbf{U}\le\Delta\mathbf{U}_{\max} \\ &\mathbf{U}_{\min}\le\mathbf{U}\le\mathbf{U}_{\max} \\ &d_{min}\le d\le d_{max} \\ &v_{min}\le v\le v_{max} \end{aligned} \tag{25}$$

Changes in the control signal, control signal, distance and speed constraint can be represented in the following inequalities

$$\begin{bmatrix} \mathbf{E} \\ \mathfrak{J} \\ \mathbf{G} \end{bmatrix}\Delta U\le\begin{bmatrix} \boldsymbol{\varepsilon} \\ \mathbf{f}-\mathfrak{J}_1u(k-1) \\ \mathbf{H} \end{bmatrix} \tag{26}$$

The values $\mathbf{E}$ and $\boldsymbol{\varepsilon}$ are the following matrix

$$\underbrace{\begin{bmatrix} -1_k & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & -1_{k=H_u} \\ 1_k & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1_{k=H_u} \end{bmatrix}}_{\mathbf{E}}\underbrace{\begin{bmatrix} \Delta\mathbf{u}(k) \\ \Delta\mathbf{u}(k+1) \\ \vdots \\ \Delta\mathbf{u}(k+H_u-1|k) \end{bmatrix}}_{\Delta\mathbf{U}}=\underbrace{\begin{bmatrix} -\Delta\mathbf{u}_{min} \\ \vdots \\ -\Delta\mathbf{u}_{min} \\ \Delta\mathbf{u}_{max} \\ \vdots \\ \Delta\mathbf{u}_{max} \end{bmatrix}}_{\boldsymbol{\varepsilon}}$$

Assumption that $\mathfrak{J}=[\mathfrak{J}_1 \quad \mathfrak{J}_2 \quad \cdots \quad \mathfrak{J}_{H_u}]$, where

$$\begin{aligned} (\mathbf{F}_1+\mathbf{F}_2+\cdots+\mathbf{F}_{H_u}) &= \mathfrak{J}_1 \\ (\mathbf{F}_2+\cdots+\mathbf{F}_{H_u}) &= \mathfrak{J}_2 \\ &\vdots \\ \mathbf{F}_{H_u} &= \mathfrak{J}_{H_u} \end{aligned} \tag{27}$$

And the value of matrix $\mathbf{F}=[\mathbf{F}_1 \quad \mathbf{F}_2 \quad \ldots \quad \mathbf{F}_{H_u}]$ is a matrix of following inequality

$$\begin{bmatrix} -1_k & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & -1_{k=H_u} \\ 1_k & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1_{k=H_u} \end{bmatrix}\underbrace{\begin{bmatrix} \mathbf{u}(k) \\ \mathbf{u}(k+1) \\ \vdots \\ \mathbf{u}(k+H_u-1|k) \end{bmatrix}}_{\mathbf{U}}\le\underbrace{\begin{bmatrix} -\mathbf{u}_{min} \\ \vdots \\ -\mathbf{u}_{min} \\ \mathbf{u}_{max} \\ \vdots \\ \mathbf{u}_{max} \end{bmatrix}}_{\mathbf{f}}$$

$$\mathbf{F_1} \qquad \mathbf{F_{H_u}}$$

Matrices $\mathbf{G}$ and $\mathbf{H}$ are the result of distance and velocity constraint from inequality equation bellow

$$\underbrace{\begin{bmatrix} -(\boldsymbol{\Theta}+\boldsymbol{\Omega}) \\ (\boldsymbol{\Theta}+\boldsymbol{\Omega}) \end{bmatrix}}_{\mathbf{G}}\underbrace{\begin{bmatrix} \Delta\mathbf{u}(k) \\ \Delta\mathbf{u}(k+1) \\ \vdots \\ \Delta\mathbf{u}(k+H_u-1|k) \end{bmatrix}}_{\Delta\mathbf{U}}\le\underbrace{\begin{bmatrix} -\mathbf{y}_{min}+\boldsymbol{\beta} \\ \mathbf{y}_{max}-\boldsymbol{\beta} \end{bmatrix}}_{\mathbf{H}}$$

where

$$\mathbf{x}(k)+(\boldsymbol{\Gamma}+\boldsymbol{\Lambda})\mathbf{u}(k-1)+\boldsymbol{\Xi}\mathbf{e}_1(k|k)+\boldsymbol{\Phi}=\boldsymbol{\beta}$$

