# Evaluation of Alternative Propulsion Concepts for Mobile Machinery: A Modelling Approach using the Example on LNG-powered Port Handling Equipment

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Keywords: Semi-physical Modelling, Evaluation of Alternative Propulsion Concepts.

Abstract: The prevailing climate goals and related emission limits for fleets are forcing industry to consider alternative fuels alongside established fuels such as diesel and gasoline. A conversion of a fleet of vehicles to another source of power comes along with an investment of money and a risk that the day-to-day operations of the new drive technology do not provide the expected effects regarding the fuel consumption and the exhaust gas emissions. In order to assess these barriers in advance, this paper presents an approach of a simulation tool based on a semi-physical modelling of the powertrain of mobile machinery to predict the impact of a conversion of a fleet from diesel to liquefied natural gas (LNG) in case of fuel consumption and exhaust gas emissions. For the semi-physical model, a combination of a physical model of the vehicle and powertrain dynamics and a black box modelling of the internal combustion engine by artificial neural networks is chosen. The simulation tool will be used in the future to assess the feasibility of converting the drive system from port transhipment facilities to LNG. The work was carried out as part of the research project *LeanDeR* financed by the European Regional Development Fund (ERDF).

## 1 INTRODUCTION

The climate targets of the European Union pose major challenges for the development and the use of vehicles. By the year 2030 greenhouse gas emissions have to be reduced by 40 % compared to the level of 1990 and by 2050 climate neutrality is to be achieved, (European Commission, 2018). In addition to the reduction of greenhouse gas emissions, it is also necessary to reduce the emission of air pollutants. Beside the industry and energy sector, the traffic and transport sector is a significant producer of emissions, (International Energy Agency, 2019). In Germany, e. g., the traffic and transport sector emitted about 18.4 % of the energy-related greenhouse gas emissions in 2017, (Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, 2019). The term transport is often confined to the category of road vehicles, as these are used in the immediate vicinity of the population and their living environment and can therefore be directly observed. Another segment of vehicles that differs in this respect is the so-called mobile machinery. Unlike road vehicles, which are primarily used to transport goods from one place to another, these machinery have the task to perform mechanical work in addition to the transport task, (Geimer and Pohlandt, 2014). A study by (Helms et al., 2017) shows that these machinery emit a non-negligible proportion of greenhouse gas emissions and air pollutants. Achieving the mentioned goals will require a conversion from established fossil fuels towards alternatives which provide less exhaust gas emissions. Suitable alternatives are, e. g., natural gas or an electrification or hybridisation of the powertrain, (Milojević et al., 2018; Lajunen et al., 2018). All these energy sources have in common, that there is a lack of sufficient tank or charging infrastructure to enable a changeover at short notice. In addition, due to the fact that most of the mobile machinery is diesel-driven and many different types of vehicles are included in this section, there is an insufficient research on whether and how everyday operation with alternative fuels can be performed. In order to counteract this, the operation of a multimodal liquefied natural gas (LNG) station infrastructure is tested in the port of Duisburg, called *duisport*, as part of the research project *LeanDeR*. To investigate the suitability of LNG for everyday use, two mobile machinery from the entire *duisport* fleet were tested with natural gas and compared with a similar diesel-powered ve-



Driesch, P., Horwat, K., Maas, N. and Schramm, D.
Evaluation of Alternative Propulsion Concepts for Mobile Machinery: A Modelling Approach using the Example on LNG-powered Port Handling Equipment.
DOI: 10.5220/0009872502250232
In *Proceedings of the 10th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2020)*, pages 225-232
ISBN: 978-989-758-444-2

hicle. For this purpose, measurement data from the LNG and the diesel-driven vehicles were recorded by autonomous data-logging systems whilst their everyday operation. One of these vehicles, a terminal tractor (see figure 1), is used to manoeuvre trailers around the port area. The terminal tractor considered in the course of the research project is powered by LNG in a mono-fuel operation.

Figure 1: Diesel- and LNG-driven terminal tractors at the *duisport*, (Duisburger Hafen AG, 2019).

