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Data-enabled Predictive Control for Stability Improvement of Articulated Vehicles

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Abstract— **Articulated vehicles are susceptible to instability issues due to their distinct dynamic properties. Most existing control strategies focus on constructing an integrated model, yet an accurate parametric model for a complex nonlinear system might be unavailable. To address this, a bilevel control structure is established, with the upper level generating corrective yaw moments and the lower level focusing on control allocation, then data-driven predictive control method is introduced, which relies only on input/output measurements to construct a non-parametric representation of the system, this method is implemented in a receding-horizon manner similar to MPC, incorporating constraints to achieve safe maneuvering. The effectiveness of the proposed controller is presented by simulation results, which further confirm its potential in vehicle dynamics control.**

I. INTRODUCTION

In recent years, articulated vehicles such as caravans and trailers have become increasingly important for both commercial and personal needs due to their efficiency and versatility [1]. Unlike single unit vehicles, articulated vehicles show different dynamic characteristics, making them prone to suffer from instability issues like jack-knifing, snaking and rollover.Advances in technology are driving the development of next-generation trailer platforms with advanced driving assistance systems, significantly improving the safety.

Extensive theoretical and validation research has been conducted to enhance the safety of such vehicles. Some research focuses on tractor control, Hac et al. [2] focuses on tractor control, developing linear models to analyze lateral motions and validate control methods like uniform braking and direct yaw moment (DYM). Mattia et al. [3] formed a SISO control scheme using a PI controller with torque vectoring(TV) to track reference states. Some focus solely on trailer controls, using trailer differential braking or active steering. Sharp and Fernandez [4] propose an active braking system for car-caravan systems, generating a braking torque on either side of the trailer to damp the oscillation on the hitch. Shamim et al. [5] examined different strategies for lateral stability enhancement based on LQR controllers, showing the efficiency of trailer active braking. Other studies prefer integrated control of both units. Jalali et al. [6] studied MPC of lateral stability of vehicles using coordinated active front steering and differential brakes. Abroshan et al. [7] presented a MPC based controller for yaw stabilisation, demonstrating the stabilizing potential of integrated differential braking. Integrated control strategies require high-fidelity models for optimal performance, while not all parameters are accessible.

In most of the previous literature, a precise formulation of a vehicle's dynamic model is indispensable for devising its controller, which requires expert knowledge and experience. While model-based methodologies like MPC are favored for vehicle control due to its capability to optimize over a prediction horizon [8], their performance relies heavily on precise system modeling. Model mismatch and uncertainties in state estimation may lead to degradation of the controlling quality, while recent advancements in data driven control theory provide an elegant approach to cope with this issue. Rooted in behavioral system theory, Data-enabled Predictive Control (DeePC) [9] is able to achieve optimal control for unknown system, requiring only input and output measurements from the system. Different from the sequential system identification, rather than generating an approximate model, DeePC relies on Willem's *fundamental lemma* [10] to directly predict future trajectory, making it suitable for articulated vehicle control, where load variability complicates system modeling.

Practical applications of DeePC have been seen in quadcopter, power grids, cruise control, etc. [11], [12], [13] The robustness of regularized DeePC for nonlinear system is discussed in [14]. Inspired by the potential of leveraging these accessible data with no need of system modelling, this paper proposes a data-driven control method for a four-wheel drive electric vehicle towing a trailer equipped with differential braking. The main contributions are summarized as follows: (i)Establishing a bilevel reconfigurable predictive control scheme for lateral stability improvement of articulated vehicles. (ii) Modify the DeePC algorithm to generate corrective yaw moments. (iii) Providing simulation results of different controller configurations to demonstrate its potential. To our current knowledge, data-enabled predictive control haven't been previously utilized for vehicle dynamic problems.

The rest of the paper is organized as follows - Section II describes the tractor-trailer dynamics system modeling and a MPC-based controller setup. Section III introduces the data-enabled predictive control approach and presents its modification and detailed implementation for vehicle stability control. Section V presents the experimental results and conclusions are drawn in Section VI.

