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# Predicting the Torque Demand of a Battery Electric Vehicle for Real-World Driving Maneuvers Using the NARX Technique

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**Abstract:** An identification technique is proposed to create a relation between the accelerator pedal position and the corresponding driving moment. This step is beneficial to replace the complex physical model of the vehicle control unit, especially when the sufficient information needed to model certain functionalities of the vehicle control unit are unavailable. We utilized the nonlinear autoregressive exogenous model to regenerate the electric motor torque demand, given the accelerator pedal position, the motor's angular speed, and the vehicle's speed. This model proved to be extremely efficient in representing this highly complex relationship. The data employed for the identification process were chosen from an actual three-dimensional route with sudden changes of a dynamic nature in the driving mode, different speed limits, and elevations, as an attempt to thoroughly cover the driving moment scope based on the alternation of the given inputs. Analyzing the selected route data points showed the widespread coverage of the motor's operational scope compared to a standard driving cycle. The training outcome revealed that linear modeling is inadequate for identifying the targeted system, and has a substantial estimation error. Adding the nonlinearity feature to the model led to an exceptionally high accuracy for the estimation and validation datasets. The main finding of this work is that the combined model from the nonlinear autoregressive exogenous and the sigmoid network enables the accurate modeling of highly nonlinear dynamic systems. Accordingly, the maximum absolute estimation error for the motor's moment was less than 10 Nm during the real-world driving maneuver. The highest errors are found around the maximum motor's moment. Finally, the model is validated with measurements from an actual field test maneuver. The identified model predicted the driving moment with a correlation of 0.994.

**Keywords:** torque demand; electric vehicle; real-world driving maneuver; NARX; neural network; machine learning



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## 1. Introduction

Empirical modeling approaches, such as black-box model identification, differ from theoretical ones. The creation of empirical models only requires measurement data of the system plant, which means modeling, especially for complex systems, can be carried out with less effort and in a shorter time than theoretical models. The comprehensive expertise necessary for creating a physically based theoretical model is not mandatory for empirical modeling. Another advantage is that the evaluation of empirical models often requires less computing time than that of physical models, which is particularly important for optimization processes requiring computational effort. A disadvantage of empirical models compared to physical models is that they do not provide direct knowledge regarding the effects of influential design factors of the powertrain [1,2].

Polynomial models are characterized by their ease of implementation and low computing time requirement for model creation. They are the most straightforward model approach and the standard model of empirical modeling [2]. Polynomial models are represented as a linear combination between regressors and coefficients. Regressors are mathematical expressions of the model inputs, usually in multiplication or exponentiation forms. Polynomial models have linear coefficients and, therefore, are characterized as linear models. The term “linear” describes the connection between the coefficient and prediction space, not the input and output variable space. Continuous differentiable nonlinear system models can be attained based on polynomial models [1].

Nonlinear regression models are generally used when polynomial models cannot adequately describe the system to be modeled. A widely used approach is artificial neural networks (ANNs), whose model structure is derived initially from biological structures within the brains of humans or animals [3]. This machine learning technique can be combined with other methods to improve the overall modeling accuracy. Artificial neural networks are capable of modeling any nonlinear mapping between several variables. Because of this feature, ANNs are used in diverse fields such as system identification, function approximation, pattern classification, regression, classification, clustering, and optimization. However, ANN performance degrades when the system contains unknown delays. The nonlinear autoregressive exogenous model (NARX) generally uses ANN internally for time series prediction applications [4]. Introducing the concept of feedback into the network provides a solution for modeling such systems accurately. The NARX networks integrate feedback between the output and input layers, which makes them a perfect choice for system identification with time delays. This property increases ANN performance, reduces the number of training data samples, promotes early convergence, and reduces error. Despite the advantages of NARX networks, they come with the price of increased complexity [5,6].

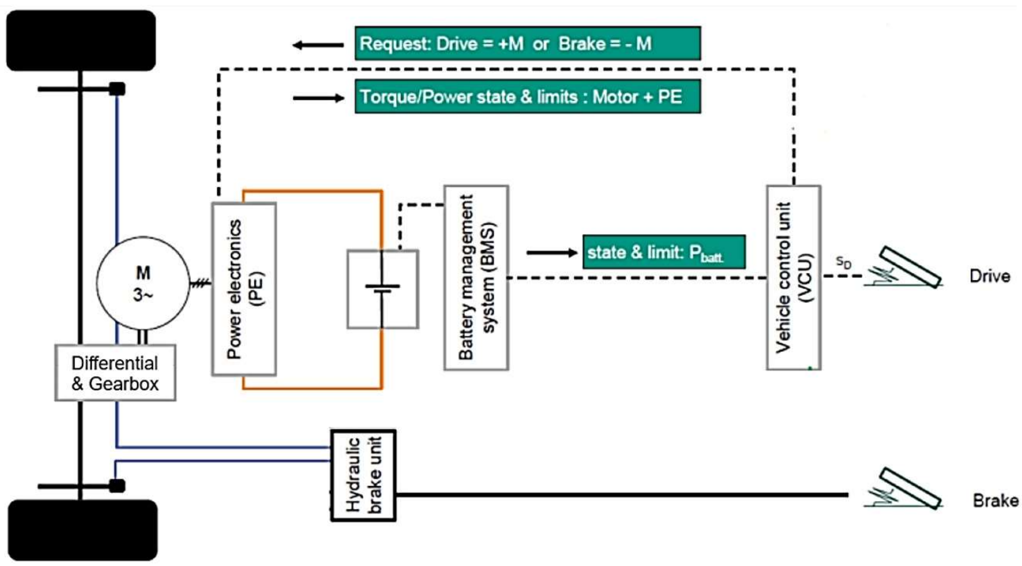
Due to their reduced computational effort, cost effectiveness, and compact structure, the ‘machine learning’ techniques are becoming one the most popular approaches for performing prediction activities, especially in the automotive industry [7]. Among the machine learning approaches, NARX modeling is a promising method for estimating the nonlinear dynamic system of the internal combustion engine (ICE) torque [7–9]. For instance, the study in reference [10] investigated different intelligent modeling techniques, specifically, the NARX neural network, linear regression, and regression error with the autoregressive moving average, for modeling a diesel engine truck’s fuel consumption and emissions. The results showed that the NARX method led to the best accuracy compared to the other methods.

