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A BIG DATA APPLICATION FOR LOW EMISSION HEAVY DUTY VEHICLES

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Recent advances in green and smart mobility aim to reduce congestion and foster greener, cheaper and with less delay transportation. The reduction of fuel consumption and CO_2 emissions have worked on light-duty vehicles. However, the reduction of emissions and consumables without sacrificing on emission standards is an important challenge for heavy-duty vehicles. The paper introduces a big data system architecture that provides an on-demand route optimization service reducing NOx emissions of heavy-duty vehicles. The system utilizes the information provided by the navigation systems, big data analytics such as predictive traffic and weather conditions, road topography and road network and information about vehicle payload, vehicle configuration and transport mission to develop a strategy for the best route and the best velocity profile. The system was proven efficient during the performance evaluation phase, since the cumulative engine-out NOx has been decreased more than 10%.

Keywords: Green vehicle, intelligent transport system, data warehouse, cloud computing, emissions.

1. Introduction

The EU currently has the largest in-use passenger car fleet and the second largest commercial vehicle fleet in the world (ACEA, 2017). The ACEA automobile industry pocket guides show that there has been a steady increasing trend in the registration of new commercial vehicles (trucks) over 3.5t in the EU at 6.5% from 2012 to 2013, 3.2% (2013-2014) and 3.7% (2014-2015), and the number of registered trucks reached 325,68 in 2015. These numbers seem to confirm that "CO_2 emissions from HDVs are expected to remain stable over the long term at around 35% above their 1990 level" (EC, 2014) as the growth in HDV transport and the improved fuel efficiency are counterbalanced each other.

Heavy-Duty Vehicles (HDVs) carry out the major part of freight transport as reported by the U.S. Department of Energy (Davis *et al*., 2013) and the Department of Transportation (Foxx *et al*., 2015) and are responsible for more than 15% of the fuel consumption in the transportation sector. A substantial effort - in recent years - has made by the automotive industry to develop powertrain technologies that improve the fuel consumption efficiency of HDVs. However, the projections indicate that total HDVs energy use and CO_2 emissions are expected to remain stable at the current level over the long term, due to increasing road freight traffic, if no policy action is taken. This is clearly incompatible with the goal of reducing greenhouse gas emissions from transport by around 60% below 1990 levels by 2050.

The fuel consumption is dependent to speed and gear applied for the same route (Saltsman, 2014). The choice of the optimum speed and gear can be supported by data collection and analysis techniques. Recent advances in information and communication technologies and especially the cloud computing (Dikaiakos *et al*., 2009), big data analytics and vehicle-to-infrastructure (V2I) communication may be used to gather real-time information from external services and the HDV in order to optimize the fuel consumption and minimize the CO_2 emissions.

The proposed system architecture tries to bring together the most advanced technologies from powertrain control and intelligent transport systems in order to achieve a global optimum for consumption of fuel as well as other energy sources and consumables while achieving Euro VI emission standards for heavy duty road haulage. Moreover, the system architecture contains a global optimizer, which consists of a set of dynamic, intelligent control and prediction components designed for effective powertrain management, utilizing the environment data related to the transport mission, road topography, weather and road conditions and surrounding vehicles (Figure 1).

The system architecture is a flexible and scalable cloud computing architecture involving leading big data management components and predictive and simulation modules. The cloud-based system architecture communicates with on-board control systems components, developed on the truck, interacting with all on-board sensors (e.g., cameras, load, temperature), actuators and already deployed control units. The primary goal of the system architecture is to generate best routes, speed profiles and optimizing the truck's emissions.

