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Performance Enhancement of Virtual Coupling Distance Control Under Communication Impairments Using State Estimation

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Abstract

This paper investigates the impact of communication loss and relative sensing disturbances on gap control in virtually coupled train sets (VCTS), as well as the effectiveness of different state estimation methods in mitigating these effects. A simulation framework incorporating train dynamics, gap controller, sensor noise and stochastic communication/sensing drop outs is used for the evaluation. Two state estimation approaches - Zero-Order Hold (ZOH) and Kalman Filter (KF) based approaches are compared. The results show that KF based approach improves control smoothness, jerk and energy consumption, compared to ZOH. In terms of gap tracking the KF based approach only offers modest improvement compared to ZOH. These findings demonstrate that KF based approach generally improves the robustness of gap control. However, state estimation its own it is not sufficient for reliable performance, especially in extreme scenarios.

Keywords: virtual coupling, Kalman filter, sliding mode control, train-to-train communication, communication impairments, packet loss, state estimation, onboard sensors, zero-order hold

1 Introduction

The demand for rail transport is increasing rapidly. Building new infrastructure to meet these demands is cost intensive and can have significant environmental impact. Virtual coupling (VC) has emerged as a promising operational concept for increasing railway line capacity, flexibility and operational efficiency by exploiting and optimizing the usage of the existing tracks [1] [2].

VC is a an operational concept where multiple trains can form platoons and drive in close succession at relatively close distances. This can be achieved through the coordinated movement of train through the continuous exchange of state information with each other in a platoon. In such a paradigm, the following train relies on the timely knowledge of the preceding train's motion, including relative distance and velocity, to regulate inter-train spacing while preserving safety, ride quality, and operational efficiency [2].

The required state information can be obtained from two different sources: through direct onboard ranging sensors, such as radar or LiDAR, or through communicated estimates derived from indirect sources, including odometry and balises [3].

Thus, the viability of safety-critical applications such as Virtually Coupled Train Sets (VCTS) depends heavily on the reliability of the communication link and sensing. To ensure low latency and reliable performance, onboard relative localization and communication are preferred [4]. However, onboard communication systems and sensors are not perfect. They are subject to packet loss and inaccuracies due to technological limitations, environmental interference, signal blockages, or even cyberattacks [5], [6].

Prior studies have identified the hazards if disturbances in V2V communications on platoons. Several studies also show that communication delays and packet dropouts can degrade platoon stability and convergence, and in the context of VCTS, packet loss has been identified as a critical factor affecting system stability and safe operation [7], [8], [9], [10]. [3] also proposes communication requirements for VCTS in various application scenarios.

Despite these challenges, many studies on VCTS often assume ideal communication conditions or do not sufficiently investigate the impact of communication and sensing degradation on gap control performance. This motivates the need for robust estimation and control strategies that can mitigate the effects of such disturbances. In this paper, the impact of packet loss in direct T2T communication and measurement disturbances in onboard relative state sensing is analyzed.

This paper presents the following contributions:

1. A simulation framework to analyze VCTS dynamics under impaired communication and sensing conditions.
2. A Monte Carlo simulation study evaluating system performance under measurement noise and packet loss.
3. Comparative evaluation of tracking performance, jerk, and energy consumption of VC train using KF and ZOH state estimation.

The remainder of the paper is structured as follows. Section 2 introduces the simulation framework, control problem, sensor and communication model, state estimation strategies and experimental design. Section 3 presents the simulation results and discussion. Finally, Section 4 concludes the paper and outlines directions for future work.

2 Methodology

This chapter details the mathematical models and simulation environment used to evaluate VC performance under communication disturbances.

2.1 Simulation Framework

The simulation framework was developed in Python using a forward propagating approach with a fixed time step. The framework consist of an environment model that define the track characteristics such as speed limits and resistance forces acting on the trains.

Furthermore, the framework allows simulation of multiple trains and their individual characteristics. The characteristics are modeled using several submodules as shown in Figure 1. They include sensor/communication model, state estimators, necessary controllers, powertrain and dynamics which are discussed in further detail in following subsections.

