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IMPERIUM – IMplementation of Powertrain Control for Economic and Clean Real driving emIssion and fuel ConsUMption

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Abstract

Fuel economy is a key aspect to reduce operating costs and improve efficiency of freight traffic, thus increasing truck competitiveness. The main objective of the IMPERIUM project (IMplementation of Powertrain Control for Economic and Clean Real driving EmIssion and ConsUMption) is to achieve fuel consumption reduction by 20% (diesel and urea) whilst keeping the vehicle within the legal limits for pollutant emissions. The approach relies on three stages targeting the improvement of the control strategy: (a) direct optimisation of the control of the main components (engine, exhaust after-treatment, transmission, waste heat recovery, e-drive) to maximize their performances, (b) global powertrain energy manager to coordinate the different energy sources and optimize their use depending on the current driving situation, (c) providing a more comprehensive understanding of the mission (eHorizon, mission-based learning) such that the different energy sources can be planned and optimized on a long term. The IMPERIUM consortium consists of major European actors and is able to provide a 100% European value chain for the development of future powertrain control strategies for trucks. This paper addresses the opportunities for powertrain optimization from the control strategy point of view, by modeling the physical behaviour of the truck, presenting the existing control strategies, and finally identifying the opportunities for additional, look-ahead mission-related information.

Keywords: heavy duty road haulage; fuel efficiency, emission reduction, eHorizon, predictive management, vehicle supervisor

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1. Introduction

In the transport sector, the reduction of real driving emissions and fuel consumption of heavy duty road haulage is one of the main societal challenges. Fuel efficiency and emissions reduction interact with each other and vary with the specific vehicle application and operating conditions. The challenge is, therefore, to develop new strategies of flexible and global engine and emissions control in an optimal way for each application and mission, in order to maximise the potential utilisation of the individual systems.

The IMPERIUM[†] concept relies on control strategy improvements around the following four technical clusters: (a) predictive management for a global powertrain and vehicle supervisor, (b) engine control, (c) waste heat recovery, and (d) hybridization. For all of these clusters, two approaches are proposed. The first improvement approach targets existing control strategies. This will mostly rely on migration from direct control strategies to model-based control strategies as well as on integration of existing strategies. The model-based control strategy approach relies on a mathematical model of the physics of parts of the system (e.g. combustion), which is running in real time on the computing platform and is able to provide more accurate information of the current state of the system. Furthermore, a mathematical (sub) system description is the base to use predictive control strategies. The integration of different control enables tighter synchronization between the (highly dependent) systems and, therefore, improved performance.

The second improvement approach targets the introduction of extended and predictive input data. This additional data will provide predictive information of the vehicle mission and environment situation, therefore enabling predictive strategies that are able to correctly control the systems according to events that will occur with high probability in the short term future. Examples are the identification of hills or traffic jams and the resulting tailoring of the control strategies up to activation or deactivation of specific auxiliaries according to this information.

Resulting to this IMPERIUM's main innovations and targeted key results are (see Fig. 1):

- Objective 1: Development of a methodology and simulation environment for assessing the performance of HD trucks in real-driving conditions
- Objective 2: Development of Dynamic eHorizon system for Heavy Duty trucks
- Objective 3: Three advanced fuel efficient Demonstrators (DAF, IVECO, VOLVO), each integrating eHorizon and providing different approaches of Vehicle Control Units and powertrain configurations
- Objective 4: Analysis and validation of the project outcomes by means of in-vehicle fuel consumption and emissions measurements integrated into the proposed simulation environment

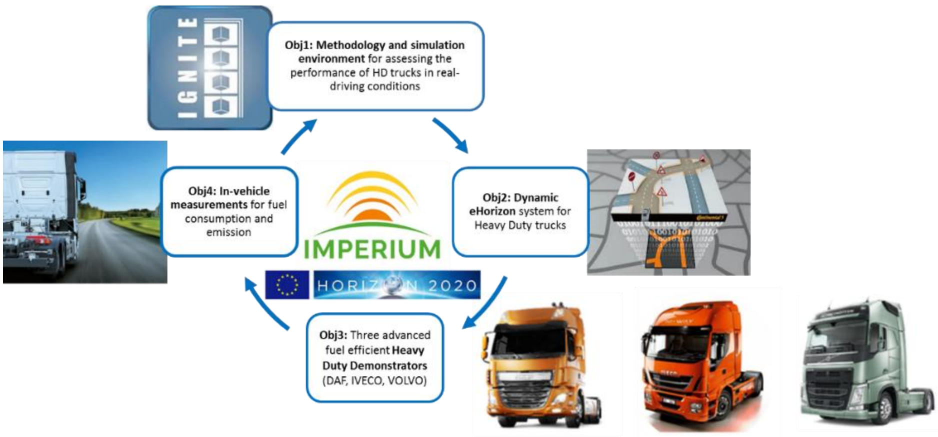

Fig. 1 The IMPERIUM Approach

The paper is organized as follows: Section 2 provides the rationales for predictive energy management. In Section 3, the dynamic look-ahead eHorizon approach is presented, while the resulting and expected powertrain improvements are discussed in Section 4. Finally, Section 5 provides an outlook and conclude this paper.