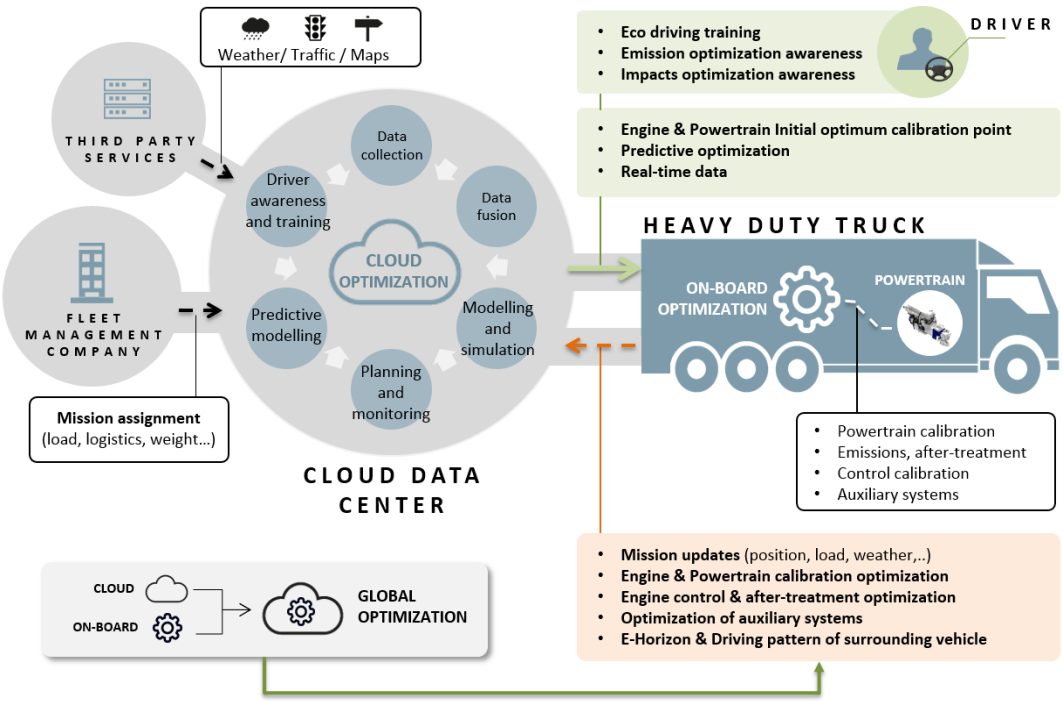

Figure 1. An Intelligent green truck

The rest of the article is organized as follows: In Section II we describe the relevant work, while the Section III presents the system architecture and Section IV presents the data warehouse approach. Section V presents the results and finally, Section VI concludes the article.

2. Relevant Work

Today's advances (Jimenez, 2017) in vehicular telematics and advances in GIS (Geographic Information System), GPS (Global Positioning Systems), ITS (Intelligent Transportation Systems), V2V (Vehicle to Vehicle) communication, and VII (Vehicle Infrastructure Integration) create opportunities for predicting a vehicle's trip information with details such as the road type, traffic, weather condition, and the driver style (Mahmassani *et al*., 2009 and Work *et al*., 2008).

There are various vehicle technologies, which focus on reducing the energy consumption and emissions of ground vehicles by using these information sources and by predictive planning of the vehicle's motion for a certain prediction horizon (Vlassenroot *et al*., 2011 and Kohut *et al*., 2009). The optimization of power-train control and calibration according to real world conditions is one of them. However, powertrain control systems receive limited or no input from the present or future driving environment, traffic and weather conditions.

Driver support information systems (Li *et al*., 2018) are getting more and more popular based on modern technologies and frequently updated databases. Existing driver information systems usually provide fuel efficient driving recommendations (acceleration and gear shifting score, cruise control usage etc.) to drivers based on their overall driving history

A number of research projects have investigated the potential of a better managed engine and driver performance by proving information based on historical and real-time processed data. CO-GISTICS (Fanti *et al*., 2014) was one of the first European projects fully dedicated to the deployment of cooperative intelligent transport systems (C-ITS) focused on logistics. The project partly aimed at the reduction of fuel consumption and the equivalent CO_2 emissions. A Decision Support System (DSS), which would support decisions of the actors involved, in order to optimize and improve the system performances and the customer satisfaction, has been developed. Operational decisions were made on a daily basis or in real-time. Similarly, to CO-GISTICS, the REDUCTION EU project (REDUCTION, 2020) has developed methodologies for providing predictive analytics based on advanced data mining technology in order to meet the objectives of fleet management, such as decision making for driver-adaption, eco-routing, and consequently CO_2 emissions control and improved fuel economy.

Another eco-driving related initiative was the eCoMove. The project aimed to develop solutions to reduce inefficiencies responsible for energy waste in road transport, which are related to vehicle, driver behaviour, and traffic management (eCoMove, 2020). This was done by utilizing V2I communication in the form of eco-messages where traffic participants share data on their destinations, traffic situation data and fuel consumption. Furthermore, a digital map enhanced with slope, historical speed profile, energy consumption data, and traffic data is used to form a so called eco-Cooperative Horizon model to calculate a fuel-efficient driving strategy. In addition, a post-trip analysis is provided to the drivers for improving their driving characteristics.

