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Application of neural networks in vehicle simulation as a substitute for driver models

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Abstract

The development and optimization of vehicle simulation models is essential for the virtual validation of new features during vehicle development. New challenges are emerging that require the application and use of innovative solutions. The use and development of artificial intelligence methods can accelerate development processes, which will require a broader investigation of their feasibility. This paper explores the potential of applying a neural network based technology to a driver model within a vehicle simulation instead of the traditional proportional-integral (PI) control methods. The artificial neural network applied here can learn the driving style of the driver and can be used in both simulation and virtual testing scenarios. The aim of this paper is to demonstrate the use of neural network to replace the PI controller throttle signal in a vehicle simulation driver model. In this novel approach, the artificial neural network can learn real driver behavior resulting in a more realistic driver model in vehicle simulation further advancing the accuracy of the simulation.

Keywords

vehicle simulation; neural network; validation; artificial intelligence; virtual test environment; development; vehicle simulation.

1. Introduction

The use of Artificial Intelligence (AI) is vital for contemporary technological progress, particularly in sectors where rapid and efficient development and testing processes are resource-intensive. Digital development enables us to expand our experiential knowledge in most areas of our lives (Zöldy et al., 2022). Tollner et al. (2019) describe an application example in the development of autonomous vehicles, where artificial intelligence assists in decision-making. AI-driven solutions present new opportunities in vehicle simulation development (Rana and Khatri, 2024; MacAdam et al., 1998; Tselentis and Papadimitriou, 2023). Currently, conventional simulation systems demand a significant amount of time and resources. Experimentation under complex conditions and the creation of realistic models present various challenges. AI-enhanced vehicle simulations can be highly effective as these systems can discern intricate patterns and forecast future events (Hermansdorfer et al., 2020; Huang et al., 2018). Artificial intelligence is recognized as a forward-looking technology for improving rail transport, where a key focus is increasing efficiency (Ficzere, 2023). Artificial neural network-based models are reliable and accurate, and accelerate the vehicle development process by making driver models life-like and which act as the real driver of a vehicle. It is possible to train neural networks for different driving styles, making this way of model definition suitable for advancing sustainable development processes.

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A crucial aspect of driving simulation is adjusting the accelerator pedal position, as throttle control is fundamental to driving dynamics. Neural networks enable the identification of complex patterns and allow for reliable data-driven predictions (Conley et al., 2001). Traditionally, vehicles employ Proportional-Integral Controllers for acceleration and deceleration commands (Ioannou and Xu, 1994). However, the rise of AI is paving the way for new control system methodologies, facilitating more sophisticated and adaptive solutions (Lee and Choi, 2021).

MATLAB's Neural Fitting tool is especially suited for learning and optimizing neural networks, predominantly for regression tasks. The focus is to achieve the best possible alignment of input data with output values for driving behavior. When constructing the model, it is crucial to implement the appropriate control mechanisms, as this significantly influences the reliability and precision of the results. If the accelerator pedal signal is generated by neural networks, the vehicle simulation model effectively serves as a substitute for a PI controller, meaning that the model's control is governed by the neural network.

The use of hybrid models in vehicle dynamics simulations presents a significant professional challenge, as they necessitate validation through real measurement data. To facilitate this, the MATLAB Simulink environment offers a highly adaptable toolbox for modeling complex systems, which enhances the design and implementation of simulation models.

This paper demonstrates the functionality of a vehicle simulation model that incorporates a neural network, detailing the learning process and the method for generating the throttle signal. The vision is to replace the traditional accelerator pedal signal, typically driven by a PI-controller, with a neural network in the vehicle simulation model.

2. Methodology

Neural networks are capable of complex pattern recognition and prediction. Building on this capability, the position of the accelerator pedal in the vehicle simulation driver model was first determined, which was examined using a forward-looking simulation method. The term *forward-looking simulation* refers to an approach used in vehicle dynamics studies. This method essentially serves to compute and model the dynamic behavior of various components of a vehicle, such as engine, transmission, final drive, and other various components of the drivetrain (Pettersson et al., 2020). The advantage of forward looking – closed-loop – simulations is that they allow for complex examination and optimization of various parameters and input signals without the need for expensive and time-consuming physical testing. MATLAB Simulink was used for setting up the vehicle simulation model. MATLAB Simulink is an integrated environment that facilitates the modelling and simulation of different dynamic systems..