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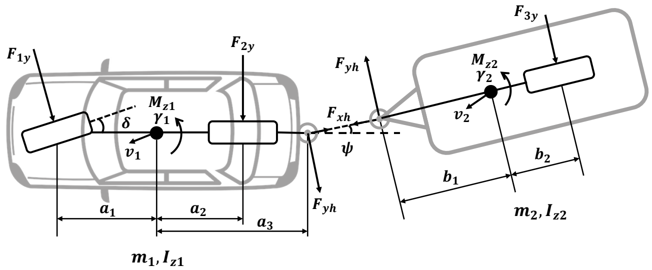

Fig. 1. Single-track articulated vehicle model

II. PRELIMINARIES

In this section, we first introduce the parametric system modeling of a tractor-trailer combination. Then, a Model Predictive Controller (MPC) is designed to compute corrective center-of-gravity (CG) yaw moments for each unit respectively, minimizing the tracking errors between actual states and the reference values, the desired yaw moments are then converted to torques on each wheel using Torque Vectoring (TV), the demand torques are generated by friction brakes or electric motors.

A. System Modeling

A single-track planar articulated vehicle model severs as the reference model, as depicted in Fig. 1. The system comprises a two-axle tractor and a single-axle trailer. To mitigate trailer sway effect, the reference model must take lateral motion characteristics of both units into consider. Based on prior research results [7], yaw stability analysis can be simplified with certain assumptions: the longitudinal speed of the vehicle is treated as positive and constant; yaw angle, hitch angle and steering wheel angle are assumed to be small. Pitch and roll movements are ignored. The hitch exerts only horizontal force. For the tractor and trailer unit respectively, it holds that:

$$\begin{aligned}
&m_1(\dot{v}_{1y} + v_{1x}\gamma_1) = F_{1x}\sin\delta + F_{1y}\cos\delta + F_{2y} + F_{yh} \\
&I_{z1}\dot{\gamma}_1 = (F_{1x}\sin\delta + F_{1y}\cos\delta)a_1 - F_{2y}a_2 - F_{yh}a_3 + M_{z1} \\
&m_2(\dot{v}_{2y} + v_{2x}\gamma_2) = F_{3y} + F_{xh}\sin\psi - F_{yh}\cos\psi \\
&I_{z2}\dot{\gamma}_2 = (F_{xh}\sin\psi - F_{yh}\cos\psi)b_1 - F_{3y}b_2 + M_{z2}
\end{aligned} \tag{1}$$

where δ, ψ denote the steering angle and hitch angle. F_1, F_2, F_3 are the tire forces on each axle, and F_{xh}, F_{yh} the forces on the hitch point. M_{z1}, M_{z2} is the corrective yaw moment on each unit.

The tractor and trailer's connection at the hitch ensures identical absolute positions and velocities at that point, resulting in the following kinematic coupling:

$$\begin{aligned}
v_{2x} &= v_{1x} + (v_{1y} - a_3\gamma_1)\sin\psi \\
v_{2y} &= v_{1y} - v_{1x}\sin\psi - (a_3 + b_1)\gamma_1 + b_1\dot{\psi} \\
\gamma_2 &= \gamma_1 - \dot{\psi} \\
\dot{\psi} &= -\frac{v_x}{l_1}\left(\frac{l_1}{l_2}\sin\psi + \left(\frac{a_3 - a_2}{l_2}\cos\psi + 1\right)\tan\delta\right)
\end{aligned} \tag{2}$$

For the tractor-trailer system, we have that, $u(t) = [M_{z1}, M_{z2}]^T \in \mathbb{R}^2$ is the control input, $x(t) = [v_{1y}, \gamma_1, \dot{\psi}, \psi]^T \in \mathbb{R}^4$ is the state vector, $y(t) = [\gamma_1, \dot{\psi}]^T \in \mathbb{R}^2$ is the output of the system, and a measurable external input $d(t) = [\delta] \in \mathbb{R}$, which means the steering angle of front axle in this case. Considering the small angle approximation, the linearized state-space representation is obtained.

