Driving force model for a real-time control concept of a hybrid heavy duty vehicle

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Abstract: The electrification of heavy vehicles and work machinery is developing rapidly. The main motivators are green transition and requirements from the customers. In Finland, there are many high-tech market-leading companies in this segment. Mass-produced equipment and machines are suitable for general applications and thus tailoring design for specific conditions and/or needs results in better productivity and efficiency. In heavy electric vehicle applications, the challenge is to make new products economically viable and configure them to meet customer needs. In these applications, the number of solutions is an order of magnitude higher than in traditional mechanical solutions. However, electronic solutions enable new features and energy efficiency improvements to have measurable benefits in the application. The research investigates the effects of electric axle solutions for hybrid heavy duty vehicles. Modelling and simulations consider both the effects of engine and usage of battery charge and surroundings of vehicle, for example road profile, traffic, outdoor temperature, and friction. A system level model of a vehicle has been utilized to simulate its longitudinal dynamics interacting with estimated surroundings followed by model-based control. The planned route can be made further favorable by utilizing real-time model predictive control (MPC) receiving online data from changing conditions. MPC gives new suggestions for optimal battery usage based on deviations from the best matching model from a database. Control strategy is important when considering economic benefits for a hybrid heavy duty vehicle with a high degree of freedom in system design.

Keywords: Electrification, Green transition, Model Predictive Control, Model Based System Engineering, Systematic Machine Design

1. INTRODUCTION

An example of promising solutions for pollution reduction are electric and hybrid electric vehicles (EV/HEV), which can be exploited for a safe environment and sustainable transportation. Designing these vehicles requires different optimization procedures, for example components, systems, and controls (Ehsani et al. 2021). A review article of path tracking strategies used in autonomous vehicle control design discusses different elements of modelling process including the criteria for evaluating the controller's performance (Ruslan et al. (2023). Extremely important part for enabling the optimization of the battery usage during the route is to have a competitive battery management system. Advanced battery management, which consists of three progressive layers. A comprehensive overview of each layer is presented, and future trends of next-generation battery management are discussed (Dai et al. 2021). A broad review to optimize the power flow in EV powertrains using multispeed discrete transmission, continuously variable transmission and multi-motor configurations. The potentials and challenges regarding for example environmental issues are discussed. They can be applied to hybrid vehicles as well. As the overall development is proceeding rapidly, it is getting more and more challenging to be able to answer all demands. A key issue is to develop optimum vehicle fulfilling, for example tighter emission regulations. This leads to reduced emissions of new vehicles, more research of advanced materials for energy storage, better vehicle connectivity and more investments in autonomous technologies. However, it causes, for example sustainability issues in production and mining, higher electricity demand requires new electricity production and socio-economic issues on technology migration (Mazali et al. 2022). The EV vehicle inverse dynamics model was developed. Then vehicle states and kinematic constraints were used to formulate the servo constraints. Finally, a procedure for optimizing trajectories was developed. The results show that the optimal trajectory uses the least amount of energy (Min et al. 2023). Hybrid powertrains having two or more different energy sources, questions arise in terms of HEV structure selection, components sizing, and energy management control. Control variables optimization is vital to find the set of optimal control rules for the minimum fuel consumption. The dynamic programming approach is a common method because of its unique ability to find the global optimum solution with a certain degree of precision. This computationally demanding optimization method combined with a gradient-based optimization algorithm was used in a systematic way to reduce execution time and to increase the precision of the result (Cipek et al. 2020)/ The optimization of battery usage in a hybrid vehicle to minimize fuel consumption is a very complex problem. Basically, this means increasing the efficiency of the combustion engine efficiency and recovering electrical energy by charging the battery when driving or braking (Anselma 2022). In (Lei et al. 2018), four operating modes were used, and they were electric driving mode, driving and charging mode, combustion engine driving mode and hybrid driving mode.