[†] www.imperium-project.eu

2. Rationales for predictive energy management

2.1. Overview

The energy management strategy (EMStr) includes planning and operation of the energy sources and consumers within a vehicle. The main objective is to fulfil all requirements (e.g. drivers torque demand, operational limits, travel time, etc.) by using the degree of freedom to minimise fuel consumption (or another target criteria). The degree of freedom creates a control problem, which is to be solved efficiently by the EMStr. This control problem can be solved locally without knowledge about the upcoming situation (non-predictive EMStr) or with information about the road ahead (predictive EMStr). To reach the global optimal fuel consumption, it is necessary to take the complete mission into consideration. In theory, a predictive EMStr is needed to achieve the optimal fuel consumption. However, a non-predictive strategy can be as good as the global optimal solution for specific missions.

Conventional trucks in Europe are typically equipped with (predictive or adaptive) cruise control and automated transmission. By using these two systems the EMStr can control the velocity and the actual gear within specific limits. Additional degrees of freedom can be introduced (e.g. a smart control of alternator and auxiliaries). In series production vehicles (especially passenger cars) non-predictive energy management strategies are state of the art. They are optimising an isolated point in time or an isolated operation point respectively [1]. Strategies which only rely on current information fail, if the amount of recuperative energy is large in comparison to the capacity of the recuperating energy storage system [2], [3]. Also, the power capability of the recuperation system plays a crucial role. If the recuperative power available is higher than the power capability of the recuperation system some of the energy will be lost.

Due to the huge mass of long haul trucks, the kinetic ($E_{Kin}=½\ m\ v^2$) and potential energy ($E_{Pot}=m\ g\ h$) is significantly more important than in passenger cars. The storage capacity is limited by road topography and the maximum drivable speed, which corresponds to legal speed limits or the surrounding traffic situation. If the vehicle speed and so the kinetic energy cannot be reduced before a steep downhill maneuver, potential energy has to be wasted by braking. Fig. 2 compares the stationary power demand for a passenger car (1.5 tons) and a truck (40 tons). While for passenger cars slope does not have such a big impact, the power demand of trucks is influenced drastically. Already at relatively small slopes high recuperative or demanded power occurs. Hence, predictive slope data is valuable information for the energy management in trucks to prepare the vehicle for upcoming events.

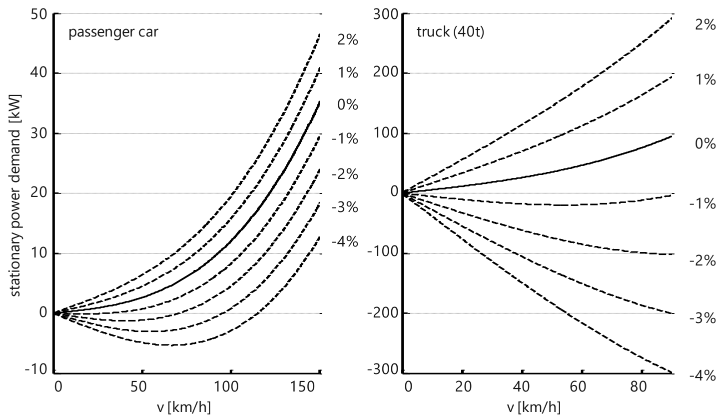

Fig. 2 Stationary power demand at various gradients

Consequently, predictive energy management systems are more commonly established in commercial vehicles compared to passenger cars. In 2009 it was already introduced in series applications. Freightliner Trucks used digital map material for its predictive speed controller “Runsmart predictive cruise”. Since 2012 Scania offers a similar system called “Active Prediction” [1]. Predictive cruise control and predictive shift strategy (both based on slope data) are currently available by almost all manufacturers of commercial vehicles.

Hybridization of a truck introduces an additional energy source and power converter to the drivetrain and therefore adds a further degree of freedom within the EMStr. Vast majority of hybrid vehicles are hybrid electric vehicles (HEV). This report will solely focus on HEVs. For a given topology and given energy capacity and power capability of the electric system, the control problem is extended by starting/stopping the engine and choosing the power split between engine and electric machine during driving. The control decision can also profit from predictive information. In a conventional truck the upper speed limit can be reached quite quickly on longer downhill stretches by converting potential into kinetic energy. The rest of the potential energy has to be wasted by braking. A hybrid vehicle makes use of that energy by regenerative braking. Due to the power limit of the electric system it is often wise to start the recuperating from the beginning of the downhill event. Thus, the potential energy is converted in kinetic energy and electrochemical energy simultaneously.