The NARX network was proven to be more capable of learning long-term dependencies than the static neural network. Moreover, it proved to be a promising technique for the online recognition of different automotive applications under real driving conditions. The NARX network was applied as a dynamic neural network with feedback and memory functions to characterize the brake intensity influenced by the driver’s sequential actions, demonstrating long-term dependencies. The braking moment values are significantly related to the driver’s behavior and driving maneuvers [11]. Moreover, the authors of [12] used a neural network to model different systems in an autonomous vehicle: the steering, acceleration, and braking systems. The neural network model efficiently tracked the target data. As a comparison, they identified the acceleration system using the NARX method but achieved less accurate results. A computationally efficient NARX ANN model was developed in [13] to describe highly nonlinear thermally sensitive hydraulic dampers for the virtual tuning of high-frequency loading passive suspension systems. A computationally physical damper model with high accuracy is used to assist with the development of the NARX model. Furthermore, an integrated time series model was developed based on multivariate deep neural networks with long short-term memory units [14]. This approach was used to estimate the dynamic brake pressure of electric vehicles (EVs). It was also found that NARX approaches perform better than other methods, such as linear regression and support vector regression prediction methods, making the NARX model an efficient ANN method for predicting nonlinear systems.

Developing torque demand predictive models became a helpful approach toward accurate energy consumption estimation during actual driving routes [14–17]. The behavior of a separately excited DC motor in the paper in reference [4] is recognized using NARX neural networks. The system identification and controller design developed based on the NARX neural networks presented a remarkable ability to rapidly track the set point variations. NARX can characterize the torque of induction machine (IM) motors as part of an electric powertrain [18]. The testing data for the NARX model were generated using a model-based EV model, and the results were validated with the data from virtually performing the WLTP standard driving cycle. Still, the ability to predict the torque demand of an electric powertrain for dynamic real-world driving maneuvers was not investigated thoroughly, which will be the focus of this study.

This work proposed a NARX sigmoid model to interpret the driving moment from the accelerator pedal position, implementing single hidden layer sigmoid networks similar to those applied in [19,20]. Besides the accelerator position value, additional quantities are required to estimate the corresponding moment, which are the electrical motor angular speed and the vehicle speed. Figure 1a shows the vehicle under test (VUT). A simplified representation of the control unit functions influencing the transmission behavior between the accelerator pedal and the electric motor is illustrated in Figure 1b. The regenerative braking system is not considered in this work.


(**a**)




(**b**)

**Figure 1.** Vehicle under test (**a**), the actual vehicle used for the field test; (**b**) schematic for the interfacing systems between the accelerator pedal and the electrical motor of the test vehicle [21].

Actual measurements from a maneuver test using this vehicle will be employed to validate the proposed identification model. The vehicle's motor is powered by alternating current (AC), delivered from the power electronics (PE) that convert the battery's direct current (DC). The battery management system (BMS) manages the processes of battery discharging and charging. The torque demand command is determined according to the actuation of the accelerator pedal. The chain of events begins with a sensor detecting the accelerator pedal angle. The digitized accelerator pedal percentage value ($S_D$) is the input variable of the vehicle control unit (VCU). An output of the VCU system is the value by which the maximum available motor torque is determined under given boundary conditions. The driver's desired moment that is determined is the basis for calculating the final driving moment ($M_{drive}$). In addition to the driver, auxiliary units, vehicle dynamics control systems, and control unit functions for components, further modifications can be placed on the VCU, which are checked for plausibility and consider the electrical motor's target moment formation. Additional control unit functions are activated during dynamic driving maneuvers to increase driving comfort. They are called comfort functions because they aim to increase the subjective driving comfort. These comfort functions also change or shape the desired motor moment. Different comfort functions are necessary depending on the drivetrain configuration [1].

## 2. Nonlinear Autoregressive Exogenous Model

Nonlinear regression models are generally used when linear polynomial models cannot adequately describe the targeted system behavior. NARX is one of the most popular model identification types in different industrial applications [8]. The NARX network, shown in Figure 2, displays nonlinear mapping with a sigmoid activation function.