Based on real-world vehicle measurements conducted on public roads, a vehicle drive cycle of 857 seconds was created, utilizing a real hybrid vehicle. The internal combustion engine of the vehicle was a two-liter, four-cylinder, 110 kW engine that operates in conjunction with a 75 kW electric motor. The vehicle's curb weight was 1950 kg without the driver. The vehicle featured a parallel hybrid configuration, allowing the internal combustion engine and the electric motor to operate either together or independently, thereby optimizing performance and efficiency. The vehicle measurements were carried out at an ambient temperature of approximately 18.75 degrees Celsius, starting from the outskirts and arriving at the center of Győr, Hungary. Among the data obtained from the road measurements, the vehicle speed is provided as an input for the vehicle simulation model. The vehicle's operating modes (electric, hybrid, or pure internal combustion engine), the torque values for the internal combustion and electric motors, and the gearbox gear number have been specified based on calculated values and a look-up table. The dynamics of the vehicle have been parameterized using mathematical equations.

The application of the neural network in the vehicle simulation model began with the training of the neural network. The first step involved determining the input parameters of the training data set, which contains data collected under various driving scenarios. In the driver model, four input parameters (vehicle speed, transmission gear number, vehicle acceleration, and engine RPM) and the target variable (gas pedal position) were trained (Figure 1). The values of the gas pedal position generated by the PI controller from the vehicle simulation model were used for the training of the neural network. In the Matlab Simulink environment, it is necessary to provide the model with an environment that allows the neural network building block to have uninterrupted access to the input data used to run the model. Therefore, the PI controller and the ANN model were run concurrently.

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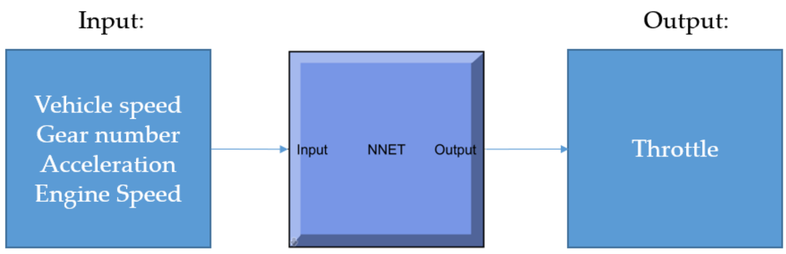

Figure 1. Neural network input and output parameters.

In the vehicle simulation's driver model, the accelerator pedal position was generated by the PI controller to train the neural network, as reintegrating it into the model allows for a clear assessment of the predicted outcomes' value. The brake pedal's function continued to be controlled by the existing PI controller established in the original model, as in this study the focus was on accelerator pedal signal only. Subsequently, the neural network was integrated into the existing simulation environment (Figure 2), where vehicle performance was analysed. The next step involved further fine-tuning the parameters of the neural network to optimize its performance.

By utilizing the MATLAB Neural Fitting toolbox and providing the input parameters, it was possible to determine the target value based on the results generated by the vehicle simulation model. In the subsequent process, the Neural Fitting tool (nftool) was used for setting the ratio of validation and testing data to 15%. The number of the neurons in the single hidden layer was set to 10 that allowed for the optimization of the model's complexity.

For selecting the learning algorithm, the Levenberg–Marquardt method was used, as this technique is well-known for its fast convergence and precise optimization in the training of neural networks. As a next step, a Simulink diagram was generated, which was integrated into the base model. This step enabled the execution of enhanced simulation.

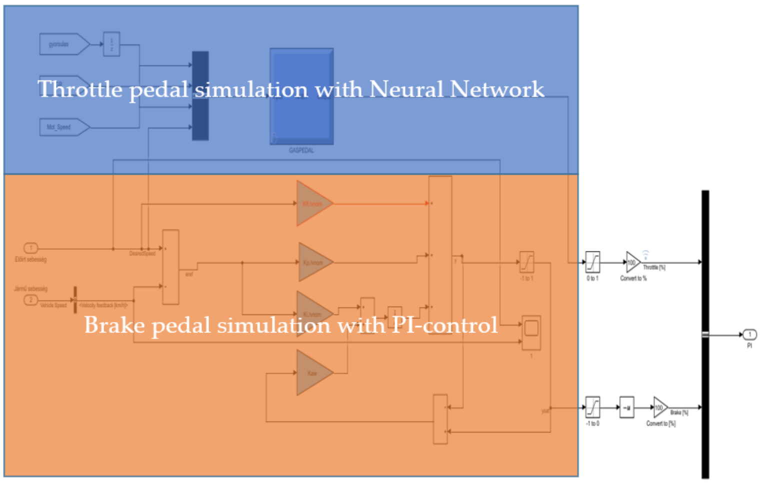

Figure 2. Application of Neural Networks in Driver model.