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Hd(t) \\ y(t) = Cx(t) \end{cases} \tag{3}$$

B. Desired Vehicle Response

To mitigate the trailer instability under extreme circumstances, active control systems should track the desired response from the reference model, prior studies [3] suggest controller based on yaw rate of the tractor and hitch error can ensure trailer safety. The desired tractor yaw rate is the steady-state response can be expressed as:

$$\gamma_1^{ss} = \frac{v_x}{l_1 + k_t v_x^2}\delta \tag{4}$$

where k_t is the combined understeer coefficient, which is defined as below:

$$k_t = \frac{m_1 a_2 l_2 + m_2 b_2(a_2 - a_3)}{l_1 l_2 C_{\alpha 1}} - \frac{m_1 a_1 l_2 + m_2 b_2(a_1 + a_3)}{l_1 l_2 C_{\alpha 2}} \tag{5}$$

where $l_1 = a_1 + a_2$, $l_2 = b_1 + b_2$.

The desired yaw rate should be bounded by driving conditions, tire saturation on a low friction road may not allow a high yaw rate demand, hence the desired yaw rate is defined as below:

$$\gamma_1^d = \begin{cases} \gamma_1^{ss}, & \text{if } \mid \gamma_1^{ss} \mid < \mu g/v_x \\ \text{sign}(\gamma_1^{ss})\mu g/v_x, & \text{if } \mid \gamma_1^{ss} \mid \geq \mu g/v_x \end{cases} \tag{6}$$

Using the kinematic relationship of the two units, the target hitch angular rate can be tracked. In a steady state, the hitch rate should be zero.

$$\dot{\psi}^d = 0 \tag{7}$$

C. Upper Level Controller

The block diagram of the proposed control scheme is shown in Fig. 2. The driver's steering command is passed to the vehicle as a feedforward input. y_d is the desired vehicle state and x the state measurements. Desired corrective yaw moments for the tractor and trailer are derived in the upper layer, and then converted into driving or braking torques on each wheel in the lower level controller.

MPC is chosen as the upper level controller in this setup, as a comparison with DeePC, it optimizes over a finite time horizon based on the prediction, minimizing the objective function using a specified system model. To facilitate the computation of MPC, the response of the system model is approximated by discretization, the input signal is reconstructed by Zero Order Hold (ZOH) with the time step T_s.

The problem statement of constrained finite-horizon optimal control can formulated. Given the current time $t \in \mathbb{Z}_{\geq 0}$, time horizon $T_f \in \mathbb{Z}_{\geq 0}$, constraint sets for input and output $\mathcal{U} \subseteq \mathbb{R}^m, \mathcal{Y} \subseteq \mathbb{R}^p$, the objective is to find a sequence of feasible control inputs that when applied

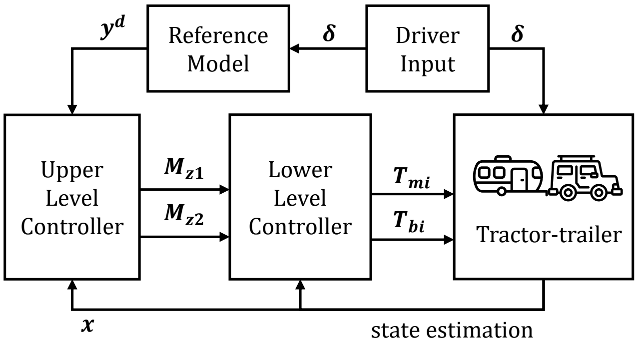

Fig. 2. Block diagram of the proposed control scheme

to system (3), minimizes cumulative stage costs without violating the constraints:

$$\begin{aligned}\underset{u,y}{\text{minimize}} \sum_{k=t}^{t+N-1} & \|y_k - r_k\|_Q^2 + \|u_k\|_R^2 \\ \text{s.t. } & x(k+1) = A_d x(k) + B_d u(k) + H_d d(k) \\ & y(k) = C_d x(k), \forall k \in \{t, \dots, t+N-1\} \\ & u(k) \in \mathcal{U}, y(k) \in \mathcal{Y}, \forall k \in \{t, \dots, t+N-1\} \\ & x(t) = \hat{x}(t)\end{aligned} \tag{8}$$

The problem should be solved in a receding-horizon manner at each step, where $N \in \mathbb{Z}_{>0}$ is the time horizon, the coefficient matrices $Q \succeq 0, R \succ 0$ are positive or semi-positive, and marks the cost on deviation from the reference value, the norm $\|u_k\|_R$ denotes the quadratic form $u_k^T R u_k$, $r_k = \text{col}(\gamma_{1r}, \dot{\psi}_r)$ denotes the reference output of the system. $\hat{x}$ means the estimate of state at time t, we assume the that the entire state is measured.