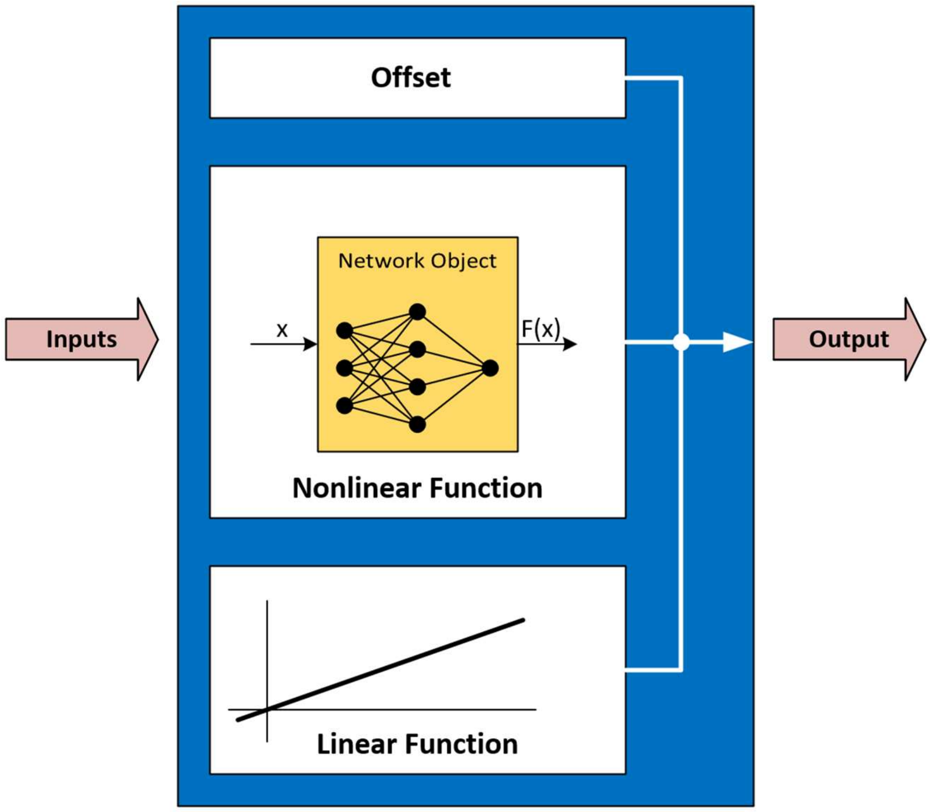



**Figure 2.** Mapping function for NARX network (https://www.mathworks.com/help/ident/ref/idneuralnetwork.html?s_tid=srchtitle_site_search_1_idNeuralNetwork, accessed on 10 February 2024).

The mapping function implements a combination of an offset, linear weights, and a nonlinear function in parallel to estimate the output [19,22]. The nonlinear function contains the sigmoid unit functions. An NARX model contains model regressors and an output function. The output function includes mapping objects; each model output has a single mapping object. The mapping object is selected as a sigmoid network. The block diagram illustrated in Figure 3 represents the arrangement of a single-output NARX model. The NARX model output $y$ is computed in two stages: Firstly, the regressor corresponding values from the current and past input data and the past output data are calculated. Secondly, the regressors are mapped to the output model by applying an output function block. The parameters of the NARX model are a collection of parameters of the offset, the linear function, and the nonlinear function. The modeling approach implemented in this work is incremental: First, a linear three-input, single-output model for the torque dynamics is estimated. Then, the NARX model is created by extending the linear model by adding a single hidden layer, a sigmoid network, in a parallel configuration.

