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Neural Observer for Nonlinear State and Input Estimation in a Truck-Semitrailer Combination

Tim Jahn * **Zygimantas Ziaukas** * **Jan-Philipp Kobler** ** **Mark Wielitzka** * **Tobias Ortmaier** *

* *Institute of Mechatronic Systems, Leibniz Universität Hannover, 30167 Hanover, Germany (e-mail: zygimantas.ziaukas@imes.uni-hannover.de)*
** *BPW Bergische Achsen KG, 51674 Wiehl, Germany (e-mail: koblerJ@bpw.de)*

Abstract: Driver assistance systems have become an indispensable part of today's vehicles technology. Especially in the commercial vehicle sector, the challenges in obtaining information increase with rising system complexity. Compared to trucks, trailers for commercial vehicle combinations are sparsely equipped with electronic components. This leads to difficulties in implementation of intelligent systems for the trailer as necessary information is not provided. Reasons for this can be an insufficient sensor equipment due to uneconomical costs or a missing communication channel between the two vehicle units, preventing the transmission of required truck related information to the trailer. A possible model-based method to obtain unmeasured states is the Extended Kalman Filter. However, this approach requires elaborate preliminary work steps of high complexity and a sophisticated domain knowledge. Alternatively, this paper proposes the applicability of Neural Networks for estimating the required state and input variables, namely the articulation angle and the truck's steering angle. Two different network types are used: the Feedforward Neural Network and the Nonlinear Autoregressive Exogenous Neural Network. The measured input variables for the networks, in accordance with the inputs of the Extended Kalman Filter in a previous publication, are merely trailer yaw rate and longitudinal speed. In conclusion, a comparison between the results of the Neural Networks and those of the Extended Kalman Filter is drawn.

Keywords: Feedforward Neural Network, Nonlinear Autoregressive Exogenous Neural Network, Extended Kalman Filter, State and Input Estimation, Truck-Semitrailer Combination

1. INTRODUCTION

Modern driver assistance systems support the driver and increase safety and comfort in road traffic. They have the ability to keep the vehicle on track, to initiate an emergency brake or to monitor the blind spot (Paul et al., 2016; Suzuki et al., 2017). In the future, these systems will take an even more important part being the foundation of highly automated and autonomous driving, respectively. Most of the intelligent systems in today's truck-semitrailer combinations are located in the truck unit. In comparison, trailers are sparsely equipped with electronic components. Therefore, online on-board solutions, which need to be supplied with trailer information, pose a tremendous challenge in commercial vehicle technology. On the one hand, an entire sensor equipment to observe every state variable of the vehicle is economically unreasonable for serial production. On the other hand, communication channels between the truck and the trailer unit, enabling the exchange of required information, are missing. Furthermore, truck and trailer do not always build up an inextricable link. One trailer usually is towed by various types of trucks. Therefore, the installation of sensors at interacting interfaces of these two components is increasingly challenging.

A well known method to determine missing information is the implementation of an Extended Kalman Filter (EKF), which permits a real-time capable estimation of state values from available trailer information. In (Ziaukas et al., 2019) this method was applied for the estimation of the articulation angle and the steering angle. The performance of the EKF is heavily dependent on the quality of the utilized model. To sufficiently fulfill these features, a profound system understanding and sophisticated identification processes are necessary (Melzi and Sabbioni, 2010).

Methods of machine learning provide an alternative promising approach for reliable state estimation. Due to the rising data recording and storage capability as well as the increasing computer performance, especially Artificial Neural Networks currently attract a lot of attention. The development of a workable Neural Network is based on a variety of real measured and/or simulated data and the correct choice of the network structure (Li et al., 2018; Melzi and Sabbioni, 2010).

