Model-Structured Neural Networks for Road Condition Identification in AI-Enabled Digital Twin Architecture

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Abstract— **Real-time identification of road conditions is essential for enhancing the performance, safety, and reliability of advanced vehicle control systems. In this work, we propose an AI-driven framework for road condition identification based on model-structured neural networks (MS-NNs), designed to support seamless integration within digital twin-enabled architectures. The proposed method relies on training multiple MS-NNs under different road conditions and performing online model selection based on real-time measured signals, enabling identification without explicitly estimating friction parameters. Within a digital twin context, this approach supports continuous synchronization between physical and virtual representations, enhancing predictive capabilities and system-level decision-making. Future work will focus on extending the integration of structured neural networks with the LuGre friction formulation and its nonlinear least squares (NLLS) structure. This includes replacing conventional parameter estimation techniques with `nnodely`-based learning approaches, with the goal of improving robustness, flexibility, and enabling easy integration within AI-driven digital twin ecosystems**

I. Introduction

The interaction between tyre and road strongly affects vehicle dynamics and the effectiveness of safety-critical systems such as traction and stability control. Real-time identification of road conditions is therefore essential for adapting control strategies and ensuring safe operation within cyber-Physical and digital twin systems [1], [2]. Classical approaches address this problem using parametric friction models such as Burckhardt and LuGre, typically identified through nonlinear optimization. In particular, nonlinear least squares techniques combined with trust-region strategies are widely used for LuGre-based formulations [2]. However, these methods often require strong assumptions, sufficiently excited conditions, careful tuning, and may be sensitive to measurement noise [3]. Purely data-driven neural networks have also been explored, but standard black-box architectures often require large datasets and may struggle to generalize outside training conditions.

In this work, we propose an AI-driven framework for road condition identification based on MS-NNs. The approach combines prior physical knowledge of vehicle longitudinal dynamics with data-driven learning components, enabling accurate modeling under limited data availability while preserving interpretability and consistency. The proposed method relies on training multiple MS-NNs under different road conditions and performing online model selection based on real-time measured signals. This strategy enables the identification of current road conditions without explicitly estimating friction parameters, thereby reducing computational complexity and improving adaptability in real-world scenarios.

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II. Methodology

The proposed approach builds upon MS-NNs to model vehicle longitudinal dynamics under different road conditions. The MS-NNs are implemented using the `nnodely` an open source framework available on github.com/tonegas/nnodely, which facilitates the incorporation of physics-based models into neural network structures, thus promoting interoperability and reliable interaction between multiple system components. Each MS-NN combines a model-based part derived from physical equations of motion and a data-driven part that captures effects not explicitly modeled. This structured design preserves physical relationships while maintaining flexibility, leading to improved generalization and sample efficiency [4]. The overall framework can be interpreted as a collection of structured models, each associated with a specific road condition hypothesis.

During the offline phase, multiple MS-NNs are trained using datasets collected under different road conditions (e.g., dry, wet, snowy, and icy surfaces), where each network specializes in a specific operating condition. Each network learns the mapping between measurable inputs (e.g., vehicle speed, brake input, engine torque, and road slope) and the resulting longitudinal acceleration [4]. The use of structured architectures enables accurate learning even with limited datasets. Multiple specialized models are trained offline and later evaluated in parallel during operation to determine the most consistent representation of the current road condition. Fig. 1 shows the results of the evaluation of road condition identification using the proposed model selection approach in a given scenario. At runtime, the framework uses prediction consistency to identify which model best explains the observed vehicle behavior, avoiding explicit friction estimation (See link for details). To better illustrate the internal structure of each model, Fig. 2 shows the model-structured architecture adopted in this work. The framework