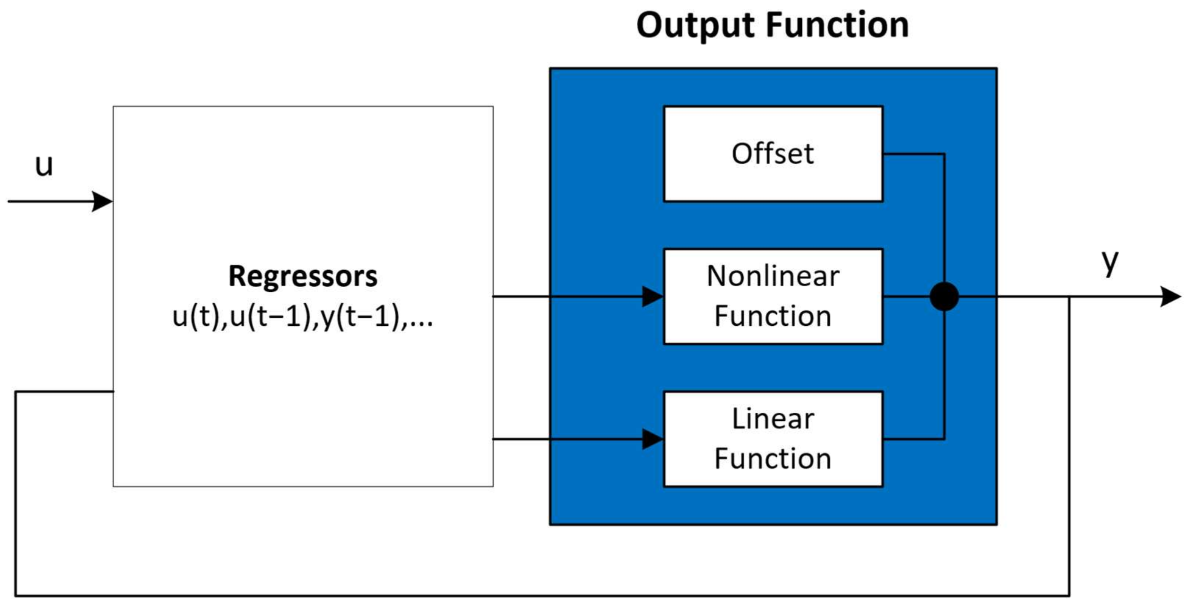


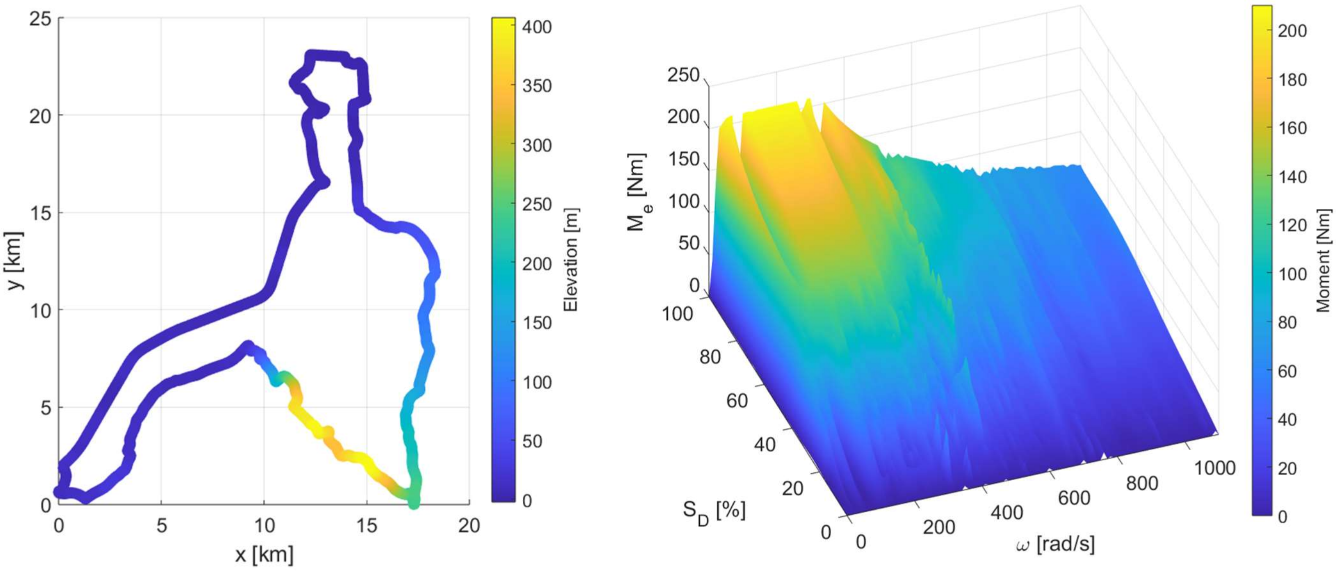

**Figure 3.** Schematic for the NARX model (https://www.mathworks.com/help/ident/ref/idnlarx.html?s_tid=doc_ta, accessed on 10 February 2024).

## 3. Training the NARX Model Using Real-World Route Data

The NARX model training process is equivalent to the optimal mapping between the current inputs and the next step prediction [23]. The validated VUT model will generate the necessary data for the empirical model. Consequently, simulation data for selected driving maneuvers will used instead of recording measurement data for the VUT to identify the NARX model. The simulation model of the VUT includes a three-dimensional body dynamics model, an empirical tire model, and a detailed electric powertrain model. Furthermore, the model is parameterized according to the VUT technical data. Finally, the proposed powertrain model is incorporated with a real-world simulation environment to create the corresponding physical quantities for the driving scenario.

Selecting a proper test maneuver to source the training or validation data should consider covering as many operating points as possible. This helps obtain sufficient information about the system's behavior with as little test effort as possible [1,7]. Based upon that, a real-world driving (RWD) scenario is implemented using a simulation model for the VUT, which was validated in a previous work [16]. This driving scenario starts in Karlsruhe, Germany, with traffic elements like other vehicles and traffic lights. Then, the test vehicle drives further to the suburban areas. After that, it takes place on the highway, where the speed reaches the maximum. Finally, the test vehicle returns to the starting point to complete a closed lap route. Figure 4a demonstrates the driving path. The route has a three-dimensional profile. It covers a long driving distance and various elevation heights that reach more than 400 m above sea level. It is expected, therefore, that the powertrain of the test vehicle will undergo dynamic driving resistance along the route, which includes straight and curved roads, uphill and downhill roads, and acceleration and deceleration.

Figure 4b shows a surface plot for the simulated pedal position ($S_D$), the average angular speed of the driving wheels ($\omega$), and the motor's estimated moment ($M_e$). This figure reveals several details: First, the complete range of each quantity is covered. Second, the moment decreases with the speed, as expected from the electric motor characteristics, as the maximum motor's power is reached. Third, the powertrain components' nonlinearity displays highly nonlinear behavior in the resulting motor's moment. The moment of an ICE was evaluated in [1] by the delivery of the percentage of the pedal value pressing during the driving maneuver. Other influencing factors are the motor's angular speed and the vehicle's speed. Likewise, the exact quantiles will be used to identify an NARX model for the electric motor moment. However, the training and validation data implemented in this work are more dynamic, which makes it even more challenging. It is worth noticing from Figure 4b that the selected maneuver has indeed covered a large amount of the scope of the overall *Me* operating points. However, some missing data appear as gaps in the surface plot. This issue could be an interesting topic for future work.




(**a**) (**b**)

**Figure 4.** Real-world driving (RWD) route: (**a**) route profile; (**b**) accelerator pedal position vs. angular speed vs. motor's moment during the RWD maneuver.

Figure 5 shows the simulation of the quantities corresponding to the driving route, including the inputs $V_x$, $S_D$, and $\omega$, and the only output, $M_e$. The maneuver lasts for 5600 s, and the data samples are taken with a sampling time of 0.1 s, which yields 56,000 training data samples. The implemented data are based on a predefined path, which needs to be prepared before performing the test run. An improvement to this approach would be integrating a path optimization algorithm so the vehicle could plan the path autonomously, as in [24].

The profile shapes of $V_x$ and $\omega$ seem analogous, so it might be assumed that having one would be sufficient. Nonetheless, subtle but significant variations manifest by correlating $V_x$ and $\omega$, as in Figure 6. The differences are significant at rotational speeds of less than 450 rad/s. Moreover, the data points are not aligned for $V_x$ and $\omega$ at higher speeds.

The dark green areas in Figure 7a,c represent the intersection between $S_D$ and $M_e$. The dissimilarity in the data distribution between $S_D$ and $M_e$ proves that $M_e$ cannot be predicted with $S_D$ alone. Another important observation in Figure 7 is the larger area of operating points covered by the RWD compared to the Artemis cycle, which proves that even dynamic standard driving cycles do not provide enough data to accurately identify the motor's moment, although they might cover the whole speed range of the VUT. For instance, Figure 7d shows that the maximum $S_D$ value recorded during the Artemis cycle is 77% and the maximum $M_e$ is 109.55 Nm, while the RWD maneuver stimulated the coverage of the whole range for both $S_D$ and $M_e$, as shown in Figure 7b. On one hand, the complete dataset is used to identify the NARX model. On the other hand, the validation dataset is the Artemis driving cycle for highways with a maximum speed of 130 km/h, selected due to its dynamic features. The schematic diagram in Figure 8 demonstrates the identification process of the NARX model.