D. Lower Level Controller

In the lower level, the corrective yaw moments derived from the upper level controller are executed by applying proper torque on the wheels of the tractor and trailer, thus the yaw moment is realized because of the longitudinal force difference on each axle. Apart from differential braking, other control scheme like active steering is also compatible with this scheme. The dynamics equations of the tractor unit can be obtained from a double-track model as:

$$\begin{cases} F_{xfl} + F_{xfr} + F_{xrl} + F_{xrr} - F_{xh} = m a_x \\ (F_{xfl} - F_{xfr})d/2 + (F_{xrl} - F_{xrr})d/2 = M_z \end{cases} \tag{9}$$

where d is the track width of the front and rear axles. Since the longitudinal force of each wheel is constrained by the road friction coefficient, the following condition should be met:

$$|F_{xi}| \le \min(\sqrt{(\mu_{\max} F_{zi})^2 - F_{yi}^2}, T_{mi}/r) \tag{10}$$

The torques are distributed according to the vertical force on each wheel, generated by in-wheel motors or differential braking, considering the capacity of the actuators.

III. DATA-ENABLED PREDICTIVE CONTROL

In this section, we briefly introduce Data-enabled Predictive Control [9] methodology, then present the problem formulation and detailed implementation of DeePC for the lateral stability improvement of articulated vehicles.

A. DeePC for LTI Systems

Data-enabled Predictive Control is non-parametric approach for identification and control of dynamic systems. It utilizes input and output data to form a Hankel matrix as a system model. DeePC excels in handling constraints and non-linearity Due to its effectiveness and simplicity of implementation, so it's adopted in this article.

Consider the system defined in (3), according to Willem's *fundamental lemma* [10], when the system is a deterministic LTI minimal realization, its controllability and observability can be guaranteed. For a data sequence of control inputs $u = \{u(i)\}_{i=1}^T \subset \mathbb{R}^m$, T is the total step of pre-collected data used to construct the Hankel matrix, the matrix has L block rows. Let $L, T \in \mathbb{Z}_{>0}$, such that $T \ge L$. The signal u is called *persistently exciting of order L* if the Hankel matrix $\mathcal{H}_L(u)$ has full row rank.

$$\mathcal{H}_L(u) := \begin{bmatrix} u(1) & u(2) & \dots & u(T-L+1) \\ u(2) & u(3) & \dots & u(T-L+2) \\ \vdots & \vdots & \ddots & \vdots \\ u(L) & u(L+1) & \dots & u(T) \end{bmatrix}$$

where $u(i) = col(u_1, u_2, \dots, u_m)$. Persistently exciting requires the sequence to be long and rich enough, specifically, the length T must satisfy $T \ge (m+1)L - 1$.

Theorem 1 $T_d, L \in \mathbb{Z}_{>0}$, $(u_{\rm d}, y_{\rm d}) = \{u_{\rm d}(i), y_{\rm d}(i)\}_{i=1}^{T_{\rm d}}$ is a sequence of signals including input and output data points of length T_d, assume the input signal is persistently exciting of order $L+n$, then $(u_{\rm d}, y_{\rm d}) = \{u_{\rm d}(i), y_{\rm d}(i)\}_{i=1}^{L}$ is a trajectory only if their exists a $g \in \mathbb{R}^{T_d - L+1}$ that satisfies:

$$\begin{bmatrix} \mathcal{H}_L(u_{\rm d}) \\ \mathcal{H}_L(y_{\rm d}) \end{bmatrix} g = \begin{bmatrix} u \\ y \end{bmatrix}$$