The literature shows a lot of successful implementations replacing model-based estimation processes by Neural Networks. One drawback of EKFs for nonlinear systems is the loss in accuracy caused by linearization. Alternatively, Unscented Kalman Filters (UKF) can be used to avoid the linearization. However, this results in an increase in calculation effort. In contrast, Neural Networks are capable of representing complex nonlinearities accurately at fairly efficient calculation effort (Li et al., 2018). In most publications the performance of simply structured Feedforward Neural Networks (FFNNs) regarding the state calculation of nonlinear systems gets researched first (Li et al., 2018; He et al., 2014; Aydogmus and Aydogmus, 2015). For more complex dependencies, in which the chronology of data is decisive, Nonlinear Autoregressive Exogenous Neural Networks (NARX-NN) are used. These reflect the dynamics of nonlinear systems better compared to FFNNs (Melzi and Sabbioni, 2010; Nguyen and Widrow, 1990). One of the most challenging and not to be neglected aspects by creating a robust Neural Network is the data acquisition. The amount of training, validation and test data affects the results to the same extent as the number of different driving situations and maneuvers and their coverage of the workspace (Graeber et al., 2018).

In the automotive sector, several studies exist using Neural Networks for state estimation, e.g. side-slip angle estimation of passenger vehicles (Graeber et al., 2018; Chindamo and Gadola, 2018; Melzi and Sabbioni, 2010) and roll angle estimation in a heavy vehicle based on simulations (Sanchez et al., 2004). In this paper, the utilization of Neural Networks is further transferred to commercial vehicles in order to estimate their specific input and state variables based on a real test vehicle. For this purpose, the applicability of two different types of Neural Networks, the FFNN and the NARX-NN, is examined. In order to make the two networks comparable to the EKF in (Ziaukas et al., 2019), they are trained with the same measurement data used for the model identification in the EKF approach. Measurement data from a random driving maneuver is used to validate the approaches. Thereby, the focus is set on the estimation of the articulation and the steering angle.

The paper is structured as follows. In section II the fundamentals of Artificial Neural Networks are presented. These include the description of the utilized network structures as well as the main mathematical background. Section III discusses the process of setting up the Neural Networks by presenting the test vehicle, the data set and the different network configurations. In Section IV the results of the estimation through Neural Networks are displayed and then compared to the results of the model-based approach using the EKF in (Ziaukas et al., 2019). The effectiveness of both estimators is demonstrated on a real validation maneuver. The paper finishes with a conclusion and outlook in section V.

2. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks are mathematical models, which adopt the principles of information processing from biological systems (Haykin, 1998). By simulating these systems, the storage capacity, the learning ability and the reproducibility of these systems are taken over. Artificial Neural Networks work as black-box modeling tools, which are able to map a p-dimensional input space onto a q-dimensional output space without knowing their dependencies (Boussaada et al., 2018). They are applied in a wide variety of areas for pattern detection, categorization, functional approximation, optimization, prediction, storage and control. Depending on the task, the appropriate network structure has to be selected from a broad pool of different network types (Haykin, 1998).

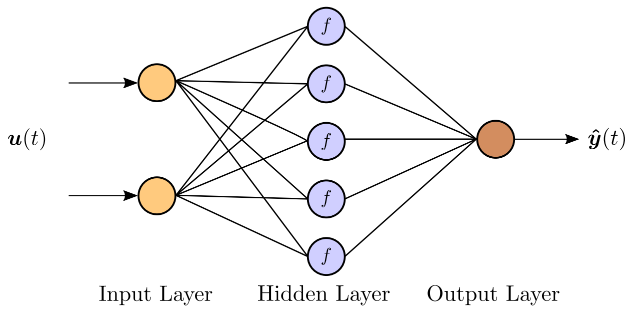

Fig. 1. Structure of a Feedforward Neural Network

2.1 Feedforward Neural Network

FFNNs are the foundation of deep learning models. As their name suggests, the flow of information takes place only in forward direction (Boussaada et al., 2018). FFNNs consist out of three different types of layers: the input layer, the hidden layers and the output layer (Fig. 1). The neurons, arranged in these layers are each connected to all neurons of the following layer (fully connected) (Zurada, 1992). The neurons represent the processing unit of a Neural Network (Fig. 2). Within these, the input component u_j resulting from the previous layer is multiplied by the weight factor w_{ij}. Subsequently, the following neuron output $\hat{s}_i$ is calculated using an activation function f:

$$\hat{s}_i = f\left(b + \sum_{j=1}^{n} u_j w_{ij}\right), \tag{1}$$

where n is the total number of inputs to the neuron, j is the index of the considered input and i represents the index of the neuron in the layer.