Since the operation of a LNG filling station beyond the end of the project at the end of May 2020, only for the refueling of two vehicles, appears uneconomical, it must be examined whether a fleet-wide switch from diesel to natural gas would bring both economic and ecological advantages. Because a failure of the machinery directly extends to further process steps in the form of process follow-up costs, a solution is needed to weigh up a fleet-wide changeover with low risk and economic expenditure simultaneously. In the course of this paper, a simulation tool will be presented using the example of the terminal tractors. This tool enables the upscaling for a complete changeover of a fleet of mobile machinery to an alternative fuel. Based on the detailed database of the individual measured vehicles, semi-physical models of the vehicles' powertrains need to be developed. These models shall predict the fuel consumption and exhaust gas emissions of the other vehicles of the entire fleet in the respective powertrain. For the rest of the fleet only the knowledge of the vehicle speed, its payload and the current ambient temperature is required. The vehicle speed can be recorded during daily operation without a great effort. To estimate the payload of the port handling equipment, an analysis of the performed manoeuvring orders can be achieved from the terminal operating system. Information about the ambient conditions can be taken from accessible weather databases. By a fusion of these information depending on the respective time stamp the required model input is provided.

In section 2 the methodical approach to the development of the simulation tool is described. Afterwards the modelling is explained in section 3. Finally, section 4 provides a summary and outlook for future work.

## 2 METHODICAL APPROACH

The objective of a simulation environment for predicting a fleet-wide changeover from diesel-driven terminal tractors to natural gas propulsion as described in section 1 requires a systematic approach. For this purpose, the following steps based on (Verein Deutscher Ingenieure e.V., 2016) are fulfilled:

1. Formulation of tasks and objectives
2. Structural and functional analysis
3. Data collection and analysis
4. Determination of the relevant model aspects
5. Problem decomposition
6. Determination of the model type
7. System and process description

### 2.1 Formulation of Tasks and Objectives

The goal of the simulation tool is to estimate unknown process variables of the remaining fleet vehicles in everyday operation with conventional and alternative fuels. For this purpose, the operation of the vehicles must be simulated with one diesel and one natural gas powertrain each, so that the resulting fuel consumption and exhaust gas emissions for both drive types can be concluded. Afterwards the sum of the fuel consumption and exhaust gas emissions of the whole fleet have to be calculated.

### 2.2 Structural and Functional Analysis

The total fuel consumption $m_{\mathrm{F},p}$ of the vehicle fleet for $p$ different powertrains as well as the corresponding masses of exhaust gas emissions $m_{\mathrm{E}\alpha,p}$ of chemical compounds $\alpha$ like $CO_2$ occur as unknown process variables and thus as output variables of the simulation tool. As mentioned before, the velocity $v$ and the payload $m_{\mathrm{Trailer}}$ of the terminal tractors as well as the current ambient temperature $T_{\mathrm{Amb}}$ during everyday operation are used as input variables. These daily operations can be subdivided into several rides from one shutdown of the engine to the next. Each ride consists of a time-dependent vector of inputs, so that for an assumed fleet of $n$ vehicles with $m$ rides each $\sum_{i=1}^{n} m(i)$ time-dependent input vectors are available. Thus, for an estimation of the fuel consumption and exhaust gas emissions of a whole fleet, the simulation process has the structure illustrated in figure 2.

Every ride needs to be simulated with $p$ different powertrains. Therefore a simulation framework predicts the mass flow of the fuel $\dot{m}_{F,p}$ and the mass flows $\dot{m}_{E_\alpha,p}$ of the corresponding exhaust gas emissions of chemical compounds $\alpha$ for every ride with $p$ powertrains.

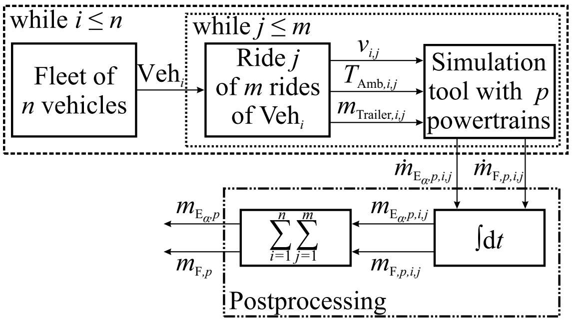


Figure 2: Structure of the simulation process.