Thus, a non-parametric model for (3) is constructed from raw data. This theorem allows us to perform an implicit state estimation and prediction based on data. Let $T_{\rm d} \in \mathbb{Z}_{>0}$ be the time horizon of data collection and $T_{\rm ini} \in \mathbb{Z}_{>0}$ be the horizon for initial state estimation. $(u_{\rm d}, y_{\rm d})$ is a sequence of input/output data collected offline, suppose the input $(u_{\rm d}) = \{u_{\rm d}(i)\}_{i=1}^{T_{\rm d}}$ is persistently exciting of order $T_{\rm ini} + T_{\rm f} + n$, we can map the data points into two Hankel matrices:

$$\begin{bmatrix} U_{\rm p} \\ U_{\rm f} \end{bmatrix} := \mathcal{H}_{T_{\rm ini}+T_{\rm f}}(u_{\rm d}), \begin{bmatrix} Y_{\rm p} \\ Y_{\rm f} \end{bmatrix} := \mathcal{H}_{T_{\rm ini}+T_{\rm f}}(y_{\rm d}) \tag{11}$$

the Hankel matrices are partitioned into *past* and *future* trajectories, where $U_{\rm p}$ consists of the first $T_{\rm ini}$ block rows of $H_{T_{\rm ini}+T_{\rm f}}(u_d)$, and $U_{\rm f}$ the last $T_{\rm f}$ block rows, the same is for $Y_{\rm p}, Y_{\rm f}$. Now let $(u_{\rm ini}, y_{\rm ini}) = \{u_{\rm ini}(t+i), y_{\rm ini}(t+i)\}_{i=-T_{\rm ini}}^{-1}$ be the $T_{\rm ini}$ most recently collected input/output measurements of the system. By Theorem 1, $(u, y) = \{u(t+$

$i), y(t+i)\}_{i=0}^{T_\mathrm{f}-1}$ would be a possible future trajectory if their exists $g \in \mathbb{R}^{T_\mathrm{d}-T_\mathrm{ini}-T_\mathrm{f}+1}$ satisfying:

$$\begin{bmatrix} U_\mathrm{p} \\ Y_\mathrm{p} \\ U_\mathrm{f} \\ Y_\mathrm{f} \end{bmatrix} g = \begin{bmatrix} u_\mathrm{ini} \\ y_\mathrm{ini} \\ u \\ y \end{bmatrix} \tag{12}$$

For the reconstructed Hankel matrix on the left side, every column of it corresponds to a pre-collected trajectory of length $T_\mathrm{ini} + T_\mathrm{f}$, and the predictive trajectory on the right side can be synthesized by a linear combination of these trajectories. The first two blocks implicitly fixed the initial condition, if $T_\mathrm{ini} > \mathcal{L}$, where $\mathcal{L}$ is the lag of the system, the future trajectory can be uniquely determined by solving the first three blocks in (12), and the output can be given by $u = U_\mathrm{f} g$.

The scheme above performs state estimation and prediction at the same time, an optimization control problem can be formulated like (8),and (12) serves as the equality constraints. This optimization problem was proved to be equivalent to the MPC form. The problem is solved in a receding horizon manner, the optimization variable g, which is a vector indicating the weight of each trajectory, is solved for every step, and the first input in the vector u is applied to the system.

B. *DeePC Formulation for trailer stability control*

In practical DeePC applications, the assumption of LTI system does not fully apply, as the vehicle model used in MPC has undergone several linearization and approximation, and the data measured may be corrupted by noise. Regularization is introduced to address this issue. An auxiliary slack variable is added to help set the initial condition, a 2-norm penalty of the deviation between estimated and measured initial state is added into the objective function, in order to ensure feasibility and improve the prediction precision.

The cost also includes penalty on g to avoid overfitting, causing the corresponding trajectory to lose its accuracy in describing the behavior of the system. For lateral stability control, steering angle is an uncontrollable but predominant factor that must be taken into account. To incorporate this external input signal into the trajectories, we construct another Hankel matrix of external input in the same way as $\mathcal{H}_L(u)$, provided the pre-collected external input signal $(d_\mathrm{d}, y_\mathrm{d}) = \{d_\mathrm{d}(i)\}_{i=1}^{T_\mathrm{d}}$, the matrix is separated into p and f parts:

$$\begin{bmatrix} D_\mathrm{p} \\ D_\mathrm{f} \end{bmatrix} := \mathcal{H}_{T_\mathrm{ini}+T_\mathrm{f}}(d_\mathrm{d}) \tag{13}$$

where D_p, D_f represent rows in the same way as (12). To estimate the initial state of external input, the past T_ini steps of $d(t)$ is measured and updated online in d_ini. The flexibility of DeePC framework enabled easy modifications to the original algorithm, any parameters can be easily taken into consider by adding its signal into the input/output measurements, requiring no extra costly system remodeling work. The final form of optimization problem is defined as:

$$\begin{aligned} \underset{u,y,g}{\text{minimize}} \quad & \sum_{k=t}^{t+T_\mathrm{f}-1} \|y_k - r_k\|_Q^2 + \|u_k\|_R^2 \\ & + \lambda_g \|g\|_2 + \lambda_y \|\sigma_y\|_2 \\ \text{s.t.} \quad & \begin{bmatrix} U_\mathrm{p} \\ D_\mathrm{p} \\ Y_\mathrm{p} \\ U_\mathrm{f} \\ D_\mathrm{f} \\ Y_\mathrm{f} \end{bmatrix} g = \begin{bmatrix} u_\mathrm{ini} \\ d_\mathrm{ini} \\ y_\mathrm{ini} \\ u \\ d \\ y \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \sigma_y \\ 0 \\ 0 \\ 0 \end{bmatrix} \\ & u(k) \in \mathcal{U}^{T_\mathrm{f}}, y(k) \in \mathcal{Y}^{T_\mathrm{f}}, \\ & \forall k \in \{t, \ldots, t+T_\mathrm{f}-1\} \end{aligned} \tag{14}$$

where $\lambda_g, \lambda_y > 0$ are the regularization term and slack variable penalty term coefficient. Note that the arrangement of the partitioned Hankel matrices does not necessarily be fixed, but the p matrices must be used for initial state estimation and f matrices for prediction. The optimization problem is solved for each iteration in a receding horizon manner, detailed algorithm of this extended DeePC scheme is shown in Algorithm 1.

Algorithm 1 Regularized and Extended DeePC

Input: constraint sets $\mathcal{U}$, $\mathcal{Y}$, reference trajectory $r \in \mathbb{R}^{pT_\mathrm{f}}$, cost matrix Q, R, regularization terms coefficient λ_g, λ_y, pre-collected data sequence $\{(u_\mathrm{d}(i), d_\mathrm{d}(i), y_\mathrm{d}(i))\}_{i=1}^{T_\mathrm{d}}$, the most T_ini recent past measurements $(u_\mathrm{ini}, d_\mathrm{ini}, y_\mathrm{ini})$.

1) Construct Hankel matrices using the pre-collected data;
2) Initialize recent data measurements before time t_0;
while True do
  3) Solve optimization problem (14) and set g^* equal to its solution;
  4) Calculate optimal input sequence $u^* = U_\mathrm{f} g^*$;
  5) Apply the first input in u^* to the system;
  6) Set t to $t+1$ and update most recent input/output measurements $(u_\mathrm{ini}, d_\mathrm{ini}, y_\mathrm{ini})$.
end while

We can now formulate the non-parametric representation of the articulated vehicles, incorporating DeePC for optimal upper-layer control, which calculates two corrective yaw moments for both units. To include steering wheel angle as an uncontrolled external input, we extended the standard DeePC algorithm. The optimization problem is formulated as (14), where $u(t) = [M_{z1}, M_{z2}]^T \in \mathbb{R}^2, y(t) = [\gamma_1, \dot{\psi}]^T \in \mathbb{R}^2$, $d(t) = [\delta] \in \mathbb{R}$. Note that future prediction of steering angle cannot be acquired in advance, it is reasonable to assume it to be zero, i.e. $d = \mathbf{0}_{T_\mathrm{f}}$, reflecting the driver's inclination towards maintaining straight driving after maneuvering.

In the offline data collection phase, obtaining extensive, rich data is essential. Although measurement noise and unpredictable driver behavior often yield full-rank data, being *persistently exciting* alone may not suffice for accurate model approximation. As suggested by [11], random inputslike white noise or PRBS signals are preferred for system excitation, but manual inputs are also suffice. However, using completely random signals is typically impractical or unsafe for high-speed vehicles, causing discomfort, loss of control, and load shifts, especially on low-traction surfaces.

In our setup, we collect data by applying uniformly-distributed input signals within a safe range to ensure excitation without causing tire saturation. Different sampling intervals are adopted for steering and yaw moment inputs due to differences in actuator response times. Considering vehicles as low-pass filters, we extend input signal over multiple steps to capture response adequately. This procedure facilitates the derivation of data sequences for Hankel matrices contruction in (14).