A review of architectures and control strategies for the dual-motor coupling propulsion system used in battery electric vehicles is presented in this article. The article describes different architectures, reviews the means of mechanical coupling and transmission, electromechanical configurations, and summarizes approaches to the control of this emerging class of battery electric vehicles. Discussion comparing the advantages and disadvantages of dual-motor coupling propulsion system technology for battery electric vehicles is presented, as well as research challenges and prospects being discussed. (Wang et al. 2022)

The integrated energy management and engine control system for HEV is introduced. The synergy of artificial intelligent control and prior information, for example about route, can be exploited to boost the control performance together, with the engine being optimally controlled. (Zhang et al. 2022)

Having as an objective to decrease fuel consumption, the implementation of an adaptive, optimal neuro-fuzzy inference control was introduced (Saju et al. 2022). When evaluating fuel and electrical energy capabilities, it is usually assumed that the route and velocity profiles are known (Anselma 2022). By applying models, an optimal battery usage plan can be developed. For example, nonlinear programming, genetic algorithms and dynamic programming have been used in such optimization tasks. The problem, however, is that the overall driving power demand must be approximated accurately, which is very difficult in practical cases. For real-time control, the equivalent consumption minimization strategy and model predictive control (MPC) have been used. For MPC to be efficient, the model used must be accurate for future driving information estimation, which is not necessarily the case (Peng et al. 2017). Being capable of managing multi-variable problems and to consider constraints on states and control actions, with capability to predict future behavior of the process, MPC is widely used for trajectory tracking. This literature review discusses the research conducted from 2015 until 2021 on model predictive path tracking control (Stano et al. 2023).

The design of a path tracking controller for autonomous vehicles is addressed in this paper. The Reference Aware MPC is reformulated to guarantee closed-loop stability, while maintaining a safe and comfortable ride, and minimizing wear and tear of vehicle components. For usability in online operation, a novel model for the nonlinear curvature response of the vehicle is proposed by means of Kalman filtering. (Pereira et al. 2023)

Different technologies' potential for fuel consumption improvement of heavy-duty vehicle has been investigated in literature (Dünnebeil and Keller Heidelberg 2015); Schade (unpublished). According to high interaction between different technology packages system-level simulation should be implemented to overcome the complexity of powertrain design (Delgado et al. 2017). Developing a hybrid powertrain, system-level simulations enable the possibility to calculate vehicle fuel consumption and battery state of the charge for which are the main control strategy objectives (Enang and Bannister 2017).

The aim of this research is to develop a tool which could give a good platform to scheme suitable structures for electric axle. The goal of this paper is to first discuss shortly the concept of the planning process and then more in detail those parts, which concern the control strategy of vehicle environment and main variables effecting on it. This paper considers an approach where an approximation of the overall driving power is made with the simple driving force equation.

2. SYSTEM MODELLING FOR OPTIMIZATION

The optimization of battery usage of a hybrid vehicle requires a couple of models. First, it needs a model for the resistive forces acting on a vehicle that must be overcome with the force provided by either the combustion engine or battery. This overall force is called the driving force in (Lei et al. 2017) and (Koch et al. 2021). The optimization scheme also needs a model of the vehicle including the battery model describing the usage and charging of the battery. This paper concentrates on the model of the driving force while the vehicle model is described in (Banagar et al. 2024).

2.1 The driving force model

The driving force model is described in literature for example in (Lei et al. 2017), (Koch et al. 2021), (Anselma 2022) and (Chu et al. 2022). The references use different notations and thus the notations in (Koch et al. 2021) are adopted here. The driving force denoted by F_W is the sum of four forces which are functions of vehicle velocity (v) or acceleration (a). These forces are the resistance due to road slope with angle α, rolling friction, aerodynamic drag and the force to overcome vehicle