In total $p \cdot \sum_{i=1}^{n} m(i)$ simulations must be carried out. To estimate the total mass of fuel and exhaust gas emissions for the whole fleet for $p$ powertrains, the mass flows are integrated and added up for every powertrain in a postprocessing.

## 2.3 Data Collection and Analysis

The development of simulation models requires knowledge about the system which shall be described. This is gained from the analysis of the everyday operation of the reference vehicles during a measurement period from January 2019 to May 2020 in course of the research project *LeanDeR*. The vehicles were equipped with self-sufficient data-logging systems which permanently recorded measurements of the ambient temperature, the GPS data set, the accelerations in three space dimensions as well as data from the CAN bus of the vehicles with a measurement frequency of 1 Hz. Thus measurements like the engine speed, its torque, the temperature of the engine coolant, the massflow of exhaust gas recirculation, the massflow of intake air and the massflow of consumed fuel were available. Furthermore, the volume concentration of the chemical compounds CO, $CO_2$, $NO_x$, $CH_4$ and $SO_2$ of the exhaust gas emissions were measured at the exhaust pipe with an exhaust gas emissions measurement system of type *J2KNpro* from the manufacturer *ecom*. Since permanent operation of the exhaust gas analysis device is not possible due to protective mechanisms in the device against the poisoning of individual sensors and a renewed calibration of the sensors to prevent measurement drift, measurements were performed at specified times. To determine the mass flows of the respective exhaust gas component, a mass-based calculation according to (European Parliament and the Council, 2017) was carried out. At the end of February 2020 the data base consisted of 11,460 km driving distance and 1,244 h driving duration of the diesel-driven terminal tractor. For the LNG-driven terminal tractor 11,909 km driving distance and 1,237 h driving duration were recorded. A distance of 261.3 km at a driving duration of 27.3 h were driven by the LNG-driven terminal tractor while an exhaust gas emissions measurement was executed. For the diesel-driven terminal tractor 138.9 km driving distance at 14.1 h of driving time during exhaust gas emissions measurement were recorded. In addition to the measurements of the motion of the vehicles, information regarding the load of the vehicles at specific timeslots can be taken by the terminal operating system. This system organizes the cargo handling and provide the gross weight of handled container which are placed on the trailers. These gross weight of the container includes the weight of the container itself and the goods inside the container, (Zhao et al., 2020).

## 2.4 Determination of the Relevant Model Aspects

Internal variables are required to implement the relationship between the input and output vectors shown in the system structure in figure 2. An analysis of the physical relationship between the inputs and outputs points out, that the combustion engine of the vehicles acts as the essential interface. It converts the chemical energy of the fuel by internal combustion into mechanical power on the crankshaft, causing exhaust gas emissions. This mechanical power is transferred through the powertrain to provide the required driving force at the wheels. Accordingly, the engine speed $n_{\mathrm{Engine}}$ and its torque $M_{\mathrm{Engine}}$ are defined as internal variables of the simulation tool.

## 2.5 Problem Decomposition

By considering vectors of internal variables, a defined connection exists between the input and output vectors of the simulation tool. Thus the overall simulation model can be subdivided into two subsystems for every powertrain $p$, as figure 3 illustrates, where the internal variables are the output of the first and the input for the second subsystem. Thus both subsystems can be developed in parallel and optimized specifically with the available database. The first subsystem includes the modelling of the dynamics of the vehicles and their powertrains to determine $n_{\text{Engine}}$ and $M_{\text{Engine}}$ by $v$, $T_{\text{Amb}}$ and $m_{\text{Trailer}}$. To estimate the mass flows of the fuel consumption $\dot{m}_{\text{F}}$ and the chemical compounds of the exhaust gas emissions $\dot{m}_{\text{E}_\alpha}$, the second subsystem represents a model to describe the combustion process of the engine of the respective powertrain. This model uses the outputs of the first subsystem and also some of the global inputs, e. g., the ambient temperature $T_{\text{Amb}}$ as inputs.