The selection of the right activation function f is network-specific and depends on the exact application. Particularly in hidden layers, sigmoid activation functions are suitable for modeling non-linear relationships between the input and the output data. Moreover, these accomplish the requirements of continuity, differentiability and monotony. In the output layer, a linear activation function is usually used to map the current state of the neuron to a desired value range (Zakharian et al., 1998).

After the network setup is completed successfully, a first random initialization of the weights follows. Subsequently, the weights are adjusted step by step using a suitable algorithm in the training process (Haykin, 1998). For this purpose, the Neural Network is fed with input data $\boldsymbol{u}$ and the associated outputs (targets) $\boldsymbol{y}$. By comparing the resultant output signal $\hat{\boldsymbol{y}}$ with the target signal $\boldsymbol{y}$, the occurring error can be calculated by using a cost function. A frequently chosen cost function is the mean squared error (MSE):

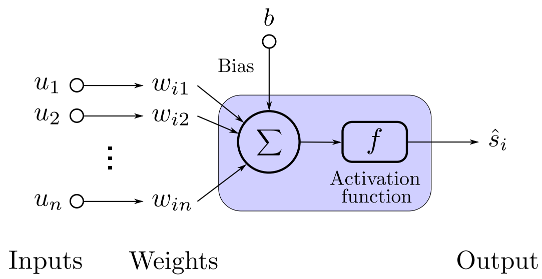

Fig. 2. Artificial neuron: the elementary unit in a neural network

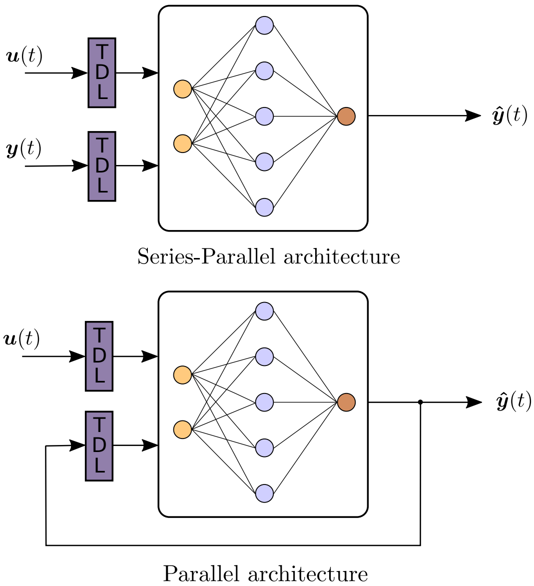

Fig. 3. Architectures of the Nonlinear Autoregressive Exogenous Neural Network

$$\text{MSE} = \frac{1}{m}\sum_{z=1}^{m}\left(\boldsymbol{y}_z - \hat{\boldsymbol{y}}_z\right)^2 \tag{2}$$

where m represents the number of training samples.

Based on this cost function an adaption of the weights is finally made. The described process gets repeated until the difference between the output signal $\hat{\boldsymbol{y}}$ and target signal $\boldsymbol{y}$ is reduced to a minimum.

2.2 Nonlinear Autoregressive Exogenous Neural Network

The NARX-NN represents a useful extension of the FFNN, especially with regard to the modeling of nonlinear processes and time series (Ruslan et al., 2013). The NARX-NN is a recurrent dynamic Neural Network, linking several layers via feedback connections (Li et al., 2018). In contrast to many other network types, the structure of the NARX-NN implements a memory capability. This feature allows the inclusion of previous values from determined or real time series, exploiting the full performance of the NARX-NN (Boussaada et al., 2018).