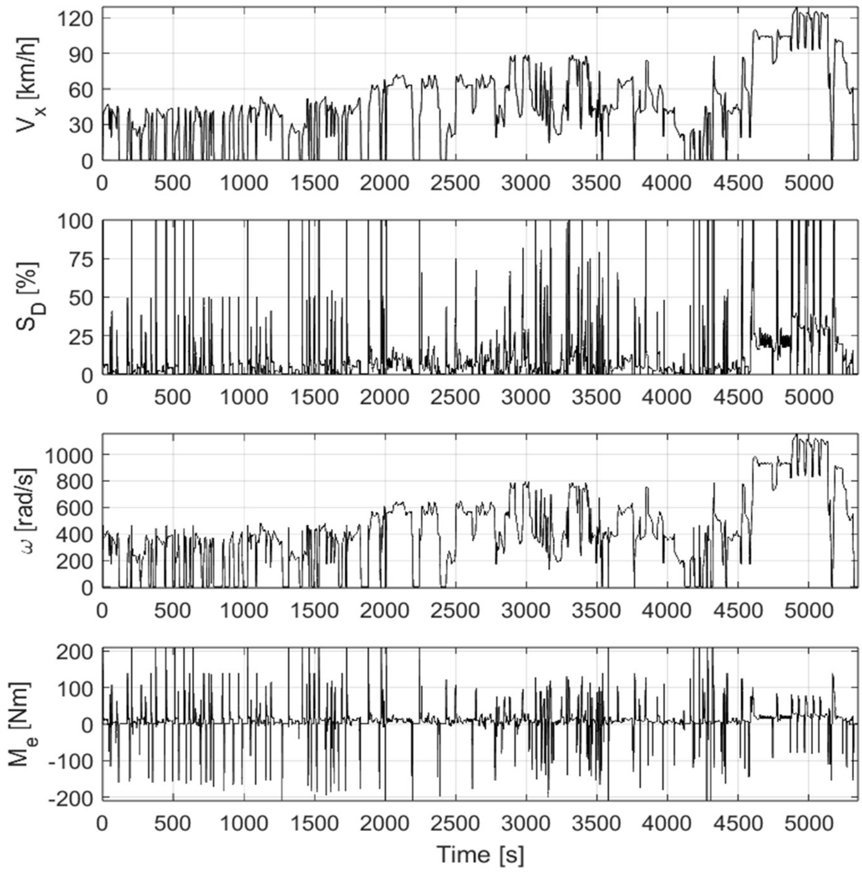



**Figure 5.** Simulated data corresponding to the real-world driving maneuver, including the vehicle's speed, accelerator pedal percentage actuation, wheels' average angular speed, and the electrical motor moment.