2.2 Train Dynamics and Powertrain Model

To simulate VCTS, a point-mass train dynamics model was implemented in the dynamics model. The longitudinal dynamics are described by the following equations of motion:

$$\dot{s} = v \tag{1}$$

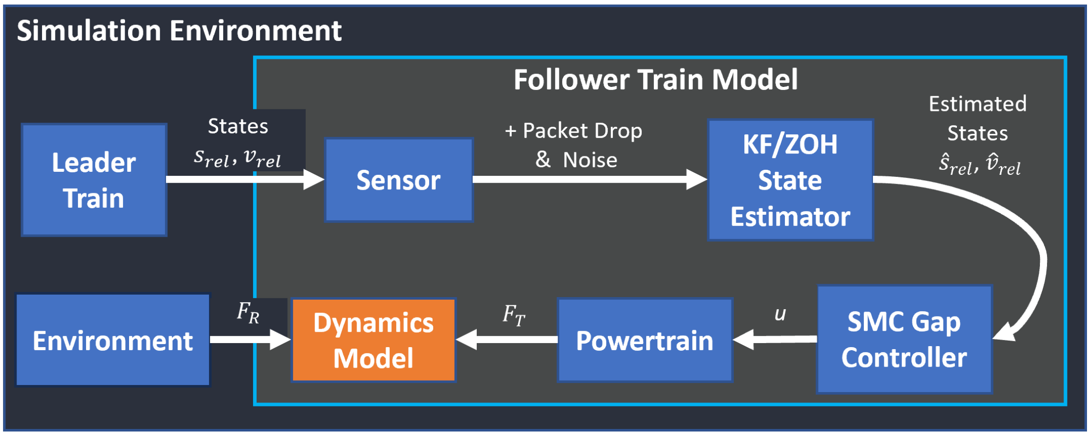


Figure 1: Simulation framework

$$\dot{v} = \frac{F_{\mathrm{T}} - F_{\mathrm{R}}}{m} \tag{2}$$

where s denotes the train position, v the velocity, F_{T} the traction force, F_{R} the resistance force, and m the mass of the train. The resistance force is computed using the Davis equation [11]:

$$F_{\mathrm{R}} = A + Bv + Cv^2 + mg\sin(\theta) \tag{3}$$

where the terms A, B and C are the Davis coefficient and θ denotes the gradient of the track.

The powertrain model calculates the required traction force F_{target}. This is calculated based on the control input u which is normalized within $[-1, 1]$, where negative values correspond to braking and positive values to traction. The target traction force F_{target} is computed as

$$F_{\mathrm{target}} = F_{\mathrm{max}}\, u \tag{4}$$

where F_{max} denotes the maximum available traction or braking force. The maximum traction force constrained by the adhesion limits between wheel and track and strength of the powertrain components involved.

Due to actuator dynamics, the requested force cannot be achieved instantaneously. This behavior is modeled using a first-order delay:

$$\dot{F}_{\mathrm{T}} = \frac{1}{\tau}\left(F_{\mathrm{target}} - F_{\mathrm{T}}\right) \tag{5}$$

where F_{T} denotes the traction force applied at the wheel and τ is the time constant representing the powertrain response.

2.3 Sensor and Communication Model

For the sensor model of the VCTS ranging relative speed measurement, a radar-based system similar to those used in Automotive applications is assumed. The sensor will be located in front of the following train, similar to the setup tested in [4] . Typical radar sensors used in Automotive applications have a maximum range of up to 250 meters [12]; therefore, the scope of this paper is limited to this range, which corresponds to typical coupled driving scenarios for regional trains [13], [3]. Within this range a constant packet loss rate is assumed. The values chosen were considering communication deadlines defined for similar application in [3]. Beyond this deadlines VCTS may have to go into fallback mode.

To simulate such a scenario, the sensor model of the follower train has access to the true relative distance and velocity, to which it adds disturbances via measurement noise and packet loss events. The noise can be interpreted as inaccuracies in measurements and packet drop outs represent packet loss due to interference, fading and shadowing. These corrupted measurements from the sensor model are then propagated to the VCTS gap controller of the follower train.