B. Multi-Argument Switching

In this study, the author simulates adaptive cruise control by using 2 modes, namely cruise mode and follow mode. In this method, the system will choose from one of the available modes based on the switching strategy. Cruise mode is used when no vehicle is detected in front of a controlled vehicle so the vehicle will maintain the speed according to the driver's settings. While follow mode is used when a vehicle is detected in front of a controlled vehicle so that the vehicle will maintain a safe distance from the vehicle in front. Figure (1) shows a diagram block of multi-argument switching.

In this study, cruise mode uses a PI controller based on the deviation value between the current velocity and the target speed to calculate the acceleration target. Whereas to follow mode it aims to make the speed deviation and distance remain zero at the same time. Therefore, the controller for follow mode is based on the speed deviation and distance deviation.

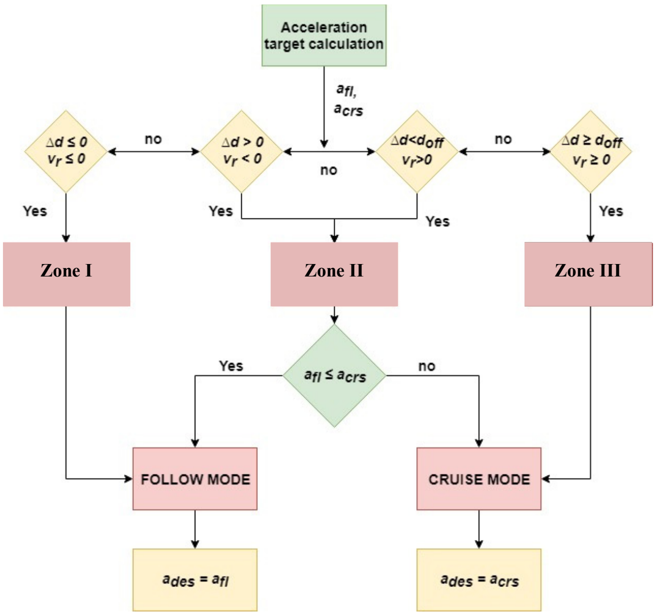


Figure 1. Decision ACC Algorithm

Table 1. Control mode ACC

Mode	Decision Algorithm
Cruise Mode	$a_{des-crs} = k_p(v_{des} - v_{ego}) + k_i \int (v_{des} - v_{ego})dt$
Follow Mode	$a_{des-fl} = k_v(v_p - v_{ego}) + k_d(d - d_{des})$

where $a_{des-crs}$ is acceleration target of cruise mode, v_{des} is velocity target of cruise mode which is regulated by driver, v_{ego} and v_p is velocity of host car and lead car respectively. k_p and k_i is constants from PI controller, a_{des-fl} is acceleration target of follow mode, d and d_{des} is actual distance and distance target, then k_v and k_d is velocity and distance coefficient.

The switching method is divided into 3 zones according to [6] as shown in Figure (2). In zone I it is defined as an area with a relative distance and speed that is negative. In zone II is an area between 2 blue lines. In zone III it is defined as the upper right area. In zone I, the value of distance and relative speed are negative. It means that the distance between host vehicle and lead vehicle is smaller than the target distance. Relative velocity is negative which means that the distance will become shorter between two vehicles. Then it is necessary to maintain the distance between the two vehicles so that the collision does not occur so that the ACC is switched into follow mode (FM).