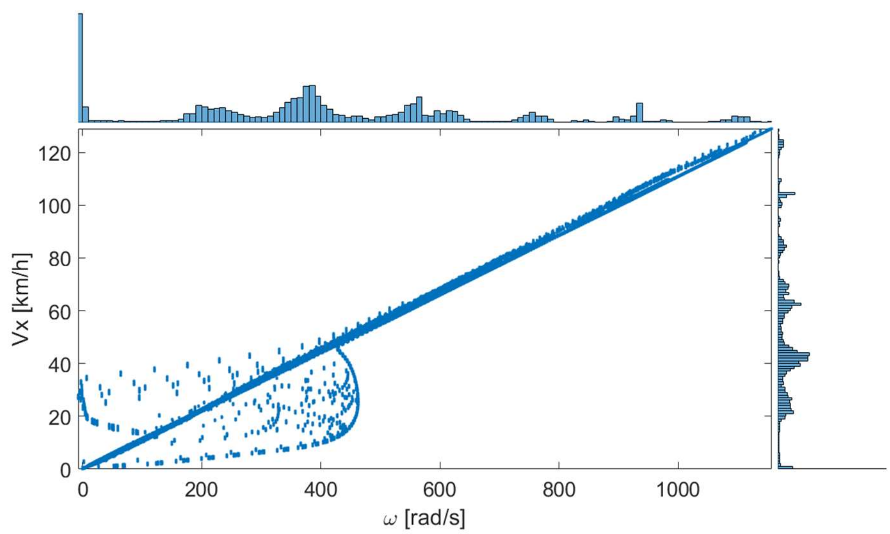



**Figure 6.** Comparing $V_x$ and $\omega$ data distribution.

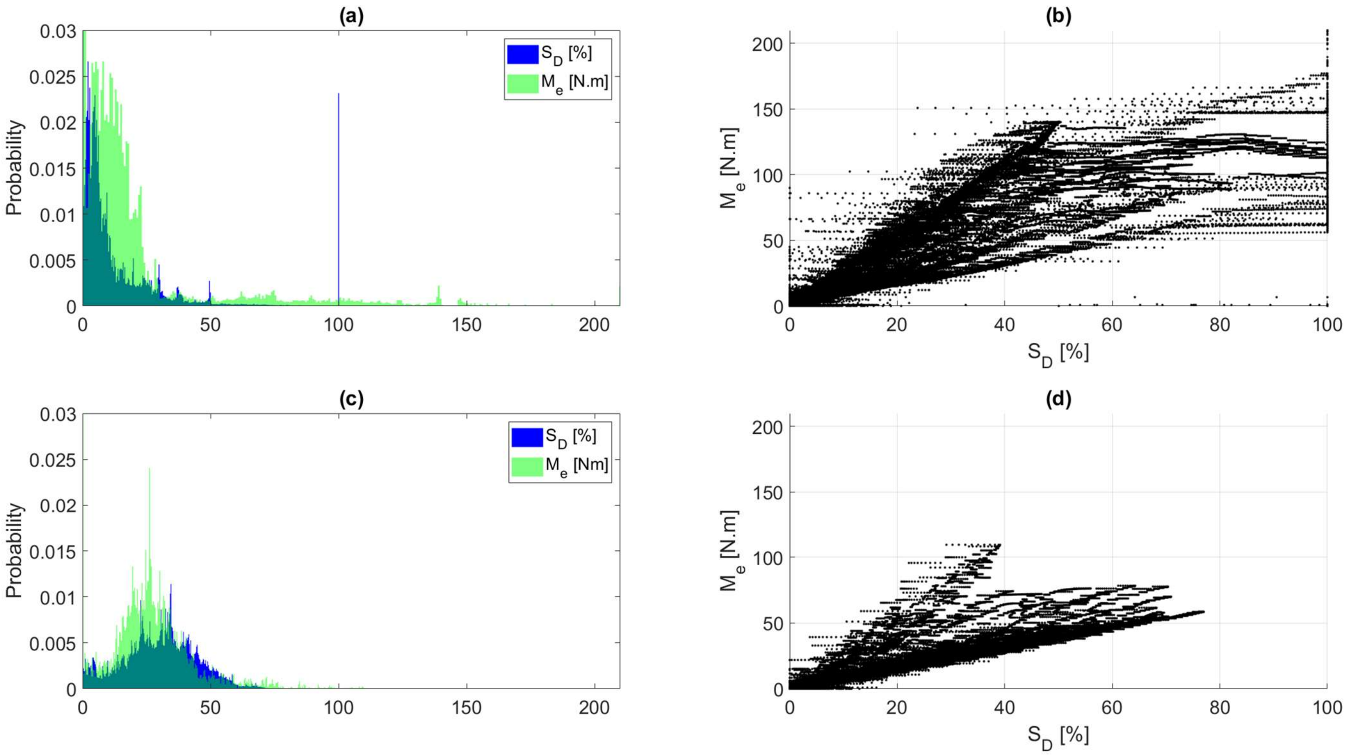



**Figure 7.** Data distribution of $S_D$ and $M_e$ for the estimation data (RWD maneuver) and the validation data (Artemis driving cycle): (**a**) histogram of $S_D$ and $M_e$ for estimation data; (**b**) $S_D$ vs. $M_e$ for estimation data; (**c**) histogram of $S_D$ and $M_e$ for validation data; (**d**) $S_D$ vs. $M_e$ for validation data.

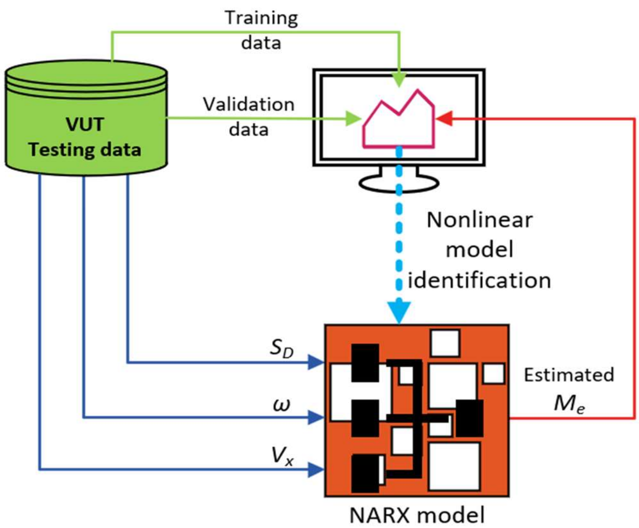



**Figure 8.** Identification of the NARX model using the RWD data.

For almost all applications of empirical models, modeling aims to predict points at which the system behavior cannot be measured. Validation points are used in addition to estimation points to examine a model for suitability in this regard. A quadratic coefficient of determination can usually be calculated for these validation points [1]. The difference between the quality measures should be at most 0.3. Otherwise, there will be a big difference between the model's ability to reproduce measured values and predict unmeasured points. Validation points should be used to check a model, especially if there is uncertainty about a suitable model approach for a modeling task [25].

## 4. Results

The first step is to identify the linear function part of the NARX model, as shown in Figure 9. The fitness of the estimated data to the reference data, i.e., training or validation data, is evaluated with the Normalized Root Mean Square Error (NRMSE). The best fitness value for the linear estimation function is 57%, which confirms that a nonlinear model is required in this case. The next step is to extend the identified linear function to the complete NARX model by identifying the nonlinear and the offset parts. Then, the identification process is performed for the aggregated model of all the parts. Figure 10 illustrates excellent fitness values of 98.25% and 98.03% for the training and validation data, respectively. The errors in predicting the values of each estimation data point by the NARX model are represented in Figure 11.

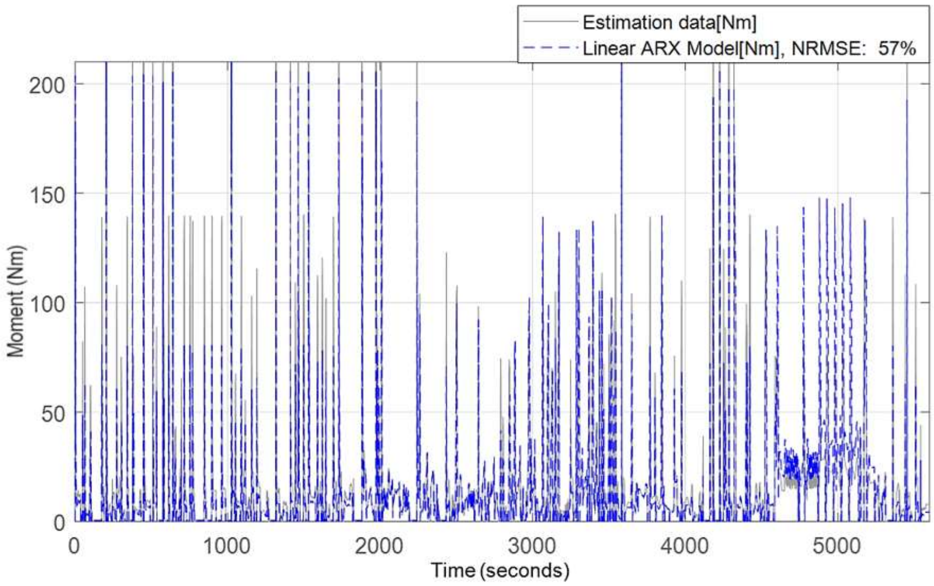



**Figure 9.** Fitness of the linear part of the NARX model to the estimation data of the RWD maneuver.

The identified model was able to define the majority of the points with high precision. Few points are overestimated, with a maximum difference of 0.5 Nm. The worst errors appear at $\omega$ less than 100 rad/s and $S_D$ larger than 50%, where the motor's moment is underestimated. The error increased gradually from an $S_D$ equal to 50% until it reached $-9.4$ Nm at an $S_D$ equal to 100%. The locations of these errors take us back to Figure 4b. Some discontinuities were observed around the addressed areas, which promotes the possibility of casing these errors due to excluded operational points.