In summary, the main steps for working with neural networks in the vehicle simulation model are as follows:

- refinement of the vehicle simulation model for training;
- execution of the vehicle simulation and processing of the resulting data;
- training the neural network with the data;
- implementation of the neural network component into the model;
- running the neural network model;
- evaluation, analysis, and comparison of the vehicle simulation model enhanced with the neural network.

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3. Results and discussion

Upon completing the model development, a comparison was made between the driver model created using the new modelling technique and the original driver model used in the vehicle simulation. In simpler terms, the generation of the throttle position was replaced in the original vehicle simulation model by the artificial neural network (ANN) based driver model. Thus, the two different models were compared under the same boundary conditions. It is noteworthy that the engine and electric motor speeds depend on the transmission gear, and an agreement of engine and electric motor speeds were matched as well as the control strategy of the hybrid system.

The results of the simulation were compared to real life measurements for validation purposes. With the application of the new modelling technique, an investigation was conducted to verify the correct functioning of the ANN-based throttle position generation. The results corroborated with the satisfactory performance of the new type of modelling, which is illustrated in Figure 3. The figure displays the vehicle speed as a function of time. Values marked in blue represent the vehicle simulation results operated by the original model, while those in green show the results generated using artificial neural networks.

The comparison between the two driver models not only attracts scientific interest but also contributes to a deeper understanding of driver's behavior and the development of modelling techniques. The Root Mean Square (RMS) was calculated for both vehicle simulation models. The basic model showed an RMS value of 0.776, while the calculation using the new method yielded an RMS value of 0.7411, reflecting the discrepancies between the target speed and the vehicle speed calculated by the simulation.

It is noticeable that throughout the entire simulated period, the new method produced throttle position values corresponding to the required vehicle speed with smaller errors (0.03 RMS value). During the investigation, the hybrid control strategy, as well as the engine speeds and gearbox numbers, were reviewed, demonstrating consistency in both models.

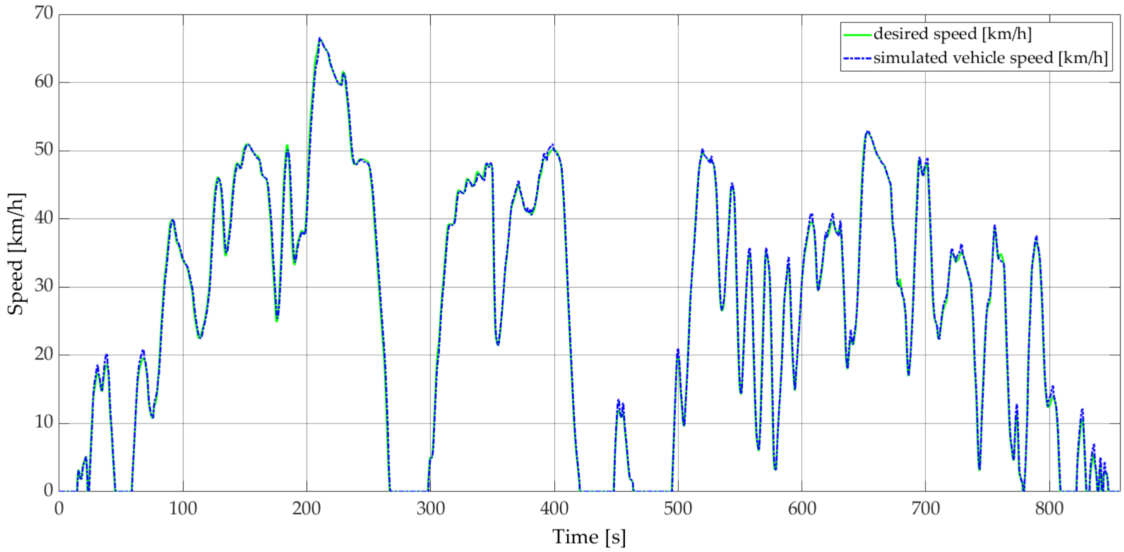

Figure 3. Vehicle speed reached using the PI-based driver model and the ANN-based driver model.