A very recent and on-going research initiative from US is the so called "Co-Optimized Delivery Vehicles" (VPRO, 2020). It is aimed at technologies to improve the fuel efficiency of delivery vehicles through real-time powertrain optimization using two-way vehicle-to-cloud connectivity. A predictive cloud-based approach (physics-aware spatiotemporal data analytics, PSDA) is used to control the hybrid powertrain using efficient computational techniques combined with physics models for computational efficiency. Additionally, powertrain calibration is optimized and downloaded to the vehicle using V2C connectivity in real-time during a delivery route, compensating for exogenous parameter changes or unpredicted driver behaviour.

The proposed architecture presents the creation of a global optimizer which consists of a set of dynamic, intelligent control and prediction components designed for effective powertrain management, utilizing the environment data related to the transport mission, road topography, weather and road conditions and surrounding vehicles.

3. System Architecture

The system architecture consists of several software modules distributed in two separate optimizers that work in a coordinated fashion. The first one is the cloud computing optimizer while the second is the on-board optimizer. This logical subdivision is reflected in the design of two separated but strongly inter-connected systems, the cloud computing system and the on-board system, respectively operating in a Platform-as-a-Service (PaaS) (Dhuldhule *et al*., 2015 and Boniface *et al*., 2010) cloud computing environment and on the truck.

The system architecture (Figure 2) presents a high-level representation of the two main subsystems and their modules. On the left side, the external data sources are presented. The data that are sent to the cloud computing system are the maps and topographic data, including basic geographical maps and ADAS information. Additionally, the weather forecast data, including short- and long-term information about climate condition on specific areas, and the traffic forecast data, including information on real-time traffic condition and incidents. Finally, mission data are sent from the fleet management company, including information about the departure and destination for a given mission and the truck's characteristics. Maps, weather and traffic data are received by the cloud computing system through specific data service interfaces.

In the central part of the diagram, the cloud computing system implements the following functionalities:

- Data storage, including all database entities to store real-time and historical data from the external data services, mission related data, data from the on-board system and results of the cloud optimization process.

- Data flow management architecture, including data fetching, data transformation and data feeding components operating on raw data and post-processed data storages components.
- Cloud optimizer, including vehicle models and eco-route-planning/route-prediction component.
- Mission dashboard, including a frontend for the fleet management company to upload the mission data and monitor status of the missions.

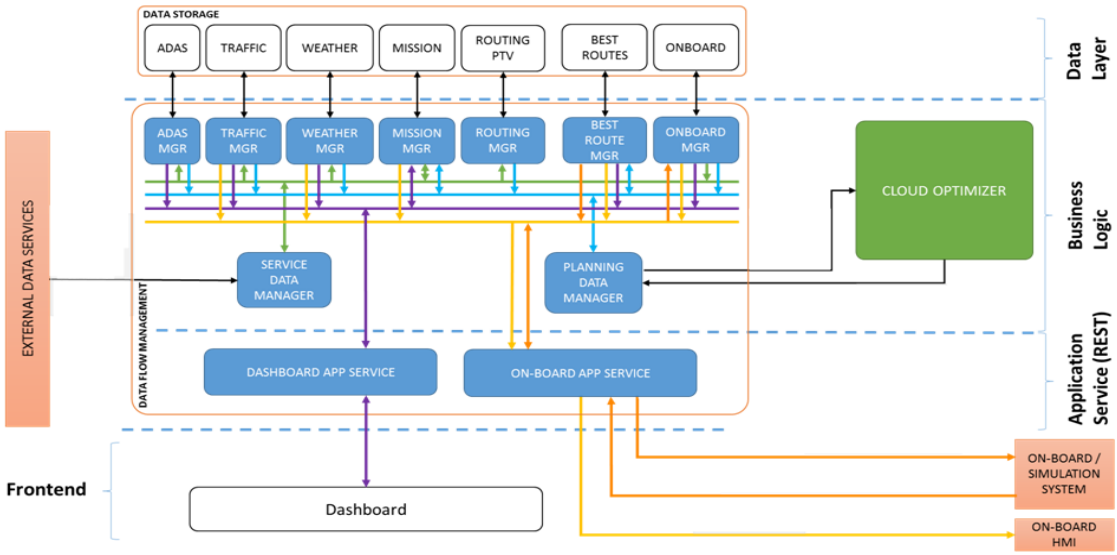

Figure 2. System architecture

The cloud computing system consists of several software components (managers). The service data manager is responsible to fetch periodically the data from the external data services and send them to the data storage in order to guarantee that enriched data for each mission are stored in the data storage. The communication between the external data services and the service data manager is based on the standard REST architecture. The ADAS manager is the component responsible to store and retrieve ADAS data to/from the data storage. The traffic manager is the component responsible to store and retrieve traffic data to/from the data storage. In the same way the weather, mission, routing, on-board manager are the components responsible to store and retrieve the weather, mission, routing and on-board data to/from the data storage.