Two different architectures of NARX-NN are distinguished, the series-parallel architecture and the parallel architecture (Fig. 3)(Ruslan et al., 2013). The corresponding equations of the two structures are as follows:

$$\hat{\boldsymbol{y}}_{\text{SP}}(t) = \boldsymbol{g}\begin{pmatrix}\boldsymbol{y}(t-1), \boldsymbol{y}(t-2), ..., \boldsymbol{y}(t-k_y), \boldsymbol{u}(t), \\ \boldsymbol{u}(t-1), \boldsymbol{u}(t-2), ..., \boldsymbol{u}(t-k_u)\end{pmatrix}, \tag{3}$$

$$\hat{\boldsymbol{y}}_{\text{P}}(t) = \boldsymbol{g}\begin{pmatrix}\hat{\boldsymbol{y}}(t-1), \hat{\boldsymbol{y}}(t-2), ..., \hat{\boldsymbol{y}}(t-k_y), \boldsymbol{u}(t), \\ \boldsymbol{u}(t-1), \boldsymbol{u}(t-2), ..., \boldsymbol{u}(t-k_u)\end{pmatrix}, \tag{4}$$

in which $\hat{\boldsymbol{y}}(t)$ is the output of the NARX-NN at time t. $\hat{\boldsymbol{y}}(t-1), \hat{\boldsymbol{y}}(t-2), ..., \hat{\boldsymbol{y}}(t-k_y)$ are the previous outputs of the NARX-NN and $\boldsymbol{y}(t-1), \boldsymbol{y}(t-2), ..., \boldsymbol{y}(t-k_y)$ are the true previous values of the time series, which are also described as target output values. $\boldsymbol{u}(t), \boldsymbol{u}(t-1), ..., \boldsymbol{u}(t-k_u)$ are the inputs of the NARX-NN. In addition, k_u and k_y describe the number of input and output delays. The approximation of the function $\boldsymbol{g}$, representing the mapping function of the Neural Network, is based on the standard Feedforward principle.

Particularly for the dynamic modeling of complex nonlinear systems, the usage of both network architectures for training is beneficial in order to take advantage of the respective configurations. For this purpose, the training process is divided into two phases. In the first phase, the network is trained in the series-parallel configuration. This leads to a stabilization of the weight adjustments of the Neural Network (Yim and Oh, 2004). After completing the series-parallel training, however, the network is only able to provide reliable predictions for a limited number of future time steps, as the series-parallel training is mainly suitable for short-term predictions. To solve this problem, the pretrained network is further trained in the parallel configuration. During this second training phase, the ability of long-term prediction is developed. If the network is only trained in the parallel configuration, the iterative learning progress can evolve in an unstable way. The reason for this behavior are the randomly generated weights at the beginning. These lead to significant deviations from the target in the first training iterations. Subsequently, the erroneous outputs are recursively fed back to the network, which in turn negatively influences the output in the next time step. The repetition of this process ultimately leads to an enormous divergence between the output and the target value (Yim and Oh, 2004). Therefore, it is advisable to train the NARX-NN in series-parallel configuration before training in parallel.

3. METHOD

The performance of Neural Networks heavily depend on the underlying data set as well as the selected network structure and configuration. In subsection 3.1 the test vehicle is presented. This serves to create an all-encompassing data set, as described in subsection 3.2. Subsection 3.3 discusses the process of optimizing hyper parameters to determine the best network configuration.

3.1 The Test Vehicle

To evaluate the usability of Neural Networks for the estimation of steering and articulation angle based on defined input variables, an off-the-shelf three-axle semitrailer is used. This semitrailer has dimensions in accordance with European legislation 96/53/EC and is equipped with air suspension (Airlight II, BPW Bergische Achsen KG, Wiehl, Germany) and an electric braking system (EBS, WABCO Holdings Inc., Michigan, USA). The connection between the trailer EBS and the truck unit is established by a point-to-point CAN-BUS (baud rate 250 kbit/s) compliant with ISO 11992. This CAN-BUS transfers the required information from the braking system and the running gear.