Predictive strategies beat non-predictive strategies, if the power demand can be shaped in a way to match the energy storage capacity so that nearly all negative power can be recuperated (using the battery or the change in kinetic energy). Possible realistic use cases are early coasting before reaching a traffic jam or having a long downhill event. Predictive EMStr demonstrates its strengths in hilly environments or often changing traffic situation/velocities. (Predictive) Energy management strategies (particularly for hybrid electric vehicles) are well covered in research literature. EMStr can be classified in heuristic, local optimal and global optimal strategies (see also [4], [5], [6], [7] for a more detailed classification). Heuristics (or rule based) strategies consist of a set of rules, which determines the degree of freedom. Currently, they are state of the art in series application. Predictive heuristic EMStr often advance the basic strategy by changing the control limits for different operating modes based on the preview information [8]. In [9] a state of charge prediction of the battery is calculated by using a neural network. [10] and [11] focus on the start and stop of the engine. [12] investigated a topography dependent adjustment of the state of charge set point [3].

Local optimal strategies use mathematical functions, which optimize the actual situation. The most widely spread use of the local optimization approach for HEVs is the equivalent consumption minimization strategy (ECMS). Based on an ECMS-factor the usage of energy is converted into a fuel equivalent. In [13] predictive information is generated into a velocity and a power prediction. The relationship between drive and recuperative power is determined to calculate an equivalence factor. [8] is based on a similar approach but integrates the shift strategy and the engine on/off decision. [4] and [14] calculate the equivalence factor by iterating the value over the prediction horizon until a balanced state of charge is reached [3].

Global optimal strategies optimize a specific (time) horizon of the control problem and are therefore always predictive. They determine the global optimal solution (e.g. the global minimal fuel consumption over a specific horizon) of a given mission. Global optimal strategies are often used as benchmark strategies because they can achieve or even guarantee the optimality of the solution. They are also the most computationally intensive strategies so that they are often not available for real time implementation. Dynamic programming (DP) is the most investigated approach to solve the global optimization problem. Often, the calculation effort is reduced by using approximations (which negatively affect the global optimality). [15] was the pioneer in implementing DP in a real-time environment by using a very short horizon. The predictive information and a driver classification were used to calculate a velocity and power profile [3].

[1] investigated a real time implementable multidimensional optimisation using DP. This work optimized the velocity, and the shift strategy. [3] used DP to solve the multidimensional optimisation problem for a hybrid vehicle. His work is based on three different optimization horizons. The long range optimization generates a velocity profile and power prediction based on predictive information. With that information the state of charge is optimized. In the mid-range horizon (~3 km) a parallel optimization of the state of charge, the velocity, the shift strategy and the mode decision is executed. The final state of charge for the mid-range is given by the long range optimization. The short range optimization is similar to the mid-range optimization but differentiates by a very short time horizon. The solution of the mid-range is used as setpoints for the short range optimization [3].

By the use of global optimization, it has been shown that the knowledge of the exact power demand over a prediction horizon and the component behaviour is necessary (power loss, limits etc.) to achieve an optimal solution by the EMStr. The fuel consumption is related to the power demand at the wheels increased by the losses in the drivetrain. The power profile P_{Dem} results from the multiplication of driving force resistance F_{DFR} and the velocity v.

$$P_{Dem}(x) = F_{DFR}(v, road, topography, vehicle) * v(t)$$

Losses occur by the power conversion starting at the fuel tank over the complete drivetrain to the wheels. Auxiliaries need to be supplied, which further increases fuel consumption. To calculate the power prediction at the primary energy source for a specific horizon, drive force resistance, velocity profile and drivetrain losses need to be predicted. In general, the performance and robustness of the predictive strategy is related to the quality of the prediction itself [3]. It is challenging to predict the future driving conditions with a sufficient accuracy [16]. The accuracy of the power prediction is the key issue to save fuel within a predictive strategy [17]. Furthermore, the correctness of data plays a crucial role [3]. In most cases, the drivetrain losses are related to friction which is usually a function of rotational speed. If they are coupled to the mechanical drivetrain they are related to the vehicle velocity. The velocity has a squared effect on aerodynamic drag, so that it influences the prediction of the drive force resistance. The basis for a high quality power prediction is a high quality / accuracy in the velocity prediction [3]. Algorithms, which predict drivetrain losses, driving force resistance and velocity, are essential for predictive EMStr. All information from an eHorizon system which can improve these prediction algorithms is adding value to the vehicle.