Additionally, to the service data manager, the planning data manager accomplishes the functionality to fetch and fuse data stored in the data lake, prepare data and send it to the cloud optimizer for the computation of the best route related to a specific mission. After the computation is finished, the outputs (best route and velocity profile) are returned to the planning data manager, to store the results of the optimization process using the functionality provided by the best route manager.

There are two phases in which the planning data manager is involved. The first phase is in the pre-mission phase: the planning data manager periodically checks for missions with the status "prepared", which means that a new mission has been submitted and the service data manager has processed it by enriching the mission data with information of external data services. After having stored the computed best route and velocity profile, the planning data manager updates the mission status to "to-be-validated". The second phase is during the in-mission phase.

The dashboard application service is responsible for the management of the missions submitted by a fleet specialist, through a web dashboard. The on-board application service is responsible for the management of the communication between the on-board components (system and HMI) and the cloud system. The main functionalities provided by the service are the uploading of a new validated mission to the assigned truck, the regulation of the mission status, the collection of the output coming from the on-board system, in order to allow the cloud optimizer to perform its computation on the basis of recent truck data and the transmission of updated best route and velocity profile data to the on-board system and to the on-board HMI.

The cloud optimizer is connected to the "data tier" and the "presentation tier" via the planning data manager and performs two key tasks, namely prediction of traffic and environment conditions and route optimization. On one hand, the traffic prediction component monitors, models and foresees the traffic and

road conditions (e.g. average speed, congestion duration and weather) ahead of the truck, and feed the predicted information into the route optimization component for route selection with minimum energy to be consumed. On the other hand, the route optimization component calculates the global vehicle speed set-point trajectory and provides it to the traffic prediction component so that local vehicle speed trajectories can be updated continuously for the optimal route. The main outputs from the cloud Optimizer are the local vehicle speed trajectories and the best route.

Regarding traffic prediction, the cloud optimizer consists of four major components. The Automatic Incident Detection component is based on unsupervised learning schemes and more precisely on auto-associative neural networks. Neural networks have also been used in Congestion Duration Prediction component, to enable the duration of incident to be forecast as accurately as possible. The Journey Time Prediction component exploits a forecasting algorithm that depends on historic traffic data. The fourth component is the Vehicle Speed Trajectory Prediction. To precisely predict instantaneous fuel consumption, Engine/Transmission/Emission models has been developed. The brake-specific fuel consumption (BSFC) map has been used for calibrating the longitudinal dynamic model, which describes engine performance and defines the ratio between consumed fuel and generated energy for various operation points (e.g. engine speed and generated torque). By collecting real-time local information as well as system information, the cloud-based speed trajectory model generates an optimal instantaneous vehicle speed profile for a short time/position horizon. Except from traffic prediction, the route optimization is another core component of the cloud optimizer that consists of two sub-components. The Transport Assignment component decides on a departure time and multi-stop route for a specific vehicle from a given origin to a given destination, given an arrival time window at the destination, and given pre-defined potential stop locations. The Eco-Route Planning component determines the optimal route that a truck has to follow in order to reach its destination minimizing the fuel consumption and optimizing the route velocity profiles. The Eco-Route Planning component is divided in three major modules: the Route Network Selector (RNS), the Planner (based on Vehicle Longitudinal Model) and the Optimizer.