In this case, the fitness values are the NRMSEs of the estimated moment compared to the training and validation data sets. The NARX model could accurately predict the corresponding motor moment based on the given inputs, even for such a highly dynamic maneuver. The Artemis driving cycle is used as a validation dataset for the NARX model. It is desired to advocate that the identified driving moment model represents the actual vehicle. So, the moment prediction model is validated using the measured data from actual test vehicle measurements. The validation objective is to find whether the data used to train the NARX model resemble the targeted system. The measured data from the field test in [16] are used for this purpose, in which the driver performed a dynamic actuation for the pedal to generate a challenging test case lasting about 385 s. The results in Figure 12 demonstrate a high Pearson's correlation coefficient (Pearson's correlation coefficient: Wikipedia, https://en.wikipedia.org/wiki/Pearson_correlation_coefficient#cite_note-3, accessed on 2 March 2024) of 0.994 between the estimated and measured motor's moment, which approves the accuracy of the identified NARX model.

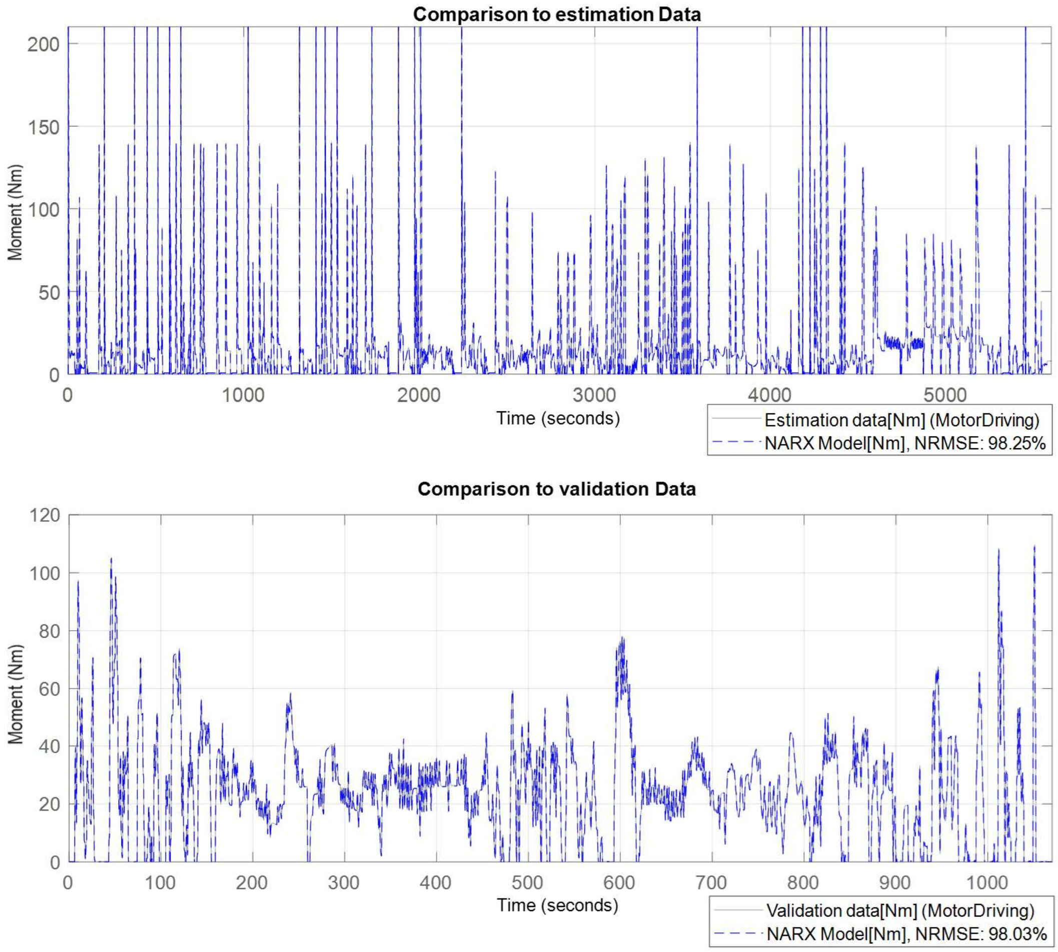



**Figure 10.** Fitness of the complete NARX model to the estimation data (RWD maneuver) and validation data (Artemis driving cycle).