IV. SIMULATION RESULTS

This section showcases the test results of the introduced method. Data-enabled Predictive Control based method is compared with linear MPC to show its effectiveness for articulated vehicle stability control. The simulation is conducted on a Windows system personal computer equipped with Intel(R)i5-10400F CPU operating at 2.90GHz. The controller is implemented in Simulink, and a co-simulation is executed using the high-fidelity, physics-based simulator, Carsim.

A. Experimental Setup

We consider an articulated vehicle assembly which consists of a large European van and an one-axle rental trailer, the two units are jointed at the pintle hitch. This setup serves as the basis for data collection and test scenarios, all of the simulations are conducted at a longitudinal speed of 80 km/h, the adhesion of the simulation roads is 0.75, the simulation time step is set to 0.5 ms.

For the offline data collection phase of DeePC, the input/output data is accessed through MATLAB-Carsim co-simulations. We use the following parameters for excitation signal, as shown in Fig. 3. The length of the collected data points used to construct the Hankel matrices in (14) is $T_{\mathrm{d}} = 176$, deriving 159 trajectories in total. A uniform distribution sampling from range $[-0.03, 0.03]$ is added on the front wheel steering angle, the sampling interval is 0.64 s. The yaw moment input on the tractor and trailer is sampled in a similar way, the range is $[-2000, 2000]$ and $[-750, 750]$ respectively with a sampling interval of 0.32 s. A rate limiter is set on the steering input, corresponding to a max steering wheel angle rate of 180 deg/s, thus enabling manual input in real world.

During online predictive control, the optimization problems in (8) and (14) are solved iteratively at a frequency of 25 Hz, for DeePC, the time horizons for past and future trajectories are set to $T_{\mathrm{ini}} = 6, T_{\mathrm{f}} = 12$. In the object function, the weight coefficients are set as $Q = \mathrm{diag}(2\times10^6, 1\times10^7)$, $R = \mathrm{diag}(3 \times 10^{-7}, 6 \times 10^{-7})$, the regularization terms are set as $\lambda_g = 4 \times 10^{-6}, \lambda_y = 1 \times 10^3$.

B. Double Lane Change Test

Double lane change (DLC) maneuver is a common test involving rapidly changing lanes twice in succession within a short distance. Driver preview time in this scenario is 0.7 s. The dynamic responses of the articulated vehicles are presented in Fig. 4, the figure indicates that the hitch angle reaches the peak during the second lane change at $t \approx 7.5$ s. For the case with DeePC, the maximum hitch angle is reduced to lower than 9 deg, but for the uncontrolled vehicle the value goes up to over 20 degree, decreasing the peak angle by 72.8%. Compared to the passive case, DeePC and MPC both improve the stability of the tractor-trailer combination, but DeePC shows better tracking performance, lateral motion of the trailer and the hitch variation are mitigated, relevant variables are kept at a minimum throughout the entire experiment, and the oscillation damps out earliest under the DeePC controller, suggesting quicker dynamic response time.