The noise is modeled as a stochastic Gaussian signal with the following characteristics which were chosen based on [14]:

Table 1: Noise characteristics in the measurement model

Measurement Type	**Standard Deviation (per 0.1 s)**
Distance	0.2 m
Velocity	0.01 m/s

The packet drop-out phenomenon is modeled using an algorithm that randomly interrupts the propagation of state information to the follower train. This event can be characterized by two main parameters: burst size and and burst initiation probability. Burst size refers to number of consecutive packet drop outs and burst initiation probability refers to the probability of such an event happening, which effectively dictates the frequency of burst events happening and delivery rate of packets transmitted.

To evaluate the effect of these parameters on the VCTS gap control performance, a wide range of values is considered, emulating mild to severe communication degradation. The following table summarizes the considered communication degradation levels:

Table 2: Communication degradation levels considered in the simulation

Severity	**Burst initiation probability (%)**	**Burst length (samples)**
Low	1% – 3%	1 – 3
Moderate	4% – 7%	4 – 7
Extreme	8% – 20%	8 – 20

Given a control update interval of 0.1 s, corresponding to a typical 10 Hz radar update rate, burst lengths of 1 to 20 samples translate to communication outages ranging from 0.1 s to 2 s. Such burst losses reflect realistic operating conditions, including temporary blockages, signal fading, and complete link interruptions.

2.4 State Estimation

To ensure continuous state availability during communication dropouts, the following state estimation approaches were analyzed:

2.4.1 Zero-Order Hold (ZOH)

A common baseline strategy in networked control systems when measurement data is missing is the Zero-Order Hold (ZOH). This method holds the last measured value as input to the controller until a new update is received.

For the measured relative state:

$$\mathbf{z}_k = \begin{cases} \begin{bmatrix} s_{\mathrm{rel},k} \\ v_{\mathrm{rel},k} \end{bmatrix}, & \text{if measurement is available} \\ \mathbf{z}_{k-1}, & \text{otherwise} \end{cases} \tag{6}$$

2.4.2 Kalman Filter (KF)

A discrete-time Kalman filter is employed to estimate the relative state between the leader and follower trains. The state vector is defined as

$$\mathbf{x} = \begin{bmatrix} s_{\mathrm{rel}} \\ v_{\mathrm{rel}} \end{bmatrix} \tag{7}$$

where s_{rel} and v_{rel} is the gap and relative velocity of the leader to the follower train.

The prediction step is based on a constant-velocity motion model:

$$\mathbf{x}_{k|k-1} = \mathbf{F}\,\mathbf{x}_{k-1|k-1} + \mathbf{B}\,u_k \tag{8}$$

$$\mathbf{P}_{k|k-1} = \mathbf{F}\,\mathbf{P}_{k-1|k-1}\,\mathbf{F}^{\top} + \mathbf{Q} \tag{9}$$

$$\mathbf{F} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \tag{10}$$

$$\mathbf{B} = \begin{bmatrix} \frac{1}{2}\Delta t^2 \\ \Delta t \end{bmatrix} \tag{11}$$

$$u_k = -a_{\mathrm{f}} \tag{12}$$

where $\mathbf{P}$ is the covariance matrix, $\mathbf{F}$ is the state transition matrix and $\mathbf{B}$ is the input matrix. The input u_k is the follower acceleration, while the unknown leader acceleration is modeled as process noise. The process noise covariance is given by:

$$\mathbf{Q} = \mathbf{G}\mathbf{G}^\top \sigma_a^2 \tag{13}$$

with $\mathbf{G} = \mathbf{B}$ and σ_a^2 representing the variance of the leader acceleration uncertainty. The measurement model assumes that both relative distance and relative velocity are directly measured and is denoted by:

$$\mathbf{z}_k = \mathbf{H}\,\mathbf{x}_{k|k-1} + \mathbf{w}_k \tag{14}$$

with $\mathbf{H} = \mathbf{I}$ and measurement noise $\mathbf{w}_k \sim \mathcal{N}(0, \mathbf{R})$, where σ_s^2 and σ_v^2 denotes the variance of measured gap and relative velocity respectively.

$$\mathbf{R} = \begin{bmatrix} \sigma_s^2 & 0 \\ 0 & \sigma_v^2 \end{bmatrix} \tag{15}$$