Finally, the on-board control system is located on the truck and implements specific modules like Predictive Cruise Control Module (PCCM), including the Enhanced Predictive Cruise Control (ePCC) and the Power Demand Estimator components. Additionally, the Rapid Control Prototyping Module (RCPM), including the Energy Flow Coordinator, the Emission Estimator, the Emission Coordinator, the Emission Compensator and the Fuel Consumption Optimizer components are parts of the on-board system. Moreover, the Engine Control Unit (ECU), including the Engine Operating Mode Coordinator component, the Sensors Fusion Module, including all the components to fuse the data from the different sensors placed on the truck (e.g., radar, cameras, location, etc.) and finally the HMI module, including a visual interface for the driver to get relevant output from the system and provide input about the route environment. The on-board control system interacts with the truck actuators and sensors through a bidirectional communication channel. The on-board control system and the cloud computing system cooperate transferring information through a bidirectional channel like 4G to allow the overall system to perform the real-time optimization.

The whole system architecture is based on the Message Queuing Telemetry Transport (MQTT) standard publish-subscribe-based messaging protocol except from the communication with the external services where the REST architecture is used. The data exchange is realized with the use of JSON format. More precisely, one JSON text has been produced for each manager and the other components (such as truck, HMI) to model the data (such as weather, traffic, ADAS, on-board information etc) exchanged and facilitate the communication.

4. Data Storage Architecture

A major component of the system architecture is the data storage (big data) component that has been developed on a cloud system. This component receives all data generated by the truck and engine auxiliary systems, powertrain and engine control systems. These data are integrated with specific mission data, navigation data and external information system such as traffic, weather forecast, road topography and road network and information about transport mission (vehicle payload, vehicle configuration etc.) to implement big data analytics and intelligent predictive model-based optimization algorithms.

The planning data manager is implemented using a star-schema approach (Kimball and Ross, 2013). This approach has been chosen because it supports the integration of heterogeneous data source well. The architecture supports a number of different data sources. Further, a data warehouse approach is good at handling large datasets while still being easy to understand and query for non-experts such as traffic planners. These queries can both be complicated historical analysis queries or predictive queries.

4.1. Mission Data

The data warehouse design for the mission data is presented in the figure below. All rectangles indicate database tables and all lines are primary key/foreign key constraints. The green tables are fact tables, the orange tables are dimension tables, and the yellow tables are utility dimension used by the planning data manager to keep track of where data is loaded from and what is the quality of the data.

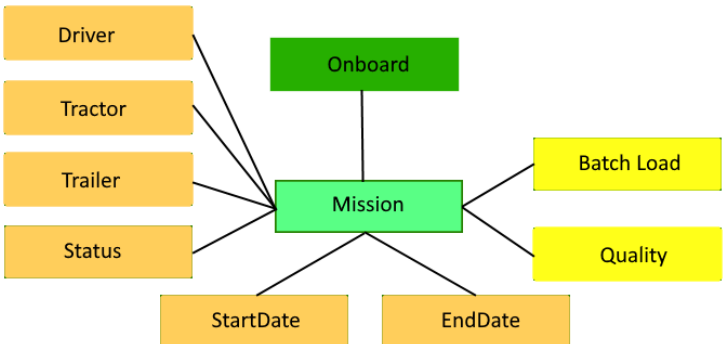

Figure 3. Mission schema design

The table Mission is the fact table (Kimball and Ross, 2013) and one or more rows are stored for each mission. The Driver dimension contains information about drivers, e.g., age, nationality and years of experience. The Tractor dimension contains information about the tractor, e.g., make, model, number of axels, and engine size. The Trailer dimension contains information concerning each trailer, e.g., length, maximum load and number of axels. The Status dimension keeps track of the status of the mission, e.g., "prepared", "on-route" or "finished". The StartDate and EndDate dimension contains temporal information; for example, to find a mission that starts on a Saturday. The Batch Load dimension contains the details from where information was loaded. This makes it easy to find exactly the data that was loaded on a particular day. The Quality dimension keeps track of the quality of each row in the Mission fact table, e.g., if the mission data was altered during the Extract-Transform-Load (ETL) phase due to quality control policies set up by the trucking company.

4.2. The Onboard Data

The onboard data refers to the GPS and CAN-bus data that is collected from the trucks and sent to the cloud system (the planning data manager) to be integrated with the other data sources (Figure 4).

The onboard schema design follows the same principles as for the mission schema. Each row with GPS/CAN bus data is stored in the Onboard fact table. To make it easy to query this data in a context, e.g., find all rows related to snow or rain, each row is annotated with information from the other data sources. This annotation is again done via the dimension tables. Please note that there are overlaps between the dimensions between the Mission and Onboard fact tables. Such shared dimensions make it possible to reuse code and better integrate data. The shared dimensions are Driver, Tractor and Trailer. The Batch Load and Quality dimensions are unique to each fact table.