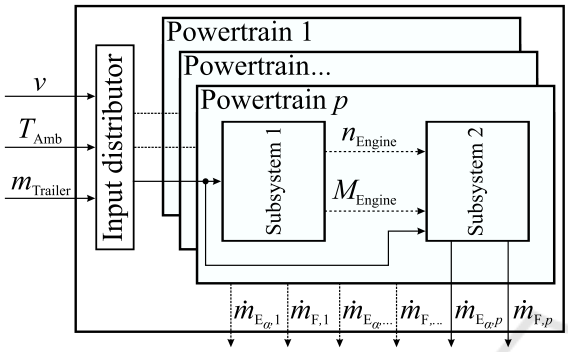


Figure 3: Problem decomposition into two subsystems for every powertrain.

### 2.6 Determination of the Model Type

The subsystems can be developed with different modelling methods. According to (Schramm et al., 2018), the dynamic behaviour of real processes is carried out either by theoretical modelling based on physical laws or by experimental modelling based on measurements of inputs and outputs. A modelling by physical laws grants the advantages that the results of the simulation are easier to interpretate physically, (Dubois, 2018). Thus a better understanding of the model is given but unknown physical parameters have to be identified. Experimental modelling, also called black-box modelling, based on a mathematical description of the relationship between the input and output measurements by, e. g., an artificial neural network (ANN) allows modelling of the system without sound process knowledge, (Xu, 1997).

For the development of the simulation tool a semi-physical modelling, i. e. a combination of both modelling forms, is chosen. Because some physical parameters of the vehicles' mechanical powertrain are provided by the manufacturer, for the first subsystem a physical modelling approach is applied. Since many different drivers with a variety of driving styles are working with the terminal tractors, a backward-facing quasi-stationary model of the vehicles' longitudinal dynamics and powertrain is used. This type of model does not require a driver model and the necessary torque and speed of the engine is calculated backwards through the powertrain based on the power requirement at the wheels to overcome the driving resistances, (Mohan et al., 2013; Wipke et al., 1999).

The mathematical modelling of internal combustion engines is complex and requires knowledge about thermodynamic conditions, e. g., in the combustion chamber and intake as well as exhaust manifolds, (Schramm et al., 2020; Guzzella and Onder, 2010; Serikov, 2010). Due to the fact that no measurements of thermodynamic conditions of the combustion engine were available, a black-box modelling approach like in (Serikov, 2010) is used. The estimation of the mass flow of fuel $\dot{m}_{\text{F}}$ and corresponding mass flows of the chemical compounds $\dot{m}_{\text{E}_\alpha}$ of the exhaust gas emissions shall be done by ANNs using, e. g., $n_{\text{Engine}}$ and $M_{\text{Engine}}$ as inputs.

### 2.7 System and Process Description

The system and process description represents the development of the system structure shown in figure 2 and the subsystems illustrated in figure 3 for $p$ powertrains. Since working with ANNs with frameworks like *Tensorflow* in the high level programming language *Python* is very common, the implementation of the physical models as well as the development of the ANNs is performed in *Python*. This means that both subsystems can be connected in the same software environment. In the following section 3 the modelling of both subsystems is described in detail.

## 3 MODELLING OF THE SUBSYSTEMS

The simulation tool consists of two subsystems which are based on different modelling approaches. Afterwards both subsystems are explained. In section 3.1 the physical modelling of the vehicle and powertrain dynamics is shown. The black-box modelling of the combustion engine is presented in 3.2.

### 3.1 Modelling of the Vehicle Dynamics

As mentioned before, a backward directed model of the vehicles' longitudinal dynamics and its powertrain shall be applied to estimate the engine speed and the torque from the vehicle's velocity, its payload and the ambient temperature. First, based on a time-dependent input vector

$$x(t) = \begin{bmatrix} v(t) & T_{\text{Amb}}(t) & m_{\text{Trailer}}(t) \end{bmatrix} \tag{1}$$

as well as vehicle and environmental parameters like the vehicle mass $m_{\text{V}}$, its front cross-sectional area $A_{\mathrm{V}}$, its drag coefficient $c_{\mathrm{W}}$, the air density $\rho$, the acceleration due to gravity $g$ and the dynamic rolling radius of the wheels $r_{\mathrm{dyn}}$, the acting driving resistances are determined according to (Schramm et al., 2020). It is assumed that the vehicle is driving straight forward and the wheels roll slip-free. Since the vehicles are moved on a surface without any significant gradient, the road inclination and thus the slope resistance is ignored. Also not considered is the wind speed, which is more or less evenly distributed in the spatial directions over time. In total, the acceleration resistance $F_{\mathrm{Acc}}$, the wind resistance $F_{\mathrm{Air}}$, the rolling resistance $F_{\mathrm{Roll}}$ and the resistance by pulling the trailer $F_{\mathrm{Trailer}}$ counteract the vehicle's movement as shown in figure 4.

