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Summary of "Closed-loop Data-enabled Predictive Control and its Equivalence with Closed-loop Subspace Predictive Control"

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Abstract: Factors like growing data availability and increasing system complexity have sparked interest in data driven predictive control (DDPC) methods like Data-enabled Predictive Control (DeePC). However, closed-loop identification bias arises in the presence of noise, which reduces the effectiveness of obtained control policies. In our Automatica paper (Dinkla et al., 2026) we propose Closed-loop Data-enabled Predictive Control (CLDeePC), a framework that unifies different approaches to address this challenge. To this end, CL-DeePC incorporates instrumental variables (IVs) to synthesize and sequentially apply consistent single or multi-step-ahead predictors. Furthermore, a computationally efficient CL-DeePC implementation is developed that reveals an equivalence with Closed-loop Subspace Predictive Control (CL-SPC). Time marching simulations of DeePC and CL-DeePC are conducted using Hankel matrices of past data that are updated at every time step to induce potentially troublesome closed-loop correlations between inputs and noise. Compared to DeePC, CL-DeePC simulations demonstrate superior reference tracking, with a sensitivity study finding a 48% lower susceptibility to noise-induced reference tracking performance degradation.

The remainder of the document is a summary of the original Automatica article: Dinkla et al. (2026). This paper should be part of the the open invited track: Data-driven Methods in Control: Analysis, Feedback Design and Optimization (code: *qdnxh*)

OVERVIEW AND MOTIVATION

Recent trends in increasing data availability and growing system complexity have stimulated significant interest in data-driven control methods. Among these, Data-enabled Predictive Control (DeePC) has emerged as a powerful direct data-driven predictive control technique that bypasses explicit model identification by directly leveraging measured input–output data. DeePC relies on Willems' Fundamental Lemma, which states that for deterministic linear time-invariant (LTI) systems, sufficiently rich input–output data can parameterize all future trajectories.

However, when DeePC is applied in realistic scenarios involving noise and closed-loop data collection, its performance can degrade substantially. In particular, feedback introduces correlations between inputs and noise, leading to *closed-loop identification bias*. This bias causes predictors obtained from least-squares regression to become inconsistent, which in turn deteriorates closed-loop control performance. Since many practical systems require feedback for stabilization or safety, this limitation is fundamental rather than incidental.

The automatica paper addresses this challenge by proposing a novel framework called *Closed-loop Data-enabled Predictive Control (CL-DeePC)*, which systematically mitigates closed-loop identification bias while retaining the flexibility and non-parametric nature of DeePC.

PROBLEM FORMULATION

The objective of data-driven predictive control is to compute future control inputs by minimizing a cost function over predicted future outputs and inputs, subject to constraints. Achieving this objective requires accurate output predictions based solely on previously measured data. When the available data is noisy and collected in closed loop, standard DeePC predictors fail to remain consistent, meaning that their expected prediction error does not vanish as the amount of data increases.

The central problem considered in the paper is therefore the following: how to construct a *consistent, non-parametric predictor* for predictive control when only noisy closed-loop data is available. The focus is not on modifying the cost function or adding robustness heuristics, but rather on fundamentally eliminating the bias introduced by feedback.

KEY IDEAS BEHIND CL-DEEPC

The proposed CL-DeePC framework builds on two core ideas.

First, the authors exploit the fact that closed-loop identification bias arises primarily in multi-step-ahead prediction. When predicting only one step ahead, correlations between inputs and noise vanish for causal controllers without

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direct feedthrough. CL-DeePC therefore constructs long-horizon predictions by *sequentially applying single-step-ahead predictors*, rather than using a single multi-step predictor.

Second, instrumental variables (IVs) are introduced to further mitigate the effect of noise. Instrumental variables are auxiliary signals that are correlated with the regressors but uncorrelated with the noise. By incorporating IVs into the data equations underlying DeePC, the resulting predictors can be shown to be consistent even when the data is collected in closed loop.

Combining these two ideas leads to a new predictor formulation in which future outputs are expressed as linear combinations of past data using IV-weighted Hankel matrices, applied sequentially over the prediction horizon.

UNIFIED CL-DEEPC FRAMEWORK

The paper presents a unified formulation of CL-DeePC that encompasses several existing approaches as special cases. The framework allows the designer to choose:

- the length of the prediction step (single-step or multi-step),
- the number of sequential applications of the predictor,
- and the choice of instrumental variables.

Under suitable assumptions on data richness, system stability, and IV selection, the authors prove that the resulting predictor is consistent, meaning that the expected prediction error converges to zero as the amount of data grows.

This theoretical result establishes CL-DeePC as a principled solution to the closed-loop identification problem, rather than a heuristic modification of DeePC.

COMPUTATIONALLY EFFICIENT IMPLEMENTATION

While the unified CL-DeePC formulation introduces many optimization variables, the authors show that for a particular choice of instrumental variables, the predictor can be implemented very efficiently. In this case, the predictor reduces to a sequential one-step-ahead form that resembles classical innovation-based predictors.

By exploiting the block-lower-triangular structure of the resulting matrices, the predictor can be constructed recursively. This not only reduces computational complexity but also guarantees causality of the predictions, a property that standard DeePC does not enforce.

EQUIVALENCE WITH CLOSED-LOOP SUBSPACE PREDICTIVE CONTROL

A key contribution of the paper is the demonstration that, under specific design choices, CL-DeePC is mathematically equivalent to Closed-loop Subspace Predictive Control (CL-SPC). CL-SPC is an indirect data-driven control method that relies on subspace identification techniques to estimate predictor Markov parameters.

The authors show that when CL-DeePC uses single-step-ahead predictors and selects the past input–output data itself as instrumental variables, the resulting predictor is identical to that obtained by CL-SPC. This equivalence bridges the gap between direct data-driven control methods like DeePC and classical subspace-based approaches, allowing insights from both fields to be unified.

SIMULATION RESULTS

Simulation studies are conducted on a noisy, marginally stable fifth-order system. The experiments compare standard DeePC and CL-DeePC under fully adaptive operation, where data matrices are updated at every time step using closed-loop data.

The results demonstrate that CL-DeePC significantly outperforms DeePC in terms of reference tracking accuracy and robustness to noise. A sensitivity analysis shows that CL-DeePC exhibits substantially reduced degradation in performance as noise levels increase, confirming the theoretical consistency results.

CONCLUSION

The paper introduces CL-DeePC as a rigorous and unifying framework for data-driven predictive control with noisy closed-loop data. By combining sequential single-step-ahead prediction with instrumental variables, CL-DeePC eliminates closed-loop identification bias while preserving the flexibility of non-parametric control.

The established equivalence with CL-SPC provides theoretical grounding and connects direct and indirect data-driven control paradigms. Overall, the work represents a significant step toward reliable and theoretically sound data-driven predictive control in realistic closed-loop settings.

REFERENCES

Dinkla, R., Oomen, T., Mulders, S.P., and van Wingerden, J.W. (2026). Closed-loop data-enabled predictive control and its equivalence with closed-loop subspace predictive control. *Automatica*, 183, 112556. doi: https://doi.org/10.1016/j.automatica.2025.112556.