The trailer is further equipped with a data acquisition system (DAQ) (SIRIUS, Dewesoft d.o.o., Trbovlje, Slovenia), supporting both analog inputs and CAN ports. The first CAN port has the function of monitoring the information flow between the truck and the trailer as specified in ISO 11992. It transmits the trailer's speed at a rate of 100 Hz, being one of two input variables of the Neural Network. Via the second CAN port, which is connected to the CAN bus of the truck unit (specified in J1939), the actual steering angle is measured at a rate of 100 Hz. This CAN connection is necessary for training and validation reasons only in order to compare the resulting output of the Neural Network with the true values. For the online estimation, however, this is irrelevant.

To generate corresponding comparative values for the articulation angle of the semitrailer, a suitable sensor is attached to the kingpin of the trailer (V.S.E. Vehicle Systems Engineering B.V., Veenendaal, Netherlands). This sensor provides the true articulation angle between truck and trailer as an analog input at a sampling rate of 1000 Hz for training and validation only. In order to achieve comparability with the model-based approach utilizing an EKF, the yaw rate of the trailer is used as the second input value of the Neural Network in addition to the trailer's speed. It is measured using a six-axis inertial measurement unit (DS-GYRO1, Dewesoft d.o.o., Trbovlje, Slovenia) at a rate of 1000 Hz, which is also fitted to the trailer.

3.2 Data Set

An all-encompassing data set for training, validation and testing is the foundation of every machine learning application. All-encompassing in context of vehicle technology means a complete coverage of the workspace as well as the inclusion of a large number of different maneuvers (Graeber et al., 2018).

A complex street ride can be reduced to a limited number of fundamental maneuver types. These are a straight-ahead drive, varying sine maneuvers including a sine sweep, a steer wheel step and constant circles at different velocities. Through the definition of different maneuver types, the generation of a transparent and high-quality data set is significantly facilitated.

In order to satisfy the requirements of a high amount of training data while covering the entire workspace, measurement data of the specified maneuvers were recorded with different amplitudes and frequencies of the steering angle and at different vehicle speeds. The resulting data set contains measurement data from 26 different maneuvers, the same as for the parameter identification in Ziaukas et al. (2019).

3.3 Network Configuration

In addition to the data set, the second crucial factor is the configuration of the network structure. The most important structural parameters of FFNNs are the number of hidden layers and the number of hidden neurons. For the NARX-NN, the number of input and feedback delays needs to be determined additionally.

Network structures with one hidden layer have proven to be sufficient in many research projects (Chindamo and Gadola, 2018; Melzi and Sabbioni, 2010; Li et al., 2018). If the complexity of the relationships to be mapped increases, it is advisable to raise the number of hidden layers. However, the implementation of more than two hidden layers is usually unnecessary, since most functions can be approximated by a maximum of two layers (Heaton, 2015).

The selection of the number of neurons in the hidden layers depends on various factors such as the amount of input and output neurons, the quantity of training data, the complexity of the approximation function. For the truck-semitrailer combination nonlinearities occur in the tire characteristics and several trigonometric functions (see Ziaukas et al. (2019)). The optimal number of neurons is determined empirically by repeating the training process for different sized networks in the range of 5 to 100 neurons per layer. Each network structure is trained with Bayesian regularization backpropagation 10 times with random initial weights. The networks with the best test performance where chosen resulting in a structure of 2 neurons for the input layer, 40 in the first and second hidden layer and 1 neuron in the output layer (2/40/40/1), whereas the network size for the NARX-NN was determined to be 2/20/1 with 2 input and 2 feedback delays. For the hidden layers a sigmoid activation function was chosen, whereas the activation function of the outputlayer is linear.

4. ESTIMATION RESULTS

This section presents the results for estimating articulation and steering angle using the FFNN and the NARX-NN. Moreover, a comparison of the presented method to the previously presented EKF is drawn.