When measurements are available the update step is performed as

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}^\top \left(\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top + \mathbf{R}\right)^{-1} \tag{16}$$

$$\mathbf{x}_{k|k} = \mathbf{x}_{k|k-1} + \mathbf{K}_k \left(\mathbf{z}_k - \mathbf{H}\mathbf{x}_{k|k-1}\right) \tag{17}$$

$$\mathbf{P}_{k|k} = \left(\mathbf{I} - \mathbf{K}_k\mathbf{H}\right)\mathbf{P}_{k|k-1} \tag{18}$$

where $\mathbf{K}_k$ denotes the Kalman gain, and $\mathbf{x}_{k|k}$ and $\mathbf{P}_{k|k}$ represent the updated state estimate and covariance matrix after incorporating the measurement.

2.5 Virtual Coupling Gap Controller

For this study, a VCTS consisting of two trains is considered. The leader train follows a predefined trajectory using a PID-based velocity controller. It operates independently and is not influenced by the follower train.

The follower train uses a sliding mode control (SMC) based gap controller, originally developed in [15], to regulate the relative distance and velocity with respect to the leader. SMC is known for its robustness against bounded uncertainties and disturbances. However, its performance can degrade in the presence of discontinuities in state information. To mitigate this effect, continuous state availability is ensured by combining the sensor model with state estimation. The control input of the SMC gap controller is computed as

$$u = \frac{K \cdot \sigma}{|\sigma| + \rho} \tag{19}$$

where K is the controller gain and ρ is the boundary layer parameter that is used mitigate chattering behaviour in SMC. σ denotes the sliding surface, which is defined as

$$\sigma = s_{\mathrm{rel}} - T_{\mathrm{h}}\, v_{\mathrm{f}} + v_{\mathrm{rel}} \tag{20}$$

Here, s_{rel} and v_{rel} denote the relative distance and relative velocity between the leader and follower trains, respectively. T_{h} is the desired constant time headway, and v_{f} denotes the velocity of the follower train.

2.6 Simulation Scenario and Parameters

To evaluate the impact of communication disturbances and packet loss on the VC controller, a representative driving scenario is defined. The scenario consists of two identical electric multiple units (EMUs) operating in a virtually coupled configuration over a distance of approximately 57 km, corresponding to a route in Germany from Arnsberg to Hagen, without intermediate stops.

The leader train follows a predefined velocity profile, while the follower train regulates the gap and relative velocity using the proposed state estimation and control strategies. The simulated track includes varying speed limits and gradients, introducing realistic disturbances to the dynamics of both trains. The track profile is illustrated in Figure 2.

The key parameters of the train model are summarized in Table 3. The parameters related to sensor noise, communication disturbances, and state estimation are provided in Table 4.

Table 3: Train model parameters

Parameter	Symbol	Value
Train mass	m	$137\,250\,\mathrm{kg}$
Max traction force	F_{max}	$111\,\mathrm{kN}$
Maximum power	P_{max}	$2000\,\mathrm{kW}$
Davis coefficient A	A	$1\,956$
Davis coefficient B	B	4.888
Davis coefficient C	C	0.1998
Powertrain time constant	τ	0.5

Table 4: Sensor, communication, and estimation parameters

Parameter	Symbol	Value
Position noise standard deviation	σ_s	$0.4\,\mathrm{m}$
Velocity noise standard deviation	σ_v	$0.2\,\mathrm{m/s}$
Process noise standard deviation	σ_a	$1.0\,\mathrm{m/s^2}$
Packet loss event probability	p_{drop}	$[0.01, 0.03, 0.05, 0.1, 0.2]$
Maximum consecutive packet drops	c_{drop}	$[1, 3, 5, 7, 10, 15, 20]$

3 Results

This section presents simulation results comparing the Zero-Order Hold (ZOH) and Kalman Filter (KF) approaches under varying packet loss conditions. The analysis focuses on tracking accuracy, energy efficiency, and control smoothness.

Figure 2 illustrates a severe communication degradation scenario with a packet loss probability of 1% and burst length of 20 packets. Shaded regions indicate intervals of packet loss. An ideal scenario with measurement noise but no packet loss is used as a baseline. Packet loss is introduced only during the coupled phase to isolate its effect on distance control.