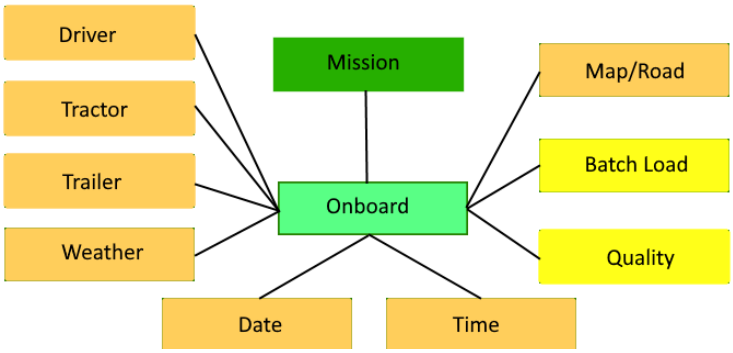

Figure 4. Onboard schema design

The Weather dimension contains information about the weather station closest to each GPS row stored in the fact table. The Map/Road dimension contains information, e.g., on the road type (motorway,

city road) speed limit, and slope. The Date and Time dimensions make it efficient and simple for users to query temporal information, e.g., all rows on weekdays between 10:00 and 11:15.

The connection between Mission and Onboard fact tables makes it possible to associate each GPS/CAN bus row with a mission and vice versa.

4.3. Point Information

A mission is planned by specifying a number of points that the truck must pass, e.g., to delivery of pickup goods. Further, many of the data sources integrated in cloud use points to indicate where information is valid, e.g., traffic accidents or weather information. To handle all points' information in a uniform manner, all data sources that provide point like information is stored in the single fact table (Figure 5).

The fact table is called Point Info. The shared dimensions are Date and Time. The new dimensions are Point that contains the latitude, longitude, and altitude. Further, well known or often used point can be named. The ADAS dimension contains information, e.g., on slope and curvature. The Accident dimension contains information on accidents, e.g., duration and changes in speed. The Weather Forecast x 2 contains information on both a short-term and long-term weather. The Manoeuvres dimension contains information such as "use right lane". The Point Info and Mission fact tables are connected to be able to query which points a mission passes and vice versa.

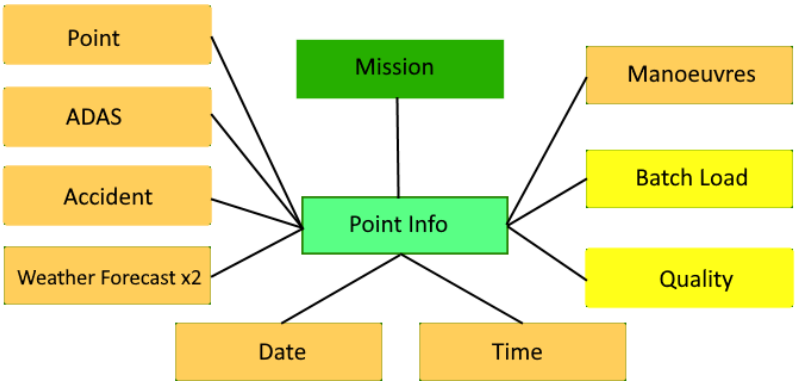

Figure 5. Point info schema design

5. Performance Evaluation

The performance evaluation of the whole system has been organized and conducted by Ford Otosan. Two 2019 model year Ford F-Max trucks with identical hardware have been used for testing purposes. Both vehicles equipped with a 500 PS diesel engine and a 12-speed automated manual transmission. Both vehicles have a gross vehicle weight rating of 42 tons. The test was conducted on July 3rd and July 4th, 2019 between two Ford Otosan locations: Sancaktepe, İstanbul (departure) and İnönü, Eskişehir (arrival). This route has been selected considering the close proximity to the Ford Otosan premises in case of a technical malfunction. It is a mix of highway and national road network, with altitude variation and very dense traffic during the rush hours. The weather conditions were very good during these two days of testing. The same mission was conducted twice on these dates to achieve consistent test results in the presence of traffic conditions. The test took approximately 5 hours in one direction.

5.1. Test Results

The whole route has been divided into three segments. The three segments have been selected according to the longest trips during which the optiTruck control system was operational in an uninterrupted manner. Due to traffic conditions, the demo driver was occasionally forced to apply brakes or accelerate while disabling the optiTruck control system completely. When the traffic conditions were suitable, the demo driver has reengaged the optiTruck control system during the mission.