2.2. Prediction of drivetrain losses

The drivetrain losses are related to the drivetrain topology and the installed components of the vehicle. They are specific for each vehicle. If a component is coupled to the mechanical drivetrain its losses are dependent on rotational speed and mechanical power. An observer may be used to calculate relevant characteristics, if the behaviour is not measurable or known [3]. A predictive control of the thermal management of the engine can be used to reduce the fuel consumption by reducing friction and lower power consumption of the pumps [18], [19]. Further components and systems (e.g. low voltage power supply, air pressure system, air conditioning system etc.) can also profit from a predictive control [3], [20], [21].

All predictive controls found in literature sources, which focus on drivetrain losses, make use of vehicle specific information and sensors together with a power prediction at the wheels. Because of the dominant influence of vehicle specific information predictive calculation of drivetrain losses are normally located in a vehicle ECU. These strategies profit from an accurate velocity and drive force resistance prediction, which can be improved by an eHorizon sensor. In addition, temperature and humidity can be helpful information. The dynamics of these parameters are very limited, so that for most applications an actual measurement is sufficient.

2.3. Prediction of drive force resistance

The drive force resistance consists of rolling resistance, aerodynamic drag, climbing resistance and acceleration resistance. It is dependent on vehicle speed, vehicle specific variables and ambient parameters. It can be simply expressed.

$$F_{dem} = F_{air} + F_{cl} + F_r + F_a$$

The aerodynamic drag is a function of the aerodynamic shape of the vehicle ($c_d \cdot A \ldots\ vehicle\ specific$), the density of air ($\rho_{air} \ldots ambient\ specific$), the wind speed against the direction of moving ($v_{wind} \ldots ambient\ specific$) and the driven velocity. The angular direction of the wind can increase the aerodynamic drag.

$$F_{air} = \frac{c_d \cdot A \cdot \rho_{air}}{2}(v - v_{wind})^2$$

The density of air can be expressed as a function of temperature, humidity and ambient pressure. These variables could be provided by an eHorizon system but could also be measured within the vehicle due to their low dynamic. The wind speed is a very dynamic variable and very difficult to predict or even to measure. In literature a prediction with sufficient accuracy for mobile application is not known to the authors.

Climbing resistance is related to the mass of the vehicle ($m_{total} \ldots vehicle\ specific$), gravitational acceleration ($g \ldots ambient\ specific$) and gradient angle ($\alpha_{cl} \ldots ambient\ specific$)

$$F_{cl} = m_{total} \cdot g \cdot \sin \alpha_{cl}$$

The gravitational acceleration is dependent of the actual position on earth as well as the vehicle altitude. It can be simplified as a constant in Europe. The topography of the road ahead defines the gradient angle. It is dynamic and has a significant influence on the climbing resistance. Tyres, road and skew influence the rolling resistance. Important parameters of the tyres are material, tyre pressure, velocity, type of the tyre and many more variables. Those are vehicle specific and can even differ between vehicles of the same model. Bumps on the road, material combination between tyre and asphalt, plastic deformation (e. g. rail grooves) influence the rolling resistance and can maybe be predicted in a general manner (e. g. provide information about type and condition of a road). Rain and wet roads (displacement of water volume) affect the rolling resistance and can be predicted, but calculating an actual flush resistance might need more detailed knowledge. Skew occurs through cornering, slip angle or changed suspension geometry. Road curvature can be used to calculate sideslip forces during cornering situations. If slip is neglected, the rolling resistance is a function of the mass of the vehicle ($m_{total} \ldots vehicle\ specific$), the gravitational acceleration ($g \ldots ambient\ specific$), the coefficient of friction ($f_r \ldots partly\ vehicle, ambient, and\ velocity\ specific$), the gradient angle ($\alpha_{cl} \ldots ambient\ specific$), the flush resistance ($F_{Flush} \ldots partly\ vehicle\ and\ ambient\ specific$) and the sideslip resistance ($F_{sideslip} \ldots partly\ vehicle\ and\ ambient\ specific$)

$$F_r = m_{total} \cdot g \cdot \cos \alpha_{cl} \cdot (f_r + f_{r,plast}) + F_{flush} + F_{sideslip}$$

The acceleration resistance is dependent on the rotatory and inertia and the acceleration of the vehicle. A mass factor e_i is used to convert rotatory inertia into an increase of translatory inertia. The inertia is specific for each vehicle. The acceleration is the derivative of the velocity.