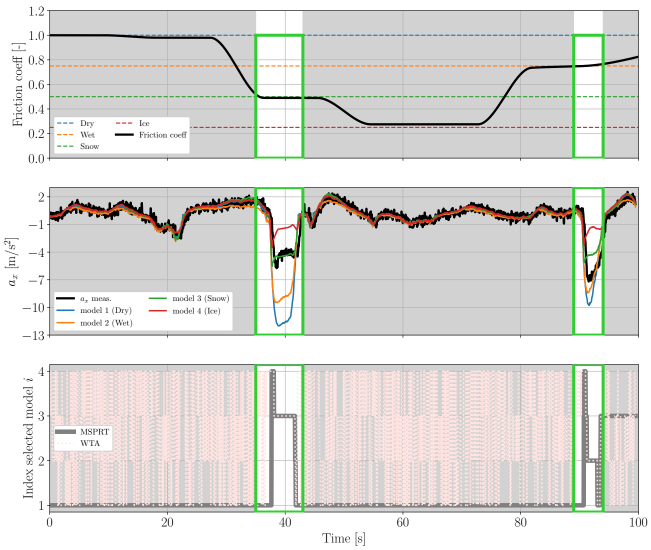

Fig. 1. Results for road condition identification using the proposed model selection approach in a test scenario in a green-highlighted period of reliable identification. The last picture shows the index of the identified model, where 1 represents dry, 2 wet, 3 snow, and 4 ice asphalt conditions.

follows a digital twin perspective, where physical modeling components are combined with data-driven elements to capture both known dynamics and unmodeled effects. The physical model captures the main vehicle longitudinal dynamics, while additional learnable blocks compensate for unmodeled effects and uncertainties. In particular, the model-based component encodes known relationships between inputs and outputs, whereas the data-driven part refines the prediction by learning residual dynamics. This separation allows maintaining physical consistency while improving accuracy. In the online phase, all trained MS-NNs are evaluated in parallel using real-time measurements. Road condition identification is performed by comparing the measured vehicle signals with the predictions generated by each MS-NN. The model whose predictions are most consistent with the observed data is selected as representative of the current road condition, enabling a lightweight and scalable real-time implementation.

III. Conclusion and Future Work

The proposed approach highlights how structured neural architectures can bridge the gap between model-based and data-driven methods. Compared to classical parameter estimation techniques, the method avoids solving nonlinear optimization problems online, reducing computational complexity and sensitivity to initialization, while the integration of physical knowledge improves generalization and robustness. In addition, shifting the complexity to the offline training phase enables efficient real-time deployment. This work presented an AI-driven framework for road condition identification based on MS-NNs, implemented using the `nnodely` environment, with a perspective toward integration within digital twin-enabled systems. The proposed approach avoids explicit friction parameter estimation and instead relies on structured learning combined with model consistency to identify road conditions in real time, resulting in a flexible and efficient solution that leverages both physical knowledge and data-driven adaptation. A key direction for future work is the integration of this framework with the LuGre friction formulation and its nonlinear least squares (NLLS) structure. In particular, we aim to incorporate the LuGre model within the `nnodely` environment, replacing traditional parameter estimation techniques based on nonlinear least squares and trust-region optimization [2], with learning-based alternatives that are better suited for scalable and adaptive system integration. Within an AI-driven digital twin perspective, the learnable structure of MS-NNs can be exploited to approximate or replace the estimation of LuGre parameters, enabling continuous synchronization between physical systems and their virtual counterparts. This hybrid approach preserves physical interpretability while improving robustness, reducing sensitivity to noise, and supporting adaptive behavior under varying operating conditions. Overall, this integration represents a promising step toward standardized methodologies for unifying model-based and learning-based approaches in friction estimation and vehicle dynamics, contributing to the development of reliable, efficient, and interoperable intelligent systems.

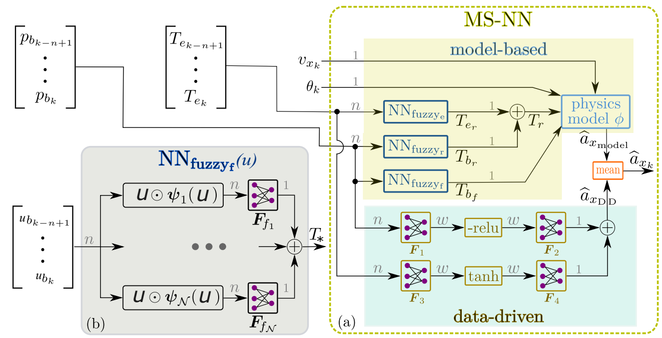

Fig. 2. (a) Architecture of the proposed MS-NN for learning vehicle longitudinal dynamics. (b) Local neuro-fuzzy models for estimating the front brake torque.

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