In order to achieve a consistent time of arrival between the reference and the demo vehicle, the reference vehicle driver was instructed to use cruise control as much as possible along the route, with a set speed of 60kph. This was required since an offline simulation of the cloud optimizer resulted in an

average speed approximately 55kph. This was also evident from the actual results, where the average speeds of both trucks were approximately 56 kph for Day 1, and 51 kph for Day 2. The reference vehicle driver has slightly reduced the reference vehicle's average speed by nearly 5kph in Day 2 in order to remain geographically as close to the demo vehicle as possible. This was required as a result of heavier traffic conditions on Day 2 which has resulted to a large number of data points at zero speed on Day 2.

The complete route was approximately 260km, and some segments had to be discarded from the analysis since the driver did not activate the optiTruck control system in these road segments. Therefore, the numerical results are provided only for the selected two road segments (Table 1).

Table 1. Test summary

Segment	Vehicle	Duration [sec]	Total Distance [km]	Mean Speed [kph]	Cumulative Engine Out NOx flow [kg.s/h]	Total Vehicle Weight [tons]
Segment 1	Demo	3939.0	49.4	45.0	0.32881	38.9
	Ref	2997.5	49.6	59.5	0.39847	38.0
Segment 2	Demo	1633.5	22.8	50.1	0.41927	35.6
	Ref	1638.6	22.9	50.4	0.48598	35.3

The results attested the efficiency and effectiveness of the system. The fuel consumption in the two segments has been similar with the usage of the system (there was a slight improvement). However, the cumulative engine-out NOx has been decreased more than 10% in each case. More precisely, in the first segment there was a reduction of 17.5%. The whole distance of the segment was around 49km. Figure 6 presents the cumulative engine-out NOx for the first segment. The figure depicts the comparison of normalized cumulative fuel flow between the reference vehicle (blue) and the demo vehicle (red). The demo vehicle has completed this segment with an average speed of 45 kph, whereas the reference vehicle had an average speed of 59.5 kph for the same segment. Additionally, the demo vehicle completed this segment 31.4% slower than the reference vehicle. The reduction of the cumulative engine-out NOx increases as the distance grows.

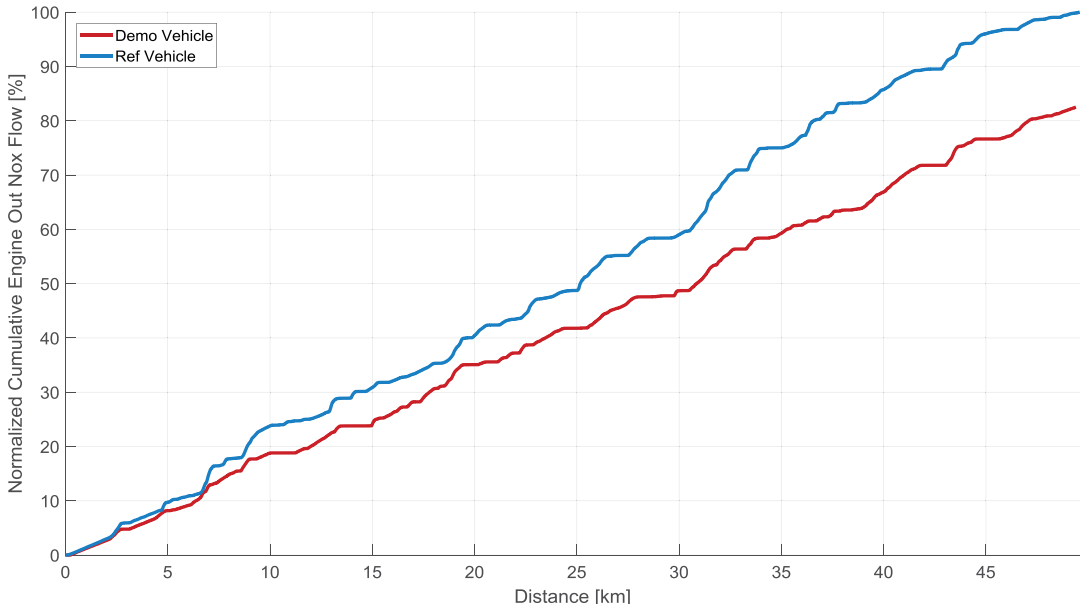

Figure 6. Segment 1 Cumulative Engine-Out NOx Flow

The second segment was 23 km long. Both the demo vehicle and the reference vehicle have completed this segment with an average speed of 50 kph. Consequently, the segment travel durations are the same for both vehicles. In this segment, the demo vehicle's cumulative engine-out NOx emissions were 13.7% lower than the reference vehicle (Figure 7).