In zone III, the value of distance and speed are relatively positive. It means that the distance between host vehicle and lead vehicle is greater than the target distance. Relative velocity is positive which means that the distance will become longer between two vehicles. So, the ACC will be switched into cruise mode (CM).

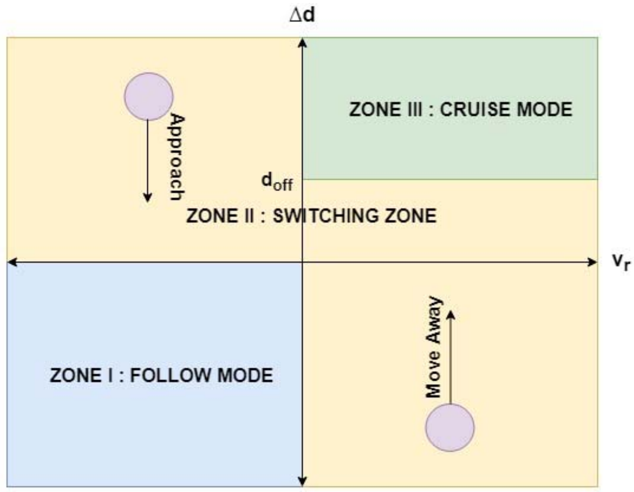


Figure 2. Switching strategy with 3 parameters

Zone II is between zone I and zone III. To determine the mode in this zone requires additional parameters, namely accelerating the target to smooth the switching process. When target acceleration of cruise mode is smaller than target acceleration of follow mode, ACC will be switched into cruise mode. When target acceleration of cruise mode is bigger than target acceleration of follow mode, ACC will be switched into follow mode. The following is a table of switching strategies [6].

Table 2. Condition switching mode from switching strategy with 3 parameters

Region	Distance deviation	Relative velocity	Target Acceleration	Control mode
I	$\Delta d \leq 0$	$v_r \leq 0$	-	FM
II	$\Delta d > 0$	$v_r < 0$	$a_{fl} \leq a_{crs}$	FM
	$\Delta d > 0$	$v_r < 0$	$a_{fl} > a_{crs}$	CM
	$\Delta d < d_{off}$	$v_r > 0$	$a_{fl} \leq a_{crs}$	FM
	$\Delta d < d_{off}$	$v_r > 0$	$a_{fl} > a_{crs}$	CM
III	$\Delta d \geq d_{off}$	$v_r \geq 0$	-	CM

C. Control Scheme

In order to verify the performance of proposed controller, we also apply the multi-arguments switching method in [6] as a comparison as shown in Figure (3). Unlike this control structure, our approach utilizes the switching mechanism as part of MPC constraints, see Figure (4). Instead of utilizing switching mode directly as inner loop of ACC, the boundary of safety distance and speed of vehicles is taken as MPC constraints into consideration.