4.1 Neural Networks

In a first working step, the performance of the FFNN described in section 3.3 is examined for estimating the articulation and the steering angle. The performance of the best resulting network, based on the MSE on the training data, is shown for a random driving maneuver with a speed between 10 and 70 $\mathrm{km\,h^{-1}}$ are shown in Fig. 4.

For the estimation of the articulation angle the FFNN shows a good performance. The result corresponds to the measured data at large angles, representing narrow turns at low vehicle speeds as well as at small angles, displaying sine travels at higher vehicle speeds. On the other hand, the estimation of the steering angle shows a strongly deteriorated result. Remarkable are the considerable delays between the calculated and the target signal. Furthermore, the extreme values of the steering angle signal are not reached when turning.

The large discrepancy in the results may be explained by the system affiliation of the two target variables. The articulation angle is obtained at the kingpin and

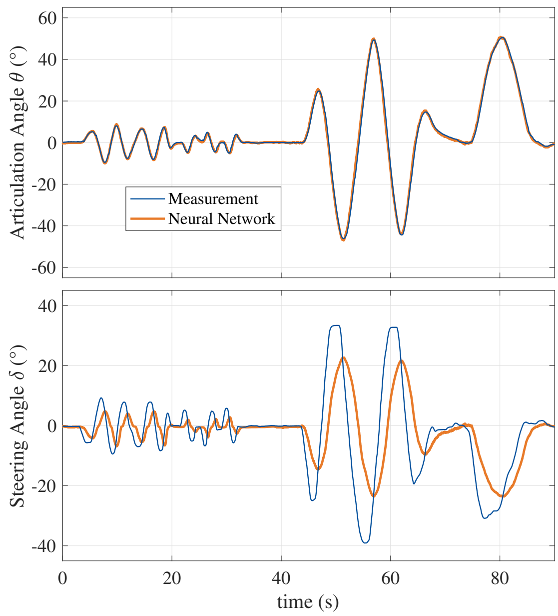

Fig. 4. Estimation result for articulation (θ) and steering angle (δ) with FFNN (2/40/40/1) for a test maneuver.

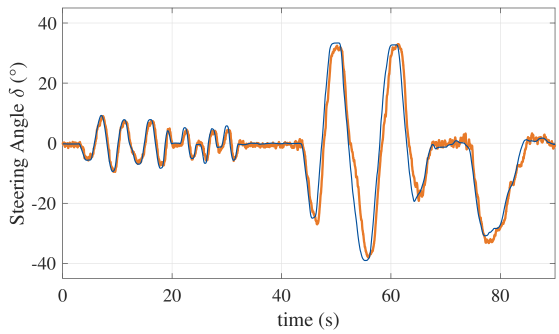

Fig. 5. Estimation result for the steering angle (δ) with the NARX-NN (2/20/1) for a random maneuver.

thus at the junction of the truck-semitrailer combination. Therefore, the state variable of the articulation angle can be counted both to the trailer unit and to the truck unit. By contrast, the input variable of the steering angle only belongs to the truck unit. The input variables of the Neural Network are solely data that relate to the trailer unit. Due to this fact also input or state variables of the trailer unit, in this case the articulation angle, seem better predictable by the FFNN. Input or state variables which do not correspond to this subunit of the system, in this case the steering angle, seem correspondingly worse represented by the FFNN.

Because of the unsatisfactory results of the steering angle prediction, a NARX-NN is used subsequently. This network type has significantly better properties for mapping dynamic characteristics. It is configured as described in section 3.3. The results are shown in Fig. 5.It is noticeable that the final result is much more congruent with the real measured steering angle. The delays within the course are clearly reduced. Furthermore, the extreme points are mapped much better.