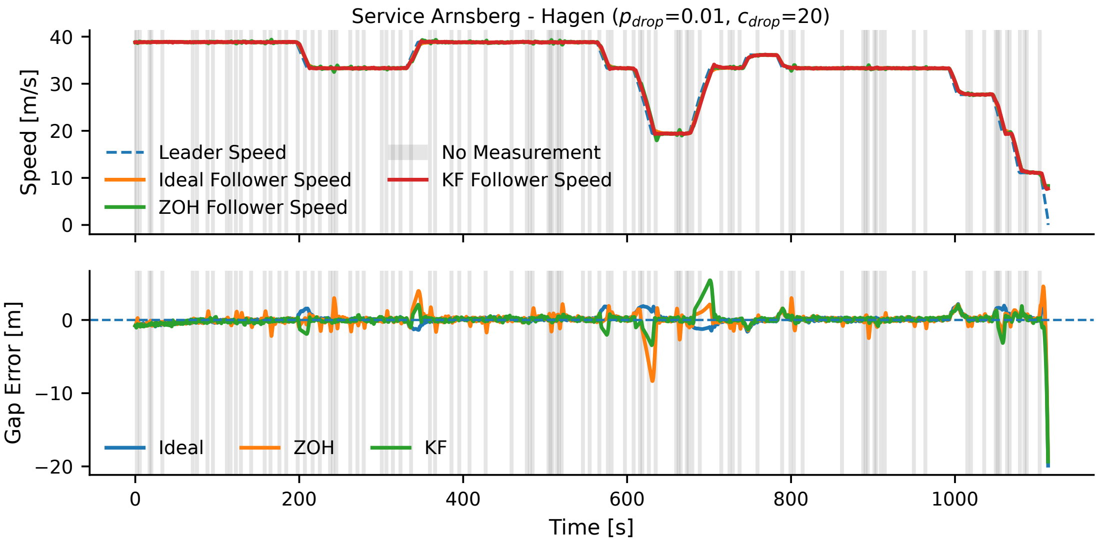


Figure 2: Example VCTS scenario with degraded communication

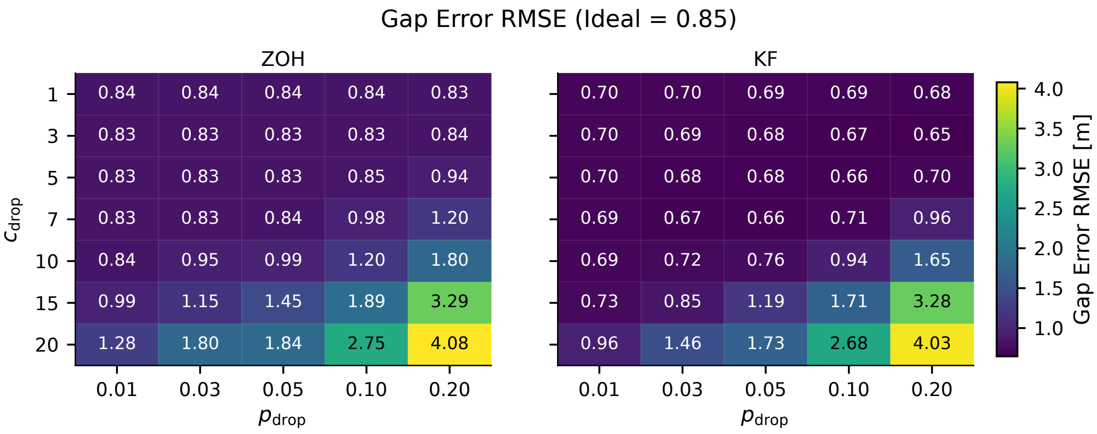
The results show that the KF maintains trajectories closer to the ideal baseline, particularly during constant-speed operation. In an ideal world ZOH should be optimal since relative distance and velocity do not change. However, in practice due to disturbances in the system and measurement noise and this leads to deviations from the target. The KF is able to account for such effects by using the motion model and mitigating the measurement noise by incorporating uncertainties in its estimation.