The neural network is capable of responding accurately to unexpected environmental changes and complex driving situations, similarly to traditional PI controllers. The results also indicate that neural networks can learn from the dynamics of the vehicle, thereby autonomously improving the system's efficiency.

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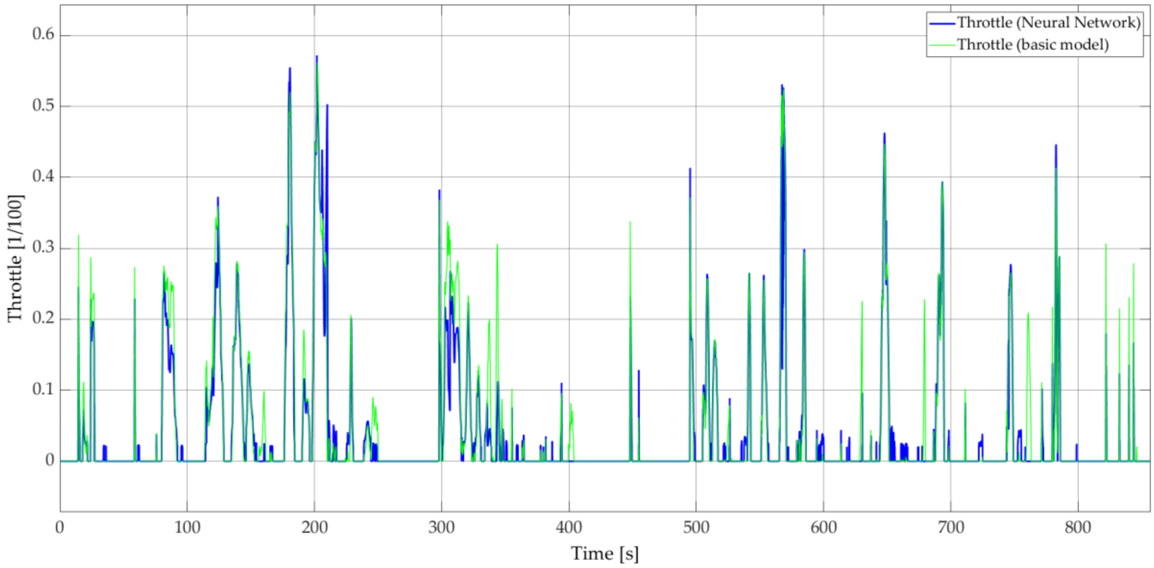

Figure 4. PI-based model and ANN-based driver model generated gas pedal values.

4. Conclusion

This vehicle simulation example is an excellent illustration of how modern AI-based simulation techniques can contribute to the success of automotive developments. Such simulation techniques provide opportunities to optimize vehicle performance while reducing cost and time investment during the development process. Generating gas pedal signals with neural networks can revolutionize vehicle simulation driver modelling, allowing for enhanced control and increased adaptability to real life situations.

In summary, replacing the PI based driver model with a neural network based one in a vehicle simulation model presented an error in RMS values of 0.03, showing that this method can be advantageous in the field of vehicle modelling. This can be used in numerous areas of development such as vehicle architecture and control strategy optimization, as well as performance, fuel consumption, and emissions optimization. This method offers avenues for future advancements, such as more refined and safer control of autonomous vehicles as well. Further research should explore additional refinement opportunities during vehicle development to better leverage the potential of neural networks in the automotive industry.

Replacing the traditional PI-based driver model with a neural network based one presents a practical example in the development of vehicle simulation systems, paving the way for dynamic and intelligent control strategies. Compared to PI controllers, this approach does not only improve performance but also contributes to the development of more sustainable and innovative transportation systems.

The example of hybrid modelling in vehicle dynamic simulation raises several issues that developers encounter, even if the course of development shifts in other directions. The proposed solution is applicable in any vehicle technology environment. Therefore, the application of artificial networks represents an exciting and rapidly evolving field, offering numerous research and development opportunities. Projects of this nature contribute to the innovation and efficiency of future transportation systems.

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