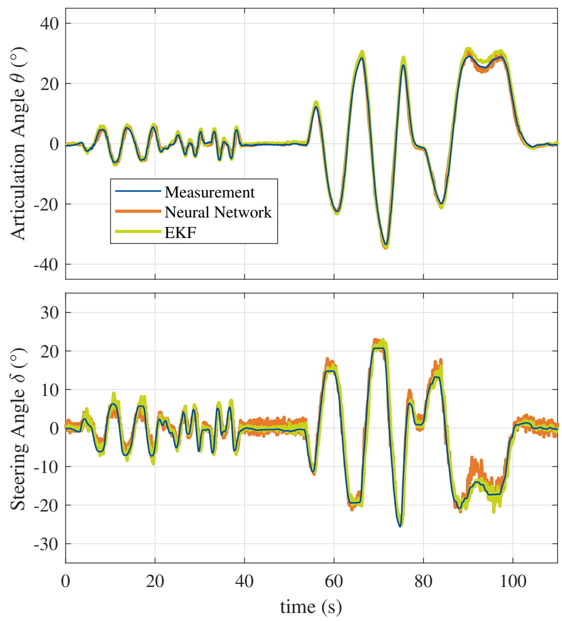

Fig. 6. Comparison between the results of the Neural Networks and the EKF for a similar maneuver.

The identical network configuration has also been investigated for the prediction of the articulation angle. The results do not significantly differ from the results of the FFNN shown in Fig. 4. However, the training time of NARX-NNs is approximately 2 to 5 times longer depending on the number of hidden layers. In addition, the FFNN offers the possibility of tearing data series apart and thus using each individual data point as an independent training state. With the NARX-NN, the individual maneuvers must remain in their original form. Considering these aspects a preference of the NARX-NN is not reasonable. Therefore, the estimation of the articulation angle is performed with the FFNN.

4.2 Comparison to Extended Kalman Filter

Finally, the developed results of the Neural Networks are compared to those of the EKF similar to Ziaukas et al. (2019) in terms of their performance, see Fig. 6, and their complexity . For the estimation of the articulation angle, the machine learning approach provides a slightly better result. The MSE of the Neural Network is $0.9\,(°)^2$, whereas the MSE of the EKF results to $0.9823\,(°)^2$. The estimation of the steering angle yields in a similar result. The EKF performs worse with an MSE of $4.6845\,(°)^2$. The MSE for the Neural Network is calculated to $3.0983\,(°)^2$. In both cases, however, a minimal time delay remains in the estimated curves.

Concerning the development effort, the model-based EKF approach is quite consuming. The model needs to be derived from the underlying physical effects by domain experts. In case of a grey-box model, as presented in Ziaukas et al. (2019), a parameter identification procedure, which includes solving a nonlinear optimization problem, becomes necessary. Furthermore, the EKF covariances have to be determined posing another challenge. A total of 38 parameters need to be determined.The benefits on the other hand are a distinguished system understanding and insight. In comparison, the main challenges of the machine learning Neural Network approach are the selection of a suitable network type and the development of a complete and prepared data set. In addition, the optimal network configuration has to be determined, causing problems, since no consistent procedure exists for the setting/selection of the hyper parameters. The FFNN has a total of 1801 parameters and the NARX-NN a total of 121. It is advantageous that the setup of Neural Networks does not require a profound knowledge of the system relations.

5. CONCLUSION AND OUTLOOK

In this paper, two different types of Neural Networks, the FFNN and the NARX-NN, have been presented for estimation of articulation and steering angle in a truck-semitrailer combination. A structured comprehensive data set has been developed and the best possible network configurations have been determined. For the estimation of articulation angle, the FFNN shows a very good performance. Results for estimating the steering angle using the FFNN are significantly worse, leading to the application of NARX-NN with better results. Comparing the Neural Networks with the model-based approach of an EKF, it can be concluded that the Neural Networks show a slightly better performance for the test maneuvers. The development of the model-based approach requires profound domain knowledge and also involves nonlinear identification processes. For these reasons, Neural Networks for state estimation should be considered as an alternative.