$$F_a = (e_i \cdot m_{veh} + m_{load}) \cdot a_x$$

The quality of the power prediction is directly related to the quality of the prediction of the driving force resistance. A better prediction of the coefficients directly increases the accuracy of the force prediction at the wheels. Errors occur through the use of parameters which are calculated under ideal and stationary measurements. Influences with low dynamic like temperature, mass or other coefficients can be achieved by estimation procedure. Online applicable approaches are described in [22], [23], [3]. The difficulty of the estimation procedure is to filter the numerous perturbations, so that suitable situations play an important role to increase the quality of the estimation [24]. Well suited are driving situations with a high dominance of the interesting signals in comparison to the perturbations [25]. Especially traction mode, free wheel and coasting allow a separate identification of the coefficients [26]. The driving force resistances appear at the same time, so that a detailed allocation is not needed. Implementing a polynomial for representing the aerodynamical and the rolling resistance can be a useful simplification [1]. The current slope can be estimated by the difference of measured acceleration on an inertia based sensor and measured difference in velocity [27], [1]. However, for calculating a power prediction the dynamic of the slope has to be taken into account. Due to the high mass of long-haul truck, slope data is the most important parameter to predict. Further parameters can be valuable (e.g. curvature, air density, etc.).

2.4. Prediction of the velocity profile

The product of the prediction of drive force resistance and the prediction of the velocity profile is the power prediction. The quality of the power prediction is directly related to the accuracy of the velocity prediction. An inaccurate prediction of the velocity affects significantly the fuel benefit of predictive strategies [3]. Independent from accuracy of the predicted power, the velocity and acceleration is chosen by the driver or an advanced driver assistance system as a final instance. However, the decision is highly influenced by the surrounding traffic situation, legal speed limits and other ambient conditions [3], [28].

In the literature predictive information is repeatedly used to generate a range of feasible velocities along the path [1], [28], [3]. Typical information used is map based legal speed limits, road curves, road grades, traffic sign recognition and adaptive cruise control sensor information. [28], [29], [30], [31], [1]. Often this information is not sufficient for a high-quality speed prediction in realistic situations, because the traffic situation can dominate the driven velocity. Some research literature investigate traffic information mostly based only on simulation using historical information [17], [32] and assuming that the driven speed meets perfectly the average traffic speed. Speed prediction using live traffic information is a focus of ongoing research activities. Floating car data and cellular floating phone data [33] are currently used to generate live traffic information. Here Maps, Inrix, Google Maps, Tomtom and other suppliers offer live traffic information. They combine historical and live traffic information to also generate a prediction of the traffic situation [3].

Suppliers of live traffic information normally use reference speed or free flow speed. This speed is generated during times of the day, in which a reduced traffic situation is assumed (e.g. during the night). This information gives a maximum speed per road segment. This often differs from legal speed limit, for example a narrow corner on a rural road or a roundabout [3]. The velocity information is currently an average value of all measured vehicles in that segment. Standstill situations like a crossroad or traffic light can falsify the average speed. Taking traffic lights and crossroads into consideration can improve the velocity prediction especially in city driving situation. Highways have a high density of sensors (active navigation system of the vehicle or the phone) and are therefore very well mapped [3]. The length of a segment is influencing the quality of the traffic information [3]. The final driving speed is decided in the vehicle and highly related to the specific driver or ADAS. Thus it makes most sense to predict the velocity in the vehicle. In recent research, neural network and stochastic Markov chain are used to predict driver behaviour and so the short-term velocity. For analysis historical driven speed profiles (e.g. from a traffic database or in vehicle measurements) are used. [17], [32]. An ADAS, which controls the velocity of the vehicle, can reduce the uncertainty of a velocity prediction significantly.

Literature often differentiates between short term and long term prediction. For the latter, live traffic information provides very valuable information and is another boundary condition of the speed profile [28]. [3] pointed out the relevance of accurate live traffic information for predictive energy management strategies. Velocities given by live traffic information correlate well with the driven velocity. Due to their discrete steps, they are not well suited to be directly used for a power prediction. The difference between predicted and driven speed can be minimized in combination with a driver model or an ADAS algorithm. In [3] live traffic information was only accurate on highways and deviated on other road classes.