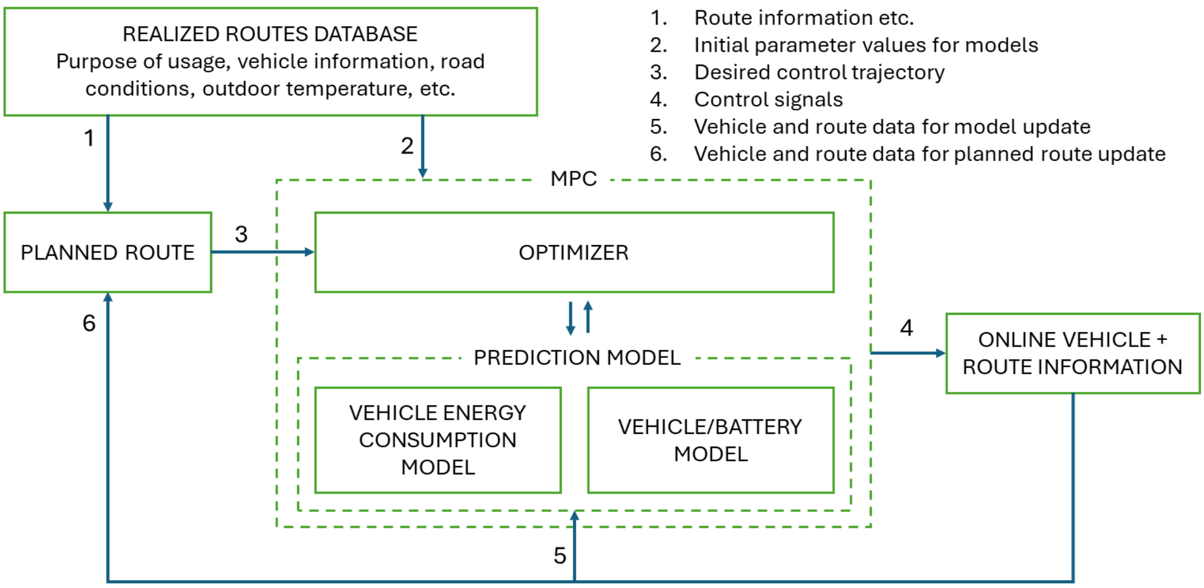

Fig. 2. The overall MPC-based control concept.

inertia. The driving force is calculated in equation (1) from (Chu et al. 2022):

$$F_W = mg\sin(\alpha) + mgf_r\cos(\alpha) + \frac{c_w A_f v^2}{21.15} + me_i a. \quad (1)$$

Above in equation (1), m is the vehicle mass, g is the gravitational constant, f_r is the friction coefficient, c_w is the drag coefficient, A_f is the vehicle frontal area and e_i is an equivalence factor. The torque required at wheels is given by equation (2):

$$T_W = F_W r_W. \quad (2)$$

Above, r_W is the radius of the wheels.

2.2 Vehicle model

The target vehicle is a rigid chassis heavy-duty truck with an 8x4 axle configuration and a gross weight of 33 tons. The plan is to replace one axle with an e-axle. The e-axle system includes for example a 15-kwh battery and an electric motor with a rated torque capacity of 880 N.m. The longitudinal dynamic model of the vehicle has been developed by implementing the AVL Cruise M vehicle module. AVL Cruise M /AVL Cruise M/ is a dedicated tool for vehicle and powertrain components simulation. Different powertrain components of the targeted vehicle have been modeled using an available dataset from the vehicle. A map-based model has been selected for the internal combustion engine and electric motor. The battery pack has been simulated implementing an Equivalent Circuit Model (ECM) component of AVL Cruise M. More detail about the parameters and simulation set up has been provided in (Banagar et al. 2024). The schematic of the vehicle powertrain architecture and the simulation set-up have been depicted in Fig 1.

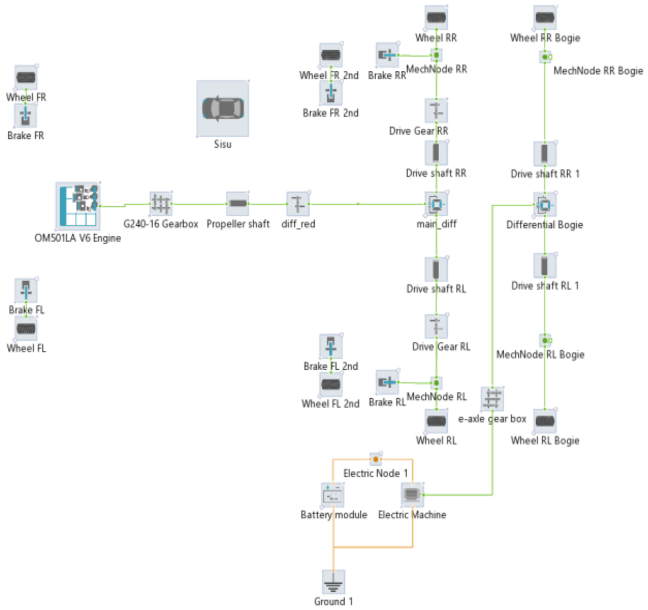

Fig. 1. The schematic of the vehicle's powertrain architecture.