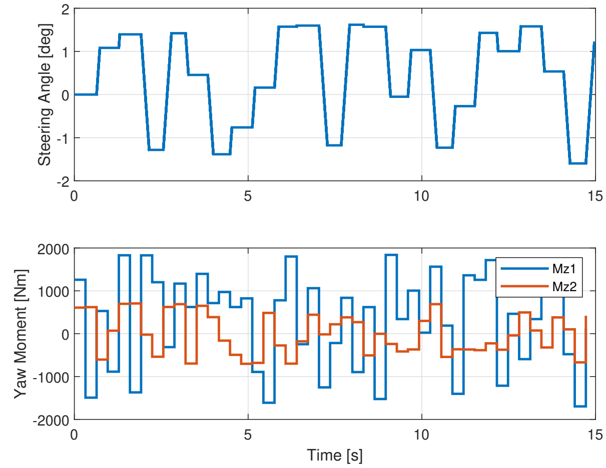

Fig. 3. Excitation signals for data collection

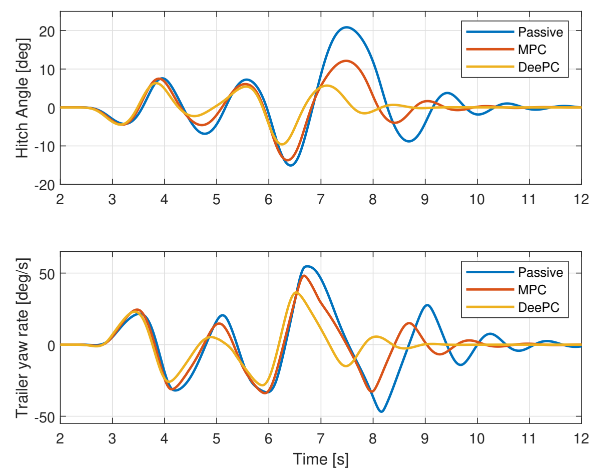

Fig. 4. Tractor-trailer responses to the DLC test

C. On-Center Steer Test

The vehicle is vulnerable may suffer from instability in snaking conditions, we initiate this instability by conducting

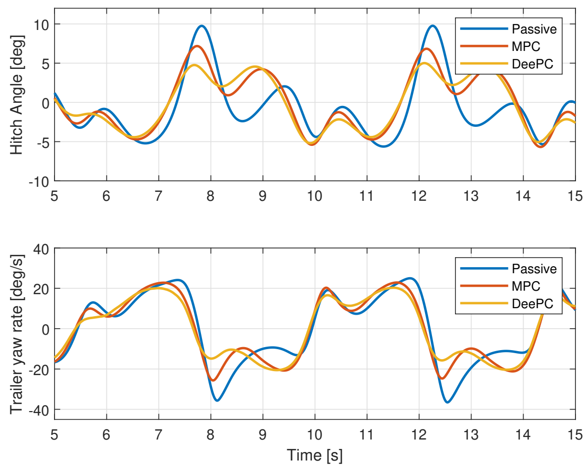

Fig. 5. Tractor-trailer responses to the On-Center steer test

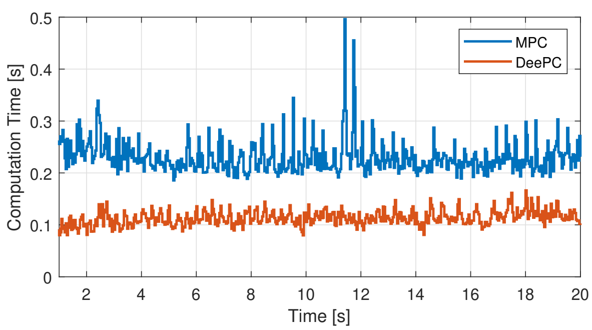

Fig. 6. Computation time for each step

an on-center steer test. Driver preview time in this test is 0.85 s. From the results shown in Fig. 5 we can conclude that DeePC apparently mitigates yaw movement for the trailer. In the passive case the trailer shows large amplitude oscillations, the peak hitch angles are decreased by 26.5% and 50.8% respectively in other cases, similar results apply for the lateral motion of the trailer. Both MPC and DeePC has contributed to improvement on stability but DeePC clearly has more capacity to track desired values. To sum up, the results indicate that the trailer controlled by DeePC has better lateral stability than MPC, which means lower peak values and shorter responsing time.

We also recorded the computation time for each step during the simulation, which is shown in Fig. 6. MPC and DeePC have the same prediction horizon and control horizon in this setup, and the average computation time for DeePC is 0.1116 s, which is 52.3% lower than that of MPC, 0.2339 s. The computation time of MPC nearly doubled in the worst case. Both optmization problems are solved by `fmincon`, while DeePC shows low computational complexity throughout the run. The efficiency and effectiveness of DeePC is well demonstrated in this scenario, making it possible for a real-world implementation.

V. Conclusions

This study presents a data-driven predictive control method for sway mitigation in tractor-trailer assemblies, utilizing vehicle control input and output data instead of parametric models. Simulation results show that the DeePC algorithm outperforms MPC in tracking accuracy and solution speed for real-time control. DeePC is particularly beneficial in cases lacking precise first-principles models or key parameters.

Future directions include developing efficient data collection scenarios, optimizing the selection of vehicle trajectories, and enhancing the robustness and interpretability of data-driven methods through real-vehicle testing. Investigating adaptive Hankel matrices for varying driving conditions is also an interesting direction.

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