3. Dynamic Look Ahead Capability

Predictive information is very valuable, as it is able to improve the quality of the predictive algorithms in the vehicle. It can be used to reduce the possible solutions (e.g. range of possible velocities [15]) or to increase the accuracy of the calculation for specific parameters (e.g. slope data for the prediction of the drive force resistance). New (connected) sources of information in addition to the vehicle sensors open a variety of opportunities [3]. Digital map data is a basis for predictive information. It can be stored on board of the vehicle and provide static road parameters. The location identification is typically done by GPS-Positioning (including correcting signals by reference stations) and map matching algorithms. Digital maps enable a precise positioning of the vehicle. The map data is typically owned by map providers and generated via measuring vehicles [1]. Furthermore, self-learning parameters can increase or adapt the digital map data. Especially if a route is driven repeatedly, a historical data base can be generated for local information which can be used for a vehicle specific horizon [8], [34], [1]. Sensors of individual vehicles can be used to calculate relevant road parameters [35], [36]. They can be aggregated and processed to generate geolocated crowd sourced information (e.g. live traffic information). This type of information is often referred to Floating Car Data or Vehicle Probe Data and is communicated (via GSM) to a central server for processing. The aggregated information is sent back to the individual vehicles. This can enable a high coverage and correctness of data. Beside technical possibilities, data protection issues have to be addressed as well [1].

In the literature [37][38][39][21][15][17][28][40] a variety of possible road parameters were identified, which are investigated for predictive energy management strategies. For predictive energy management not only a single value but a horizon of predictive information is needed. The information can change over the distance (locally dynamic) and over time (temporally dynamic). For example, slope data is locally dynamic but static in time. Temperature has a quite low local and time dynamic for typical horizon length. A measurement at the beginning of the horizon might be also valid for the end of the horizon (if the horizon length is not too long). On the other hand, traffic information like a traffic jam position has a very high location and time variability. For information with very low local and time dynamic over the horizon, a measurement for the current time and position might be good enough. This information does not profit much from a prediction over the horizon. Information, which are locally dynamic but static in time are valuable to predict. They can sufficiently be expressed as geolocated static information in a digital map. If the information is also time dynamic, an on board stored static map cannot deliver a good accuracy. Fig 3. shows a classification of the dynamic for the predictive information.

Different source of information can be used to generate the relevant predictive information. The vehicle itself is equipped with a range of sensors (e.g. radar, thermometer, rain sensor, etc.). The eHorizon system can improve this information with temporally static information by using a digital on-board map. Via a connection to a backend, it can also deliver time dynamic information. Vehicles are often equipped with a thermometer, a rain, a light and a sun sensor [15]. Via a connection to a backend this information can also be shared with other vehicles which do not have these sensors. A road sign recognition system can detect a change of the legal speed limit. Normally this detection is too late to use such a system as an input for predictive energy management strategies. But it could be used together with a map database to learn or update the legal speed limits given in the map. Lidar or radar sensors can detect a vehicle and its velocity upfront. Also other lanes and the opposing traffic can be observed, but the length of sight is limited to the visual range of the vehicle. For ADAS functions the ensured visual range is often limited to 80 m [41][42][43]. For predictive energy management strategies, a much longer horizon would be beneficial to predict the velocity. The legal speed limit can be provided by a digital map over a long horizon, but the driven velocity can be heavily influenced by the surrounding traffic situation. This time dynamic information could be delivered by a GSM connection to a backend.

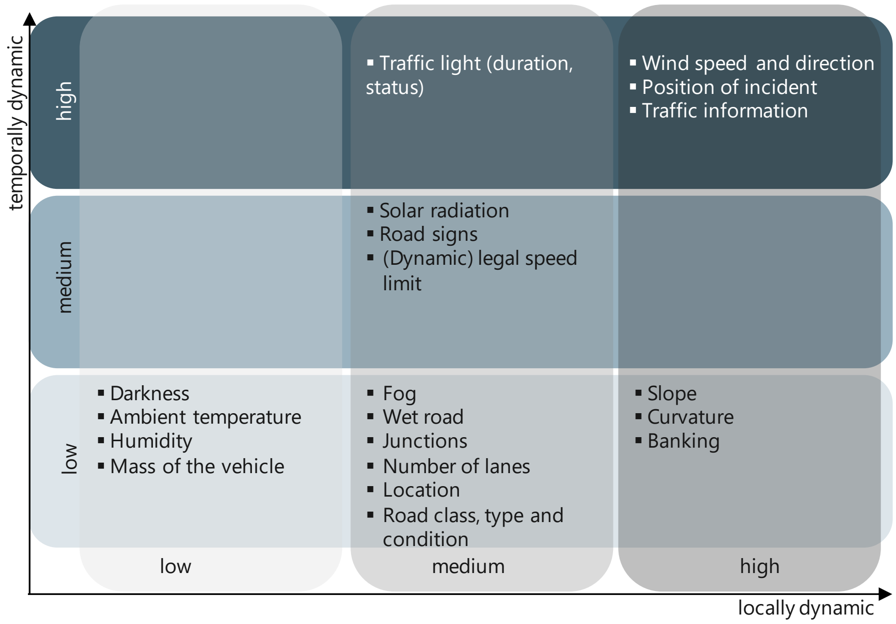

Fig. 3 Classification of predictive information by dynamic

Real time traffic information (RTTI) is already a great asset for all parties in roads and highways. Being able to reliably reroute around slow moving traffic can save hours of precious time. The accuracy of such information is very good today and will improve further going forward. Typical longitudinal accuracies are in the range one hundred of meters. The information is refreshed at a rate of less than once per minute. With this level of accuracy it could be used as input for predictive driving algorithms leading to the possibility of early adaption of the speed profile of a truck in accordance with the traffic flow in the next kilometers of highway.