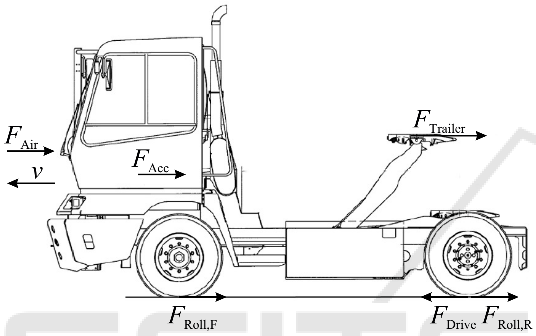

Figure 4: Acting driving resistances upon the terminal tractor in longitudinal direction, (Terberg Benschop, 2015).

The required drive force $F_{\mathrm{Drive}}$ sums up the driving resistances. Thus, the corresponding drive power $P_{\mathrm{Drive}}$ can be calculated by equation (2).

$$\begin{aligned} P_{\mathrm{Drive}} &= F_{\mathrm{Drive}} \cdot v \\ &= (F_{\mathrm{Acc}} + F_{\mathrm{Air}} + F_{\mathrm{Roll}} + F_{\mathrm{Trailer}}) \cdot v \end{aligned} \tag{2}$$

The acceleration resistance $F_{\mathrm{Acc}}$ describes the translational and rotational inertia of the vehicles which counteracts the change in motion and can be determined by equation (3).

$$F_{\mathrm{Acc}} = m_{\mathrm{V}} \cdot (1+\lambda) \cdot \frac{\mathrm{d}v}{\mathrm{d}t} \tag{3}$$

Here $\lambda$ represents the rotational mass surcharge factor, which expresses the rotational inertia $J_{\mathrm{PT}}$ in the powertrain in the form of a translatory force according equation (4).

$$\lambda = \frac{J_{\mathrm{PT}}}{(m_{\mathrm{V}} \cdot r_{\mathrm{dyn}}^2)} \tag{4}$$

The air resistance $F_{\mathrm{Air}}$ represents the aerodynamic resistance of the vehicle and is considered with equation (5).

$$F_{\mathrm{Air}} = \frac{1}{2} \cdot c_{\mathrm{W}} \cdot A_{\mathrm{V}} \cdot \rho \cdot v^2 \tag{5}$$

According to (Mitschke and Wallentowitz, 2014) the wheel resistance results mainly from the rolling resistance $F_{\mathrm{Roll}}$. Taking into account, that the wheels of the front and rear axis are similar, the rolling resistance can be described by equation (6) with a rolling resistance coefficient $f_{\mathrm{R,V}}$.

$$F_{\mathrm{Roll}} = f_{\mathrm{R,V}} \cdot m_{\mathrm{V}} \cdot g \tag{6}$$

The pulling resistance required to move a trailer is considered by a separate modelling of the trailer, (Haken, 2015). The rotational inertia of the trailers' wheels and the trailers' air resistance can be assumed to be negligible compared to the translational inertia of the trailers' mass and rolling resistance of its wheels. Thus the total resistance by pulling the trailers can be described by equation (7) with a rolling resistance coefficient $f_{\mathrm{R,Trailer}}$.

$$F_{\mathrm{Trailer}} = f_{\mathrm{R,Trailer}} \cdot m_{\mathrm{Trailer}} \cdot g + m_{\mathrm{Trailer}} \cdot \frac{\mathrm{d}v}{\mathrm{d}t} \tag{7}$$

In order to determine $n_{\mathrm{Engine}}$ and $M_{\mathrm{Engine}}$, a modelling of the vehicles' powertrains as shown in figure 5 is carried out. The powertrains include the combustion engine, an automatic transmission with a torque converter and an axle drive. Besides the mechanical power to drive the vehicle, auxiliaries, e.g., the alternator and the air conditioning are also driven.