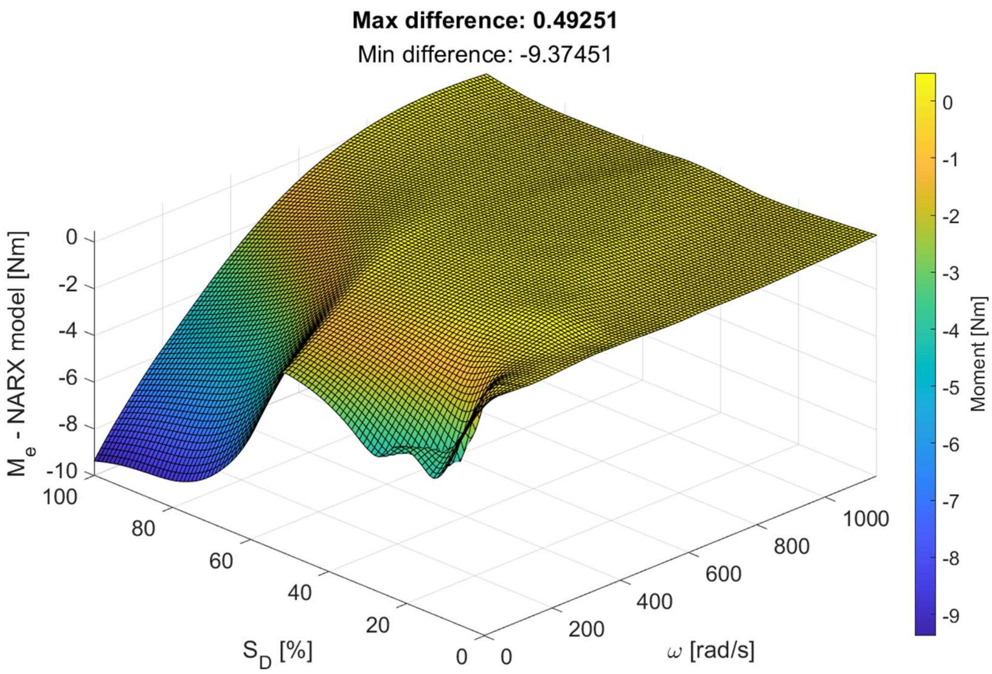



**Figure 11.** Difference between the estimation data and the corresponding NARX model outputs.

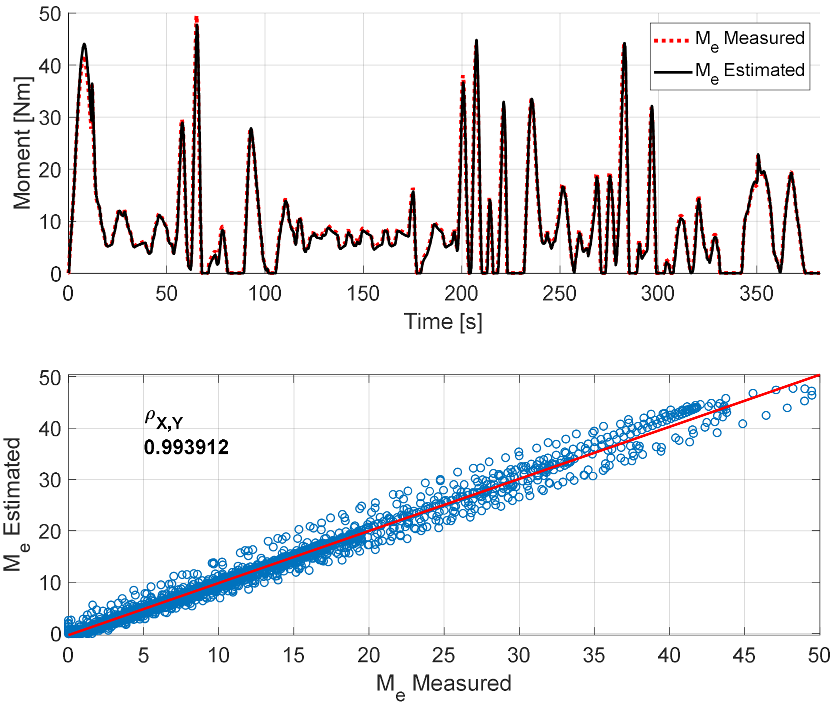



**Figure 12.** Correlation between the measured total motor's moment during the field test maneuver and the estimated moment from the NARX prediction model.

## 5. Conclusions

Analyzing the entire system's behavior between the accelerator pedal and the final motor moment is highly demanding because of the many components involved. Almost all the powertrain components have nonlinear characteristics, and the electronic components work discretely in time due to digital technology. In addition, the distribution of the extensive software across several control devices that are networked with each other makes analysis more difficult. The dependence between the driving maneuver operating points and the VCU parameters is depicted using empirical models. The quality measures used to assess the model quality are then introduced. The model assessment can be performed graphically by analyzing the result and matching the test points with the prediction points. A more precise assessment of a model takes place using quality measures. The modeling complexity level is determined based on the effort and the benefits. The more precisely the features of the components are depicted, the more valid the results are. However, the effort increases with accuracy. A linear system can sufficiently represent the components' behavior in the best-case scenario. In the worst-case scenario, the overall system behavior is influenced by latency times between the control units. In contrast, the effort to select application parameters based on measurement data can be easily estimated and is usually lower. Therefore, this is usually preferred in practice. Models based on performance maps are generally characterized by very good interpretability. An NARX sigmoid model is proposed in this work to interpret the driving moment from the accelerator pedal position. Besides the accelerator position value, additional quantities are required to estimate the corresponding moment, which are the electrical motor angular speed and the vehicle speed. Implementing a real-world driving maneuver with a large data set and acquiring high prediction exactness represent the novelties of this work. In contrast, the other related works used laboratory-created tests with smaller data sizes to train the prediction models. The proposed NARX model demonstrated a normalized root mean squared error of less than 2% for each training and validation data set. Furthermore, the proposed model is validated with an actual measurement of the target vehicle, achieving an outstanding correlation accuracy of 0.994.

This work can be extended in different scopes: investigating the causes of the missing acquired data, whether these operational points could be reached by performing other maneuvers, or whether they are unreachable by the powertrain system itself. Particular attention should be paid to the motor's maximum moment operational range since the highest errors occurred there. This scope can be further investigated by intense data acquisition within that scope. Implementing routes with varying surface frictions can extend the proposed approach by introducing tire slipping; for instance, driving on wet and icy road segments. Moreover, the NARX technique can characterize the other types of powertrain technologies, such as fuel cell and hybrid powertrains. A further area of application with high potential would be developing the powertrain test benches. This test bench needs a moment controller to generate an equivalent driving moment in the desired real-world driving maneuver. The proposed NARX model was beneficial as a source for the reference moment signal. We have a complete vehicle test bench under development that was investigated in detail in [26], which will be a future development for this area of research.

**Author Contributions:** M.A. performed the literature review, made the simulation model, generated the simulated and the measured data sets, created and performed the identification approach, and wrote the paper; F.G. supervised the project work related to this paper. All authors have read and agreed to the published version of the manuscript.

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