During acceleration and deceleration phases, both approaches show similar error behavior. This is attributed to the limited ability of both methods to capture rapidly changing dynamics: the KF relies on a constant-velocity model for prediction and considering leader trains acceleration as process noise, while the ZOH does not perform prediction.

To further assess performance, a parameter sweep over packet loss probability and burst length was conducted. For each configuration, 50 simulations were performed using identical random seeds to ensure a fair comparison under identical disturbance conditions.

3.1 Tracking Performance

To compare the tracking accuracy, the RMSE of inter-train gap is evaluated across all configurations. Figure 3 shows the heatmap of average gap RMSE for both ZOH and KF over the range of cases simulated. As expected, the tracking performance degrades with increasing packet loss probability and burst length. Longer dropout intervals reduce the availability of fresh measurements, forcing the controller to rely more on states estimates that become more inaccurate over time.



c_{drop} \ p_{drop} (ZOH)	0.01	0.03	0.05	0.10	0.20
1	0.84	0.84	0.84	0.84	0.83
3	0.83	0.83	0.83	0.83	0.84
5	0.83	0.83	0.83	0.85	0.94
7	0.83	0.83	0.84	0.98	1.20
10	0.84	0.95	0.99	1.20	1.80
15	0.99	1.15	1.45	1.89	3.29
20	1.28	1.80	1.84	2.75	4.08

c_{drop} \ p_{drop} (KF)	0.01	0.03	0.05	0.10	0.20
1	0.70	0.70	0.69	0.69	0.68
3	0.70	0.69	0.68	0.67	0.65
5	0.70	0.68	0.68	0.66	0.70
7	0.69	0.67	0.66	0.71	0.96
10	0.69	0.72	0.76	0.94	1.65
15	0.73	0.85	1.19	1.71	3.28
20	0.96	1.46	1.73	2.68	4.03

Figure 3: Comparison of gap error RMSE for varying packet loss probability p_{drop} and consecutive packet loss length c_{drop} using ZOH and KF estimator.

From Figure 3 it can be seen that KF shows a consistent but modest improvement over ZOH. The improvement comes from KF's ability to propagate state estimation using a motion model, thereby reducing the state error over short communication outages. However, as the the packet loss severity increases, the improvement of KF becomes marginal.

Another interesting observation is that with KF under low or packet loss rates the gap tracking error is lower than the ideal case. This effect can be attributed to the nature of SMC, which react aggressively to measurement noise in the ideal scenario. The presence of estimation filtering from KF seems to reduce the high frequency noise in the control loop, effectively mitigating chattering effects as a result improving tracking performance.

3.2 Jerk

Jerk refers to the rate of change of acceleration, which is a key indicator of passenger comfort. High jerk values corresponds to to abrupt control actions, which are undesirable for comfort. The heatmap shown in Fig 4 shows KF approach improves jerk consistently over the all cases that were simulated. The higher jerk in ZOH can be attributed to controller reacting to the stale measurements and making aggressive corrections when new measurements are available.

The KF in contrast provides on average a smoother state estimate allowing the controller to respond more gracefully. Furthermore, as observed in the tracking behaviour, the KF seems to have a smoothing effect on the SMC control mitigating chattering behaviour. This, further supports the observation that integrating KF based state estimator instead of ZOH reduces sensitivity to package drop outs and measurement noise. Nevertheless it should be noted that for the simulated cases even with ZOH approach, the jerk levels remain within acceptable limits for operation of rail vehicles.