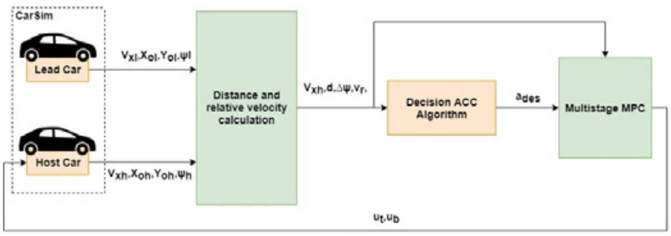


Figure 3. First Method: Multi-argument switching

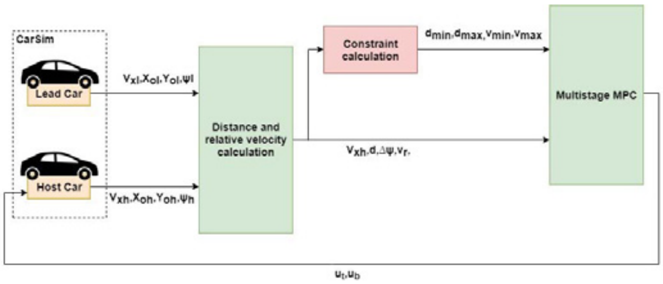


Figure 4. Control structure of constrained multistage MPC

IV. SIMULATION RESULT

A. Identification Result

The nonlinear dynamic of host-car and lead-car and the control performance are running under Carsim simulator. First step of simulation, a discrete model is derived by using identification method. The Carsim will produce 15000 pairs of input-output data, in which only 8700 data (58% of output data) are used to estimate the parameter of vehicle model, and the remaining 6300 data (42% of output data) for validation. Table (3) shows analysis of estimated vehicle model which has stable response, full controllable, full observable, and good properties of mimicking the vehicle dynamic.

Table 3. Identification results

Second stage Identification Model Performance Indicators	
Eigen Value	$0.999 \pm j0.007$; 0.99; 0.99
Rank$\{\mathbf{Q}_c\}$	4 (Full rank)
Rank$\{\mathbf{Q}_o\}$	4 (Full rank)
J_{ee}	Estimation = 0.00084339; Validation = 0.1075
FOE	Estimation = 0.0008519; Validation = 0.109

The performance indicator of identification can be obtained through 2 criteria, namely J_{ee} (loss function) and FOE (final output error) with the following formula

$$J_{ee} = \frac{1}{N}\sum_{i=1}^{N}(y(i) - \hat{y}(i))^2$$

$$FOE = \frac{1}{N}\frac{N+m}{N-m}\sum_{i=1}^{N}(y(i) - \hat{y}(i))^2$$

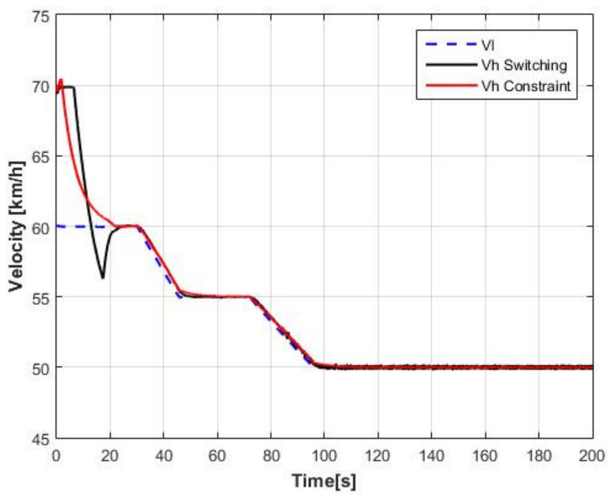


Figure 5. Comparison velocity.

B. Control Results

In the first scenario the switching and constraint method will be compared where the car in front is simulated with a fixed speed of 60 km/h. Then in the 30th second the car starts to slow down to a speed of 55 km/h. In the 70th second, the car starts to slow down again to a speed of 50 km/h. So that we get a control signal and control results as shown in Figure (5) and Figure (6).

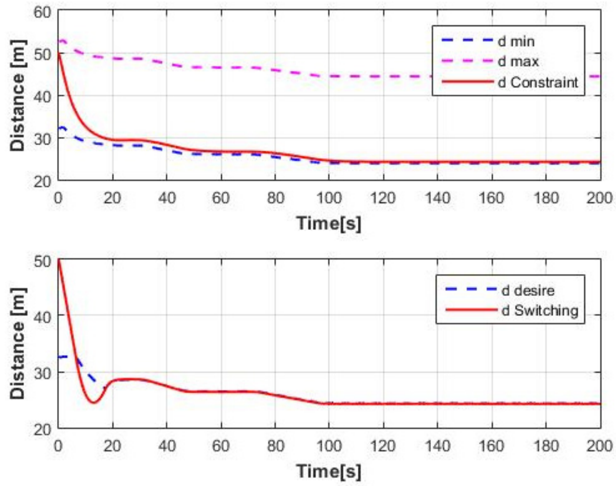


Figure 6. Comparison distance

In the picture above is a comparison between method 1 and 2. In the graph shows that method 2 has no overshoot compared to method 1. This is caused because in method 1 must adjust to the conditions of distance and speed so that overshoot occurs as adjustment. Whereas for method 2 which uses the upper and lower limits of distance and speed so that the system can adjust to the target directly. In this condition, method 1 has a greater risk than method 2 because there is a possibility that the overshoot value reaches below desire distance or less so that a collision can occur. For method 2, it is more reliable because it can directly adjust the distance and speed of the vehicle.