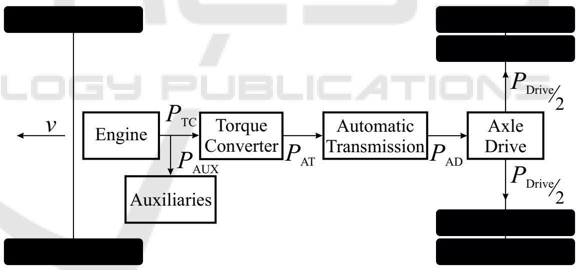

Figure 5: Overview of the terminal tractors' powertrains.

The drive power $P_{\mathrm{Drive}}$ is used as the input of the powertrain model to estimate the engine speed and the torque backwards through the entire powertrain. Beginning with equations (8) and (9) the speed and the torque of the tires, which equals the output speed and the torque of the axle drive, is calculated.

$$n_{\mathrm{Tires}} = \frac{v}{2 \cdot \pi \cdot r_{\mathrm{dyn}}} \tag{8}$$

$$M_{\mathrm{Tires}} = \frac{P_{\mathrm{Drive}}}{2 \cdot \pi \cdot n_{\mathrm{Tires}}} \tag{9}$$

By taking into account the gear ratio $i_{\mathrm{AD}}$ and efficiency $\eta_{\mathrm{AD}}$ of the axle drive, its associated input speed and torque can be determined by the equations (10) and (11). Those values equal the output speed and the torque of the automatic transmission.

$$n_{\mathrm{AD}} = n_{\mathrm{Tires}} \cdot i_{\mathrm{AD}} \tag{10}$$

$$M_{\mathrm{AD}} = \frac{M_{\mathrm{Tires}}}{i_{\mathrm{AD}} \cdot \eta_{\mathrm{AD}}} \tag{11}$$

The input of the automatic transmission is calculated with a gear ratio $i_{\mathrm{AT}}$ which depends on the selected gear $G_{\mathrm{AT}}$ and an efficiency $\eta_{\mathrm{AT}}$ by equations (12) and (13).

$$n_{\mathrm{AT}} = n_{\mathrm{AD}} \cdot i_{\mathrm{AT}}(G_{\mathrm{AT}}) \tag{12}$$

$$M_{\mathrm{AT}} = \frac{M_{\mathrm{AD}}}{i_{\mathrm{AT}}(G_{\mathrm{AT}}) \cdot \eta_{\mathrm{AT}}} \tag{13}$$

Due to the fact that the selected gear is not included in the input vector $x(t)$, an ANN as shown in figure 6 shall be used to predict the selected gear $G_{\mathrm{AT}}$. According to (Jeoung et al., 2020) the shifting of gear in automatic transmissions is controlled by the velocity of the vehicle and the position of the accelerator pedal. A change of the accelerator pedal position is related to a change of torque and thereby to a change of vehicles velocity and thus its acceleration. That is why the vehicle speed $v$ and acceleration $\frac{\mathrm{d}v}{\mathrm{d}t}$ are used as inputs, as figure 6 illustrates. The corresponding gear ratio $i_{\mathrm{AT}}(G_{\mathrm{AT}})$ is selected from a lookup-table filled with information from the data sheet of the manufacturer.

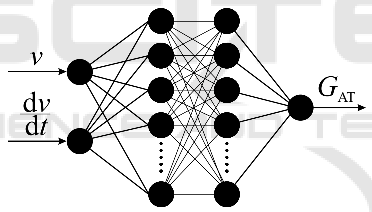


Figure 6: Neural network to predict the selected gear.

A torque converter is placed between the transmission and the engine to overcome speed differences when starting from engine idling. Since sufficient information about the dynamics of the torque converter are not available, a quasi-stationary modelling approach based on characteristic values from the data sheet of the torque converter according to (Luz, 2015) is used. The desired engine speed and the torque correspond to the input speed $n_{\mathrm{TC}}$ and the torque $M_{\mathrm{TC}}$ of the torque converter taking into account an efficiency $\eta_{\mathrm{TC}}$ as shown in equation (14) and (15).