Today eHorizon solutions already provide trucks with look ahead capability regarding static data like road slopes. The adaptation of truck speed profiles and gear shift algorithms based on this information delivers up to 3% improved fuel economy depending on road terrain. In a next step Continental has added a connectivity interface and backend connection to the eHorizon solution, as visible in Fig 4. This enables real time traffic information to be downloaded and added to the available static information per road segment. The ADASIS V2 standard used in today's eHorizon solutions has the capability to include this data

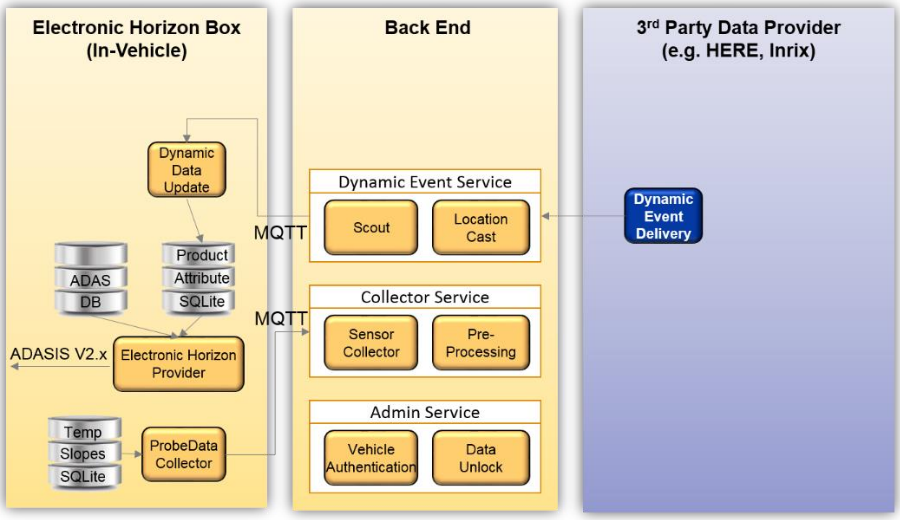

Fig. 4 High level architecture of eHorizon solution

4. Global predictive vehicle supervisor

The global control system architecture is divided into 4 levels to ensure a correct functionality of all the systems respecting all the safety aspects. This includes prediction, energy management, dynamic management and component control, see Fig. 5.