2.3 Definition of control concept

The aim of this research is to develop a general approach to optimally use HEV's electric axle and thus reduce fuel consumption. The approach is based on two models which describe the energy consumption and battery usage of HEV. This paper introduces the model for energy consumption and compares its results to real measured data. The overall control concept is presented in Fig. 2. The main idea is to plan the route beforehand. However, no model can describe that perfectly. Thus, a simple model that can capture the main trends is used here but the battery usage plan is updated online as the route proceeds. Also, the models can be updated online because there are a lot of variables that are not considered with models.

3. RESULTS AND DISCUSSION

3.1 Data description

The data used was from a real truck that drove a route from Tornio to Rovaniemi in Finland. The most important variables used for calculating the driving force according to (1) were speed and altitude. The data included also information about actual engine torque that was used for comparison to see if (1) and (2) can describe the torque needed with adequate accuracy. At this point, it is already worth mentioning that (1) and (2) give purely theoretical power requirement and thus a perfect correlation is neither expected nor needed. Instead, a rough estimate is enough because control actions are aimed to be updated continuously.

Data included about 116000 data points sampled at 0.05 second intervals. A moving average filtering without overlap was applied to lower the sampling time to 1 s. The computations are carried out with this data while for model validation the data is further filtered with a 2 min moving median filter. The altitude and speed measured are shown in Figs. 3 and 4, respectively.

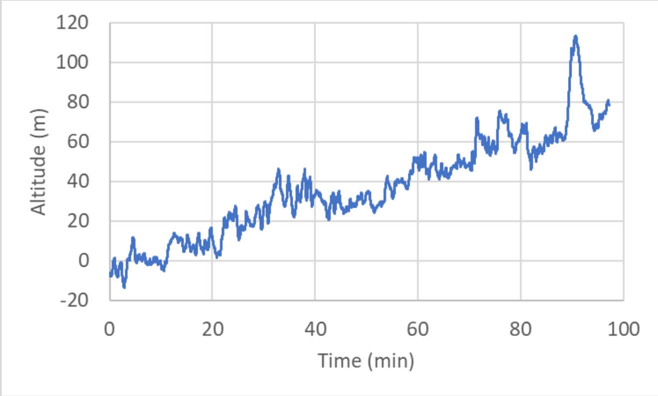

Fig. 3. The measured altitude.

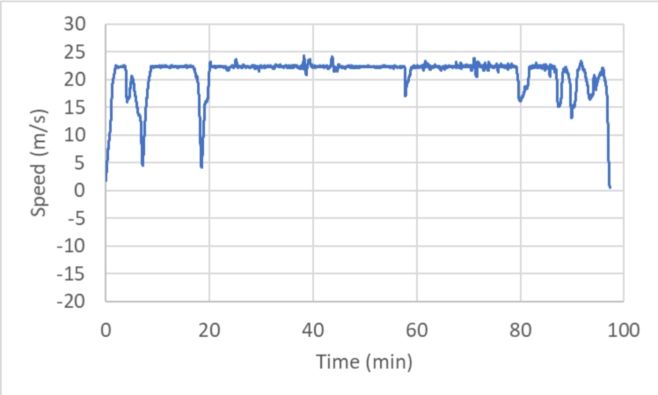

Fig. 4. The measured speed.