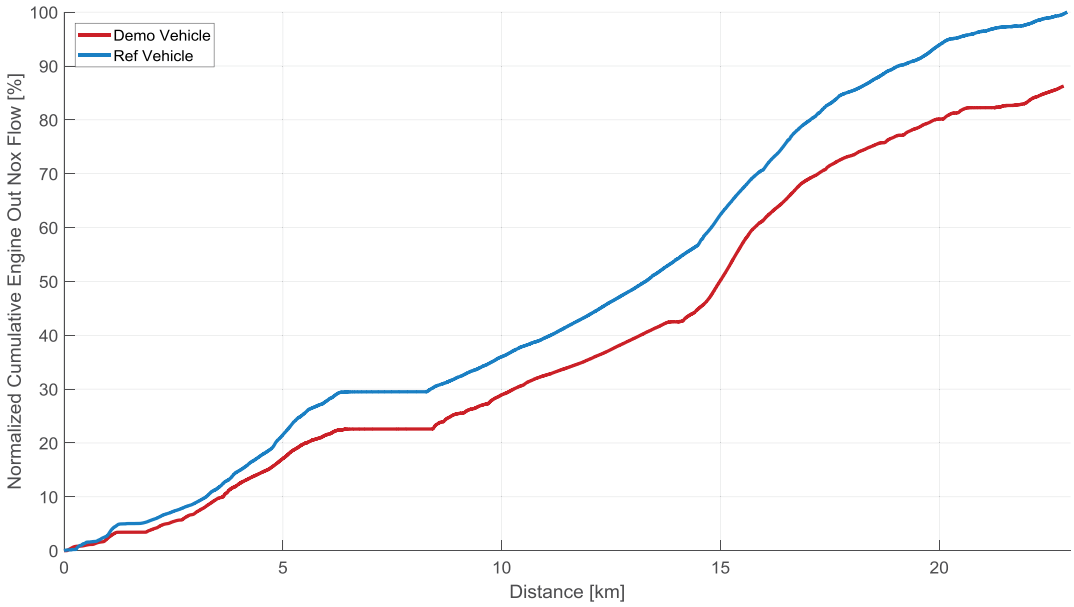

Figure 7. Segment 2 Cumulative Engine-Out NOx Flow

6. Conclusions

This paper presents a cloud-based architecture exploiting the potentials of big data analytics to deliver an on-demand route optimization service reducing emissions of heavy-duty vehicles. A highly scalable system is able to determine in real-time the best route and the optimal velocity profile, that the truck has to maintain in order to minimize engine emissions, by fusing heterogeneous sources of data. The big data architecture, that has been developed on the cloud system, receives all data generated by the vehicle and engine auxiliary systems, powertrain and engine control systems. These data are integrated with specific mission data, navigation data and external information system such as traffic, weather forecast, road topography and road network and information about transport mission (vehicle payload, vehicle configuration etc.) to implement big data analytics and intelligent and predictive model-based optimization algorithms.

The system can continuously update the best-route and the speed-profile, adapting the route to fast changing traffic conditions in urban and suburban scenarios. The flexibility of the systems is based on the capacity to deal with high velocity of data streams coming from the running HDV, which can thus create a network of connected vehicles. The system evaluation results - during daily traffic conditions - indicated a significant reduction of the cumulative engine-out NOx (up to 17.5%) in different road segments on highways in Turkey. Future work will consider a detailed analysis of the performance of the system in a more complex, fast changing roads scenarios with several trucks running at the same time and feeding the cloud systems with real time data.

Future research should consider the sensitivity of the prediction functionality in extreme circumstances, in order to determine where and when uncertainty comes from. Another important topic to be investigated is the data quality from the several sources and to what extend the accuracy of the information can influence the predicted result. Lastly, the system requires the generation, storage and processing of a huge amount of data that will control the vehicle operation. Data security on both cloud and vehicle level should be studied in combination with other data of higher security as those needed for the operation of autonomous trucks.

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