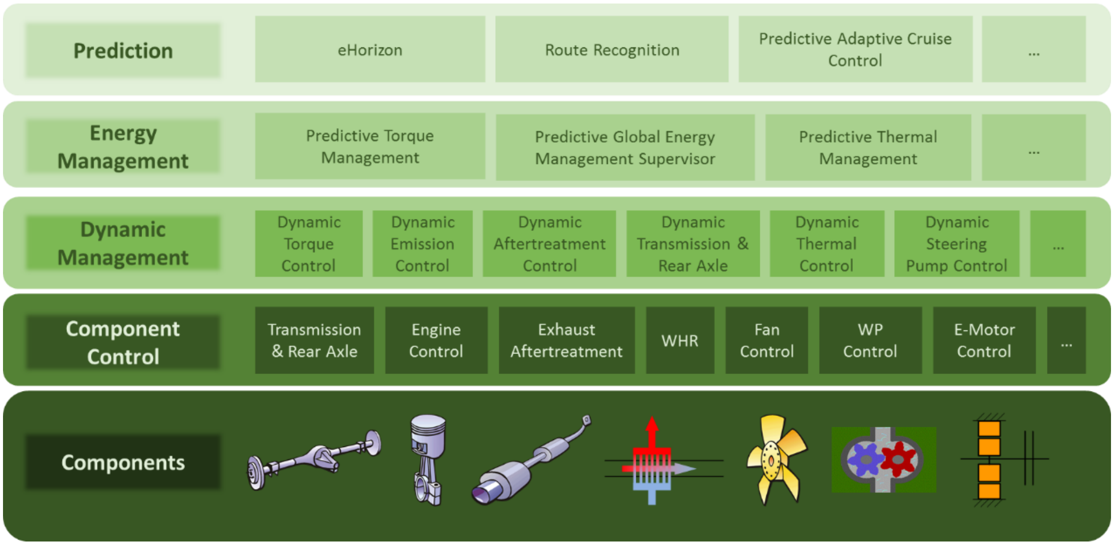

Fig. 5 Overview of the control hierarchy

4.1. Prediction Level

On this level the road and traffic conditions of the next ~8 km are predicted by the eHorizon System. The information is updated with a quite low sampling rate and availability for a small period might be lost, especially if the real mission deviates from the “most probable path” (e.g. leaves the high way on an exit) until the next “most probable path” is identified and analysed. Information which is not predictable can also not influence energy management and drivability, hence the following levels are necessary and must work autarkic. For short distance the information of the existing vehicle radar sensor (as used for the actual ACC) is also considered for the predicted mission.

4.2. Energy Management Level

The Energy management level consists mainly of the Energy management supervisory control (EMSTR) which uses the information from the prediction level to control the subsystems in the most efficient way considering the actual status and the future needs of each of them. The EMSTR mirrors the vehicle-engine system using simplified models of

- Vehicle, Powertrain incl. transmission
- Engine incl. combustion model for variable emission setups
- Exhaust aftertreatment system thermodynamic and emission reduction efficiency
- Vehicle Cooling system
- (Micro) hybrid system
- Waste heat recovery

Therefore, the EMSTR is capable to predict the thermal behaviour of the systems as well as the energy consumption of the cooling system on one hand and the emission reduction capability of the exhaust aftertreatment system on the other hand for different vehicle speed trajectories and different system uses, mainly of the (Micro)-hybrid WHR, engine raw emissions and components of cooling system like Thermostat, cooling pump, cooling fan and Grill shutters. The EMSTR includes also an optimizer to determine the optimal trajectories of the vehicle speed and the use of the different systems for lowest fuel consumption and emission compliance for the predicted mission range. The optimizer determines in a first step the vehicle speed trajectory for lowest energy consumption and in a second step the interactions of the different systems for the lowest fuel consumption assuring the emission compliance. By variation of the vehicle speed trajectory and feedback of the fuel consumption it is assured, that the total minimal fuel consumption can be found.

The emission compliance is assured by determining the tail pipe emissions using the engine raw emissions and the conversion efficiency of the exhaust aftertreatment system. Due to the combustion model, the best compromise between engine raw emission reduction and/or activation of thermal management can be found in regions, where the conversion efficiency of the exhaust aftertreatment system is reduced. To assure the emission compliance, the measured tail pipe emissions from the past and the predicted ones (integrated and averaged) must remain below the legislative limit. Based on the optimized trajectories for the vehicle speed and the use of the systems, the EMSTR asks for desired vehicle speed, desired gear and Hybrid-Mode to the Dynamic Management Level. The desired values are updated with relatively slow frequency in the range of seconds.

4.3. Dynamic Management Level

The dynamic management level contains the basic real time control modules of the different systems and defines the final control parameters of each system. Due to safety reasons the basic control parameters of the sensible and safety relevant systems are defined on this level using the less sensible requirements from the energy management level as "desired Input", which are validated and adjusted (if necessary) according the actual situation, considering also fast interventions, e.g. by the driver (through accelerator or brake pedal) or vehicle safety functions like ABS, TCS or ESP. The finally realized control functions are fed back to the energy management level, to assure that the EMSTR starts the trajectory determinations with correct values of each system. The hierarchic architecture of the Control Modules ensures that the required system power is realized with highest priority (due to safety reasons) followed by the emission compliance. Therefore, the vehicle speed and gear request is validated and corrected according short time interventions (if necessary) by the Vehicle Control. The required system power is defined as today using the conventional vehicle speed control.

4.4. Component Control Level

The execution of the control functions by the system components and the component monitoring is realized on this level, which is using in most cases the existing Component Drivers of the existing Engine and Vehicle Control Units.

5. Conclusion and outlook

Fuel economy - whilst keeping the vehicle within the legal limits for pollutant emissions – is a key aspect to reduce operating costs and improve efficiency of freight traffic, thus increasing truck competitiveness. The availability of accurate and long-term information of the mission, taking into account locally and temporally dynamic data, is a key aspect to improve fuel efficiency. It enables long term mission optimization by taking into account the vehicle (e.g., mass) and its environment (e.g., weather, road slope, traffic jams) in a comprehensive way. Finally, the different energy sources, storages and converters (such as vehicle speed, altitude or combustion engine, e-drive module, waste-heat recovery, transmission) can be used in a more optimal area according to the given mission. In this paper, the rationales and detailed technical approaches for the IMPERIUM project were presented. Until the end of the project (August 2019), these concepts will be implemented and evaluated by means of detailed simulations, real prototypes, and supported by in-vehicle measurements.

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