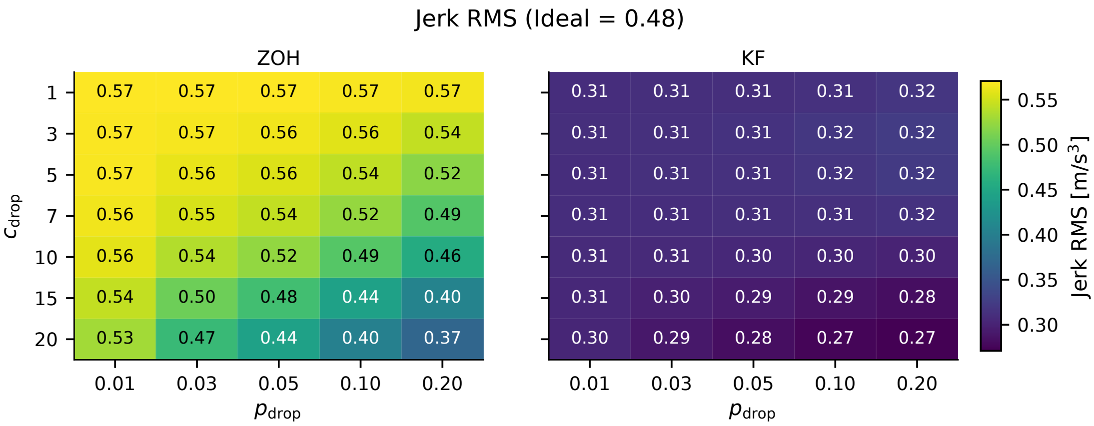


Figure 4: Comparison of jerk RMS for varying packet loss probability p_{drop} and consecutive packet loss length c_{drop} using the ZOH and KF estimator.

3.3 Energy Consumption

Energy consumption is calculated based solely on positive traction power, since no recuperation is considered. The results shown in Figure 5 indicate that ZOH approach tends to consume more energy than the KF approach, especially under sever packet loss conditions. This increase in energy can be is primarily caused by inefficient control actions. The use of stale measurements causes the controller to apply excessive traction force, followed by corrective braking, which leads to unnecessary energy expenditure.

4 Conclusion

This paper investigated the impact of measurement noise and packet loss on virtual coupling gap control and evaluated the effectiveness of Zero-Order Hold (ZOH) and Kalman Filter(KF)-based estimator.

The results show that packet loss degrades tracking performance significantly if state estimation is not used to infer the leader trains state during packet drop event. The KF improves tracking accuracy under low to moderate packet loss by providing

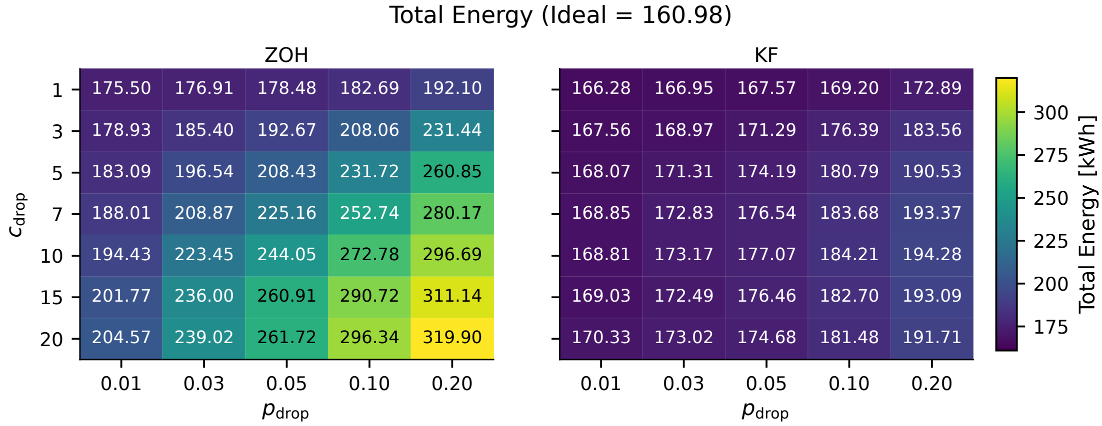


Figure 5: Comparison of total energy consumption for varying packet loss probability p_{drop} and consecutive packet loss length c_{drop} using ZOH and KF estimator.

continuous state estimation and reducing the sensitivity to measurement noise. However, under severe packet losses, the tracking performance diminishes due to mismatch in prediction over longer durations.

However, in comparison with ZOH, the KF approach consistently improves the control smoothness and energy efficiency, of the sliding mode gap controller, by reducing abrupt control action and unnecessary acceleration and braking cycles.

Overall, KF-based state estimation enhances the robustness of the gap controller against disturbances. However, in extremes cases of communication and sensing loss, state estimation alone is not sufficient to maintain reliable performance. This highlights the need for multiple redundant communication and ranging systems to reduce burst outages, improve accuracy and confidence in measured and estimated states.

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