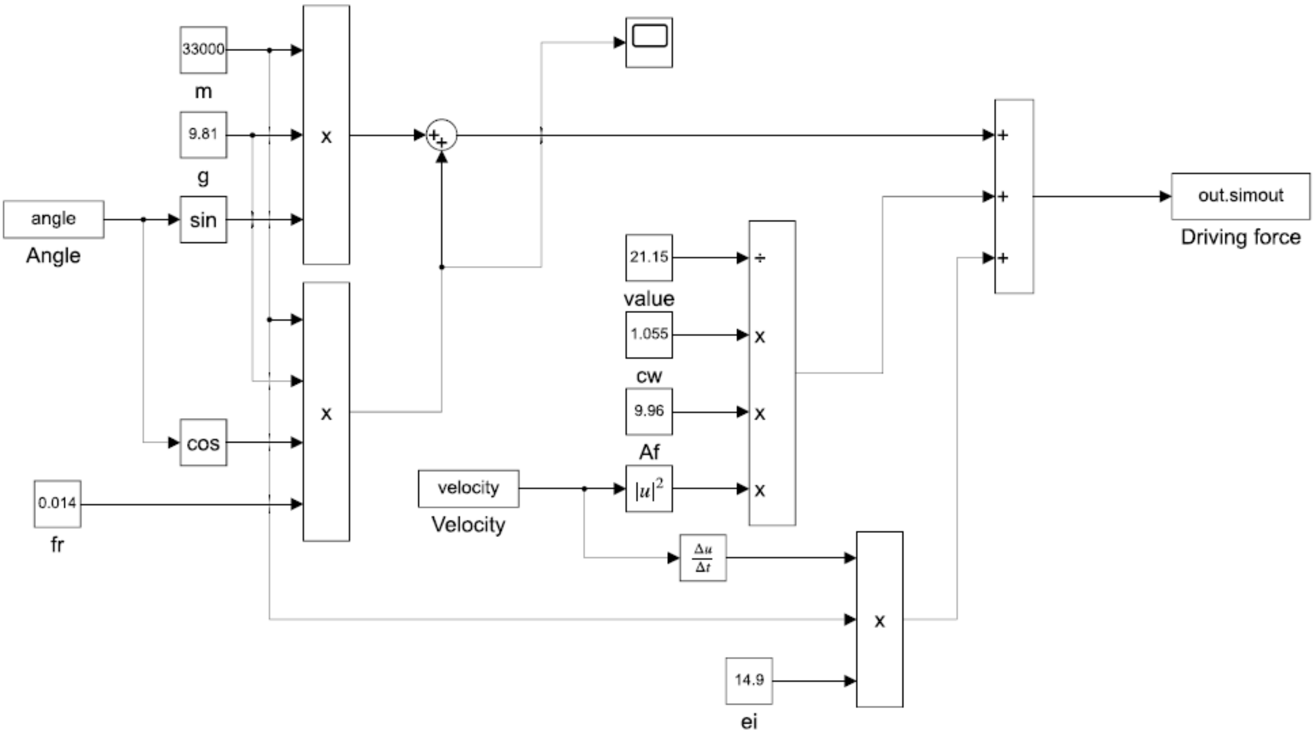

Fig. 5. Simulink® implementation of the driving force model.

3.2 The Simulink model of the driving force

The model described in 2.1 is implemented in Simulink® environment. The parameter values are taken from /Kinnunen (2023)/ and they are given in Table 1. The model is shown in Fig. 2. Also, the driving force is a function of distance. Thus, the overall driving force required is obtained as the sum of the model output in Fig. 5.

Table 1. The parameter values used.

m	f_r	c_W	A_f	e_i
33000 kg	0.014	1.055	9.96 m^2	14.9

3.3 Driving force model results

Driving force was computed according to (1) with the simulator in Fig. 5. The 2 min median filter was applied to obtain the driving force shown in Fig. 6. The high peaks of the driving force are associated with accelerations while the low peaks are associated with decelerations observed in Fig. 4.

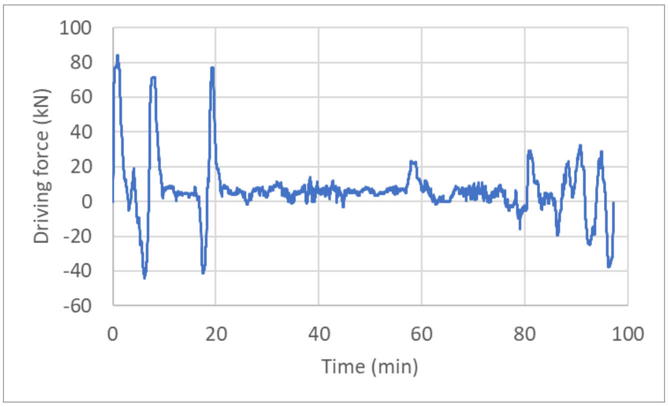

Fig. 6. The simulated driving force.