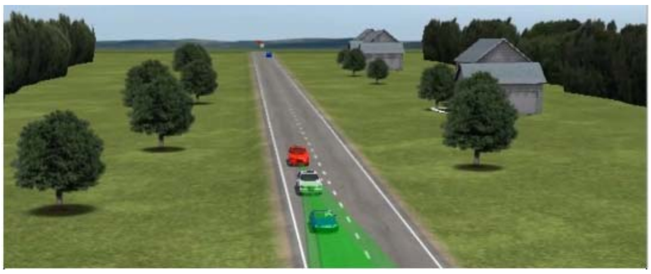


Figure 7. Experiment comparison of two method. (blue) lead car; (white) switching method; (red) constrained method

In the next experiment a simulation was carried out in 200 seconds with the vehicle speed of the leads going up and down successively using method 2 which was the best method of analyzing the experiment above. The experimental results can be seen in the picture below.

In the experimental results above, host vehicles can follow the speed of leads that have varying speeds. While the distance obtained is still within the scope of the maximum distance and the minimum distance according to the constraint. This proves that the ACC design with the MPC constraint method can be relied upon to do vehicles automatically with varying vehicle speeds ahead.

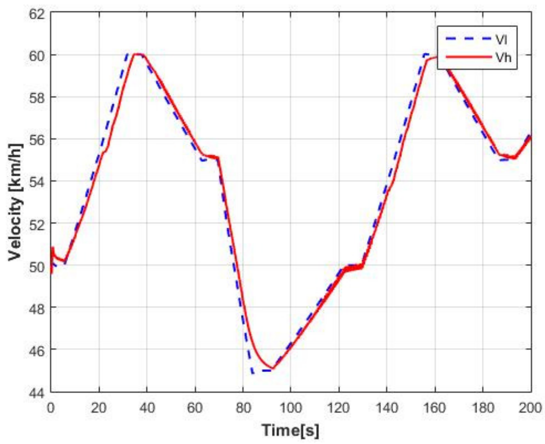
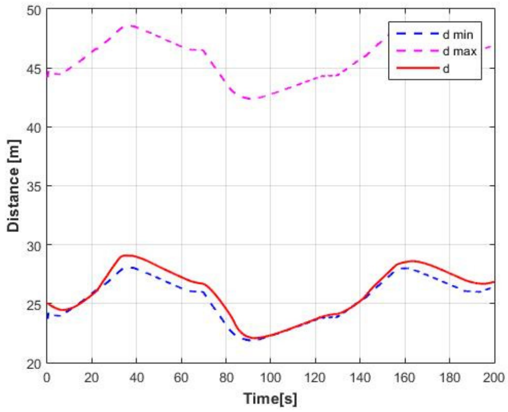


Figure 8. Method 2 velocity with lead variation speed scenario.



Gambar 9. Method 2 distance with lead variation speed scenario.

V. CONCLUSION

Based on the results of simulations carried out in the study, some conclusions can be drawn, namely:

- Multistage identification models model is able to mimic the nonlinear behavior of vehicle model.
- Multistage control models can follow reference values with various vehicle speed scenarios in front of 55 km/h to 65 km/h.
- The constrained multistage control model can follow the speed of the vehicle ahead which has a speed of 45 km/h to 65 km/h accelerated and slowed down in succession.
- ACC with switching method has a negative distance difference with the desired distance while ACC with the Constraint method has a positive difference, so the Constraint method can maintain a distance better than the switching method.

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