In addition, the engine has to power auxiliaries, which are considered by a sum of $n$ different mechanical loads $M_{\mathrm{AUX},n}$ by $\sum_{i=1}^{n} M_{\mathrm{AUX},i}$, (Schramm et al., 2020).

$$n_{\mathrm{Engine}} = n_{\mathrm{TC}} \tag{14}$$

$$M_{\mathrm{Engine}} = \frac{M_{\mathrm{TC}}}{\eta_{\mathrm{TC}}} + \sum_{i=1}^{n} M_{\mathrm{AUX},i} \tag{15}$$

In order to decide, whether the air conditioning is heating or cooling, an ambient-temperature-dependent energy demand shall be considered.

## 3.2 Modelling of the Combustion Engine

The combustion process of the engines measured during the research project is modelled as a black-box. In general, the model has to reply two questions for every time step based on knowledge from its inputs:

- Which mixture of fuel, air and recirculated exhaust gas was burned in the combustion chamber?
- Which type and amount of exhaust gas emissions are generated?

It was found that multiple factors can influence the fuel consumption, exhaust gas emissions and the performance of the engine as, e. g., the temperature of the ambient air, the engine coolant temperature or the rate of exhaust gas being recirculated to the combustion chamber, (Abdullah et al., 2015; Abdelghaffar et al., 2002; Hussain et al., 2012). Therefore all the above-mentioned variables are considered in the black-box modelling of the combustion engine. To answer both questions, the engine model is divided into two ANNs, using the outputs of the first one as input for the second ANN, as shown in figure 7.

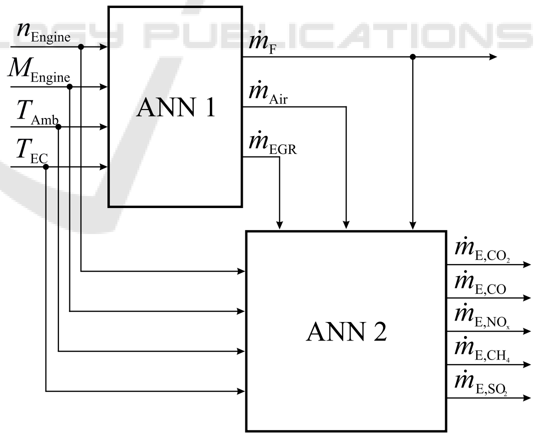


Figure 7: Structure of the black-box engine model.

In the first ANN the calculated $n_{\mathrm{Engine}}$ and $M_{\mathrm{Engine}}$ and the measured $T_{\mathrm{Amb}}$ are used as inputs. The fourth input, the engine coolant temperature $T_{\mathrm{EC}}$, is neither calculated nor measured during the operation of the entire fleet. This measurement value is just known from the individual vehicles, but because of its importance regarding the engines performance it is also considered as an input. It is therefore up to the user to define these temperatures in order to study engine performance under different engine conditions such as cold start or engine warm-up. The outputs of the first ANN – the mass flow of fuel $\dot{m}_F$, the mass flow of air $\dot{m}_{Air}$ and mass flow of recirculated exhaust gas $\dot{m}_{EGR}$ – answer the first question.

The second ANN aims to answer the second question by estimating the mass flow of carbon dioxide $\dot{m}_{E,CO_2}$, carbon monoxide $\dot{m}_{E,CO}$, nitrogen oxides $\dot{m}_{E,NO_x}$, methane $\dot{m}_{E,CH_4}$ and sulphur dioxide $\dot{m}_{E,SO_2}$. Therefore the inputs of the first ANN as well as its outputs are used as inputs to the second ANN.