Figure 7 shows the driving force computed as a function of the actual engine percentage torque measured. The correlation between these is calculated to be 0.67. As expected, the theoretical model cannot explain the actual measurement data perfectly but only the trend is captured. This is, however, expected to be enough because the control actions will be continuously updated with MPC in the overall concept presented in Fig. 2.

Figure 8 shows the fuel consumption as a function of actual engine percentage torque. The figure shows that they are highly correlated. This means that high fuel consumption is associated with high torque. This observation combined with the relationship in Fig. 7 tells us that driving force peaks observed in Fig. 6 should be avoided. This knowledge can be used when defining the optimal battery consumption trajectory for MPC.

3.4 Control concept

The first steps towards the control concept introduced in Fig. 2 are presented in this paper. The driving force model is based on physics, and it is expected to give adequate information for identifying the most promising instances to

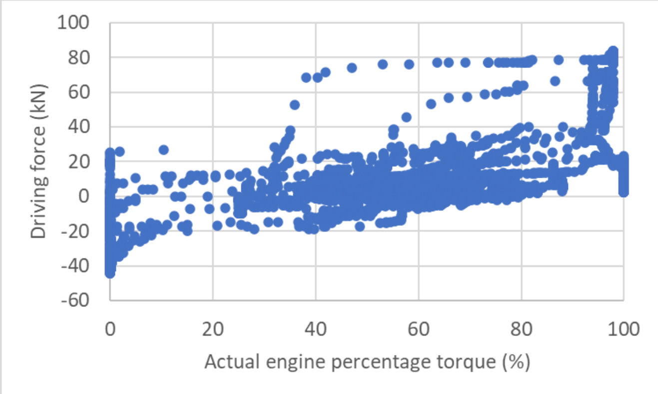

Fig. 7. The driving force computed as a function of actual engine percentage torque.

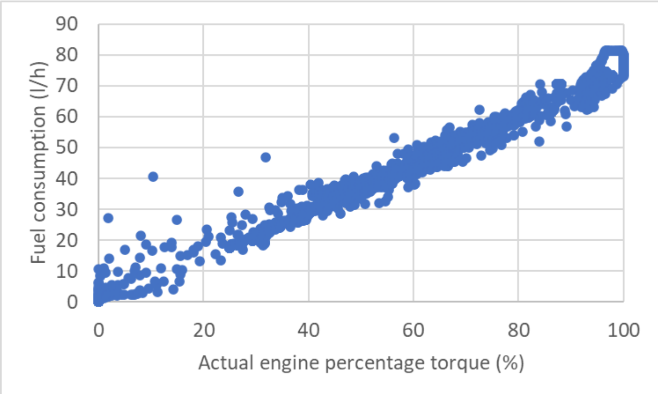

Fig. 8. The fuel consumption as a function of actual engine percentage torque.

use the e-axle for reducing the fuel consumption of the vehicle. In the future, the driving force model is further studied and further validated with more data. Of especial interest are the parameters of the model which are aimed to be defined automatically from the actual data. The driving force model is also complemented with the vehicle model to gain the information needed for making the battery usage plan.

When the models mentioned above are linked to each other, MPC will be implemented into the control approach. It will first be tested in a simulator environment with the collected data. First implementations use constant model parameters, but the alternative to continuously update them and thus adapt the models to current situation will be studied. This is because many variables have an influence on the vehicle's energy consumption and battery operation, and these are not readily included in the models. Such variables are for example the purpose of transport, constraints of battery usage, environmental temperature, tires, road conditions, speed limits, traffic and so on.

4. CONCLUSIONS

In this work the concept of planning process for e-axle used in heavy-duty vehicle was presented. The control approach using driving force and vehicle models was introduced. By choosing to use a widely accepted driving force model for computing the needed energy for driving certain routes, the acceptance of the method is easier to achieve. The driving force model was presented in this study and its results were compared with real measured data. It was noticed that the theoretical driving force model was able to capture the main trend of the engine power demand. This is expected to be enough for the MPC based control strategy.

The data used in this study was from a real truck. Future includes the usage of data collected from a truck in which a prototype of an e-axle is implemented to validate the model. A more distant goal for the future is the implementation of MPC to the prototype truck. As the model will be utilizing online data, the approach is going towards digital twin. This kind of tool can also be seen as a useful asset for several parties of industry branch in question to render the digitalization and green transition.

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