Future works may focus on combining model-based an machine learning approaches to get the advantages of both. Another aspect that should be considered is the computational effort. Due to the use of different software/libraries the drawing of a precise comparison was not possible yet. Furthermore, transfer ability to other vehicles (other truck and/or trailer combinations) and the robustness against parameter variations (e.g. load, tires) and other changing influences (e.g. environmental conditions) need to be analyzed.

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REFERENCES

Aydogmus, Z. and Aydogmus, O. (2015). A comparison of artificial neural network and extended kalman filter based sensorless speed estimation. *Measurement*, 63, 163–170.

Boussaada, Z., Curea, O., Remaci, A., Camblong, H., and Bellaaj, N.M. (2018). A nonlinear autoregressive exogenous (narx) neural network model for the prediction of the daily direct solar radiation. *Energies*, 11.3.

Chindamo, D. and Gadola, M. (2018). Estimation of vehicle side-slip angle using an artificial neural network. *MATEC Web of Conferences, The 2nd International Conference on Mechanical, Aeronautical and Automotive Engineering*, 166.

Graeber, T., Lupberger, S., Unterreiner, M., and Schramm, D. (2018). A hybrid approach to side-slip angle estimation with recurrent neural networks and kinematic vehicle models. *IEEE Transactions on Intelligent Vehicles*.

Haykin, S. (1998). *Neural Networks: A Comprehensive Foundation*. Prentice Hall.

He, W., Williard, N., Chen, C., and Pecht, M. (2014). State of charge estimation for li-ion batteries using neural network modeling and unscented kalman filter-based error cancellation. *International Journal of Electrical Power & Energy Systems*, 62.

Heaton, J. (2015). *Artificial Intelligence for Humans, Volume 3: Deep Learning and Neural Networks*. CreateSpace Independent Publishing Platform.

Li, C., Wang, Y., Zhou, Z., and Yin, C. (2018). Vehicle states estimation based on recurrent neural network and road constraints in automated driving. *SAE Technical Paper 2018-01-1613*.

Melzi, S. and Sabbioni, E. (2010). On the vehicle sideslip angle estimation through neural networks: Numerical and experimental results. *Mechanical Systems and Signal Processing*, 25.6.

Nguyen, D.H. and Widrow, B. (1990). Neural networks for self-learning control systems. *IEEE Control Systems Magazine*, 10.3.

Paul, A., Chauhan, R., Srivastava, R., and Baruah, M. (2016). Advanced driver assistance systems. *SAE Technical Paper 2016-28-0223*.

Ruslan, F.A., Samad, A.M., Zain, Z.M., and Adnan, R. (2013). Flood prediction using narx neural network and ekf prediction technique: A comparative study. *IEEE 3rd International Conference on System Engineering and Technology*.

Sanchez, E.N., Ricalde, L.J., Langari, R., and Shahmirzadi, D. (2004). Rollover prediction and control in heavy vehicles via recurrent neural networks. In *IEEE Conference on Decision and Control 2004*, 5210–5215.

Suzuki, K., Asao, T., Hayashi, J.I., and Miichi, Y. (2017). Safety evaluation of advanced driver assistance systems as human-machine systems. *Interational Journal of Automative Engineering*, 8(4), 163–170.

Yim, Y.U. and Oh, S.Y. (2004). Modeling of vehicle dynamics from real vehicle measurements using a neural network with two-stage hybrid learning for accurate long-term prediction. *IEEE Transactions on Vehicular Technology*, 53(4).

Zakharian, S., Ladewig-Riebler, P., and Thoer, S. (1998). Neuronale Netze für Ingenieure. *Vieweg+Teubner*.

Ziaukas, Z., Kobler, J.P., Wielitzka, M., and Ortmaier, T. (2019). Simultaneous estimation of steering and articulation angle in a truck-semitrailer combination solely based on trailer signals. *American Control Conference 2019*.

Zurada, J.M. (1992). *Introduction to Artificial Neural Systems*, volume 6. West Publishing Company.