# 4 SUMMARY AND OUTLOOK

This paper introduces an approach for a simulation tool with which a complete conversion of a fleet of mobile machinery to an alternative fuel can be scaled up using measurements of individual vehicles. The simulation tool includes semi-physical models of $p$ different powertrains to estimate the fuel consumption and exhaust emissions of the entire fleet for every powertrain setup. In this paper the simulation tool is explained using the example of terminal tractors and both, a diesel- and LNG-driven powertrain. Each semi-physical model consists of a combination of a physical modelling of the driving and powertrain dynamics and a black-box modelling of the engine by artificial neural networks. The development and parameterization of the models is fulfilled by measurements of the everyday operation of two reference vehicles. As inputs for the simulation tool measurements of the time-dependent velocity $v$, ambient temperature $T_{Amb}$ and payload $m_{Trailer}$ of the rides of the vehicles of a fleet are necessary. Based on these information the simulation tool predicts the massflows of fuel $\dot{m}_F$ and of the corresponding exhaust gas emissions $\dot{m}_{E_\alpha}$ for every powertrain $p$ during the ride. For the calculation of the total mass of fuel and emissions of the entire fleet for $p$ powertrains, in a postprocessing the simulation results for every ride and every powertrain $p$ are integrated and added up.

At the time of writing this paper, the physical models of the vehicle and powertrain dynamics are implemented. The ANNs for the prediction of the gear provide a sparse categorical accuracy of 95,4% (LNG) and 96,4 % (Diesel). Unknown physical parameters like the rolling resistance coefficient $f_{R,V}$ were estimated by measurements of planed test drives in which the terminal tractors did not pull any trailer. The evaluation of the calculated and measured $n_{Engine}$ and $M_{Engine}$ during the test drives resulted in a mean absolute error of 25.3 rpm and 21.9 Nm for the LNG- and 30 rpm and 24.5 Nm for the diesel-powered terminal tractor. To gain an understanding of the causes of the errors, an analysis of the simulation results was carried out. Two significant causes of failure were detected. Figure 8 presents a first excerpt of the measured test drives of the LNG-powered terminal tractor and demonstrates both types of failure. As the positions $P_1$ in figure 8 show, one cause of failure can be vehicle standstill, where the engine load is independent of the input data and deviates from the usual loads. In addition, errors may occur if the estimated gear differs from the measured gear (see $P_2$), resulting in a different gear ratio.

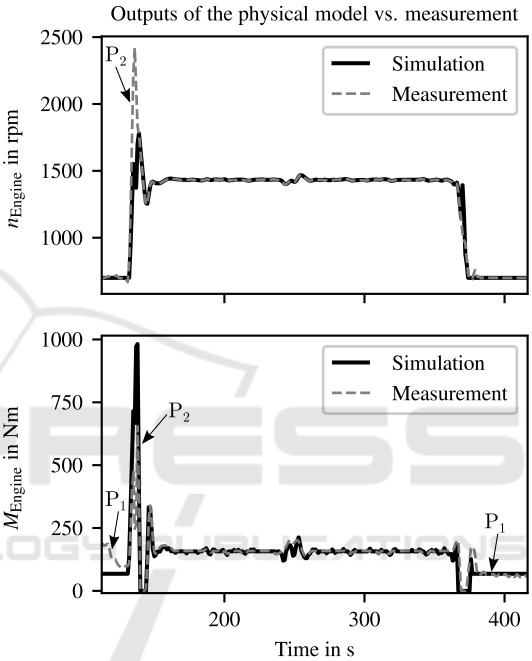


Figure 8: Measured and simulated $n_{Engine}$ and $M_{Engine}$ during a test drive of the LNG-powered terminal tractor.

The next step is to identify the unknown rolling resistance coefficient $f_{R,Trailer}$ of the trailer model. To do this, both, the measured data and the information from the terminal operating system are linked together. Then the internal structure of the ANNs in the black box model of the combustion engine in each powertrain has to be determined and data sets for training, testing and validation have to be created. Next, suitable hyperparameters of the ANNs must be found by hyperparameter optimization. Afterwards the accuracy of each ANN must be verified. Finally, the physical model and the black box model for each powertrain must be linked together and the accuracy of each complete model must be examined. The complete models can then be used to predict and discuss the fuel consumption and exhaust emissions of the fleet of terminal tractors at *duisport* for the diesel- and LNG-powered powertrain.

## ACKNOWLEDGEMENTS

The work presented here was carried out within the framework of the research project *LeanDeR*. This project was funded by the European Regional Development Fund (ERDF) and the state government of North Rhine-Westphalia, Germany.

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