A Cloud Computing Architecture for Eco Route Planning of Heavy Duty Vehicles

Maria Pia Fanti, *Fellow*, *IEEE*,
Agostino M. Mangini, *Member*, *IEEE*,
Giuliana Rotunno
Dept. of Electrical and Information Engineering
Polytechnic of Bari
Bari, Italy
{mariapia.fanti;agostinomarcello.mangini; giuliana.rotunno}@poliba.it

Giambattista Fiume
Department of Engineering and Architecture
University of Trieste
Trieste,Italy
gfiume@units.it

Alfredo Favenza
Manuel Gaetani
Istituto Superiore Mario Boella
Torino, Italy
{favenza, gaetani}@ismb.it

***Abstract*— This paper deals with the problem of reducing fuel consumption and pollutant emissions of Heavy Duty Vehicles (HDVs). The overall objective of improving the efficiency of the HDVs can be obtained by employing additional information about road topography, altitude or slope, traffic and weather conditions. To this aim, a cloud computing architecture is proposed to support the fleet companies to manage the HDV route planning. The cloud system receives the transport mission data (departure, destination, waypoints, maximum mission duration time, etc.) and calculates the best eco route and the optimal velocity profiles minimizing fuel consumptions by a cloud-based optimizer. The optimization is performed taking into account not only road topography (2D maps and altitude) but also other sources of heterogeneous data such as traffic and weather conditions. Some case studies show the efficiency (fuel consumption savings and travel times) of the proposed smart technology.**

Keywords*— *Eco-routing; intelligent route selection; heavy duty vehicles emission savings.

I. Introduction

The impact of road traffic on energy efficiency is a major global policy concern and has inspired a substantial body of innovation aimed at improving vehicle and traffic management technologies. Many of the current decisions to reduce energy consumptions and emissions of air pollutants worked on light-duty vehicles but are not feasible for Heavy Duty Vehicles (HDVs) applications. In the recent years the automotive industry has made a substantial effort in developing power train technologies to improve fuel efficiency on HDVs.

Due to the increasing of the road freight traffic, projections indicate that total HDV energy use and CO2 emissions are expected to remain stable at the current level over the long term, whether 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. Hence, reduction of fuel consumption and emissions of air pollutants is an important required challenge for HDV.

In real transport missions, many optimization possibilities based on the most advanced technologies in powertrain control and intelligent transportation systems can be employed for balancing fuel efficiency and emissions reduction [1]. The research in this area studies four main aspects that may contribute for the HDV fuel reduction: driver behaviour, road density evaluation, route planning and speed control.

In this paper the route planning issue is mainly treated. Usually, the route planning objective is to find the optimal route to follow by minimizing the route distance or the travel duration time. This paper aims to determine an optimal route and the velocity profiles that minimize the HDV fuel consumption. Moreover, a novel cloud computing system based on optimization and control strategies is proposed that can integrate different data and information: predictive traffic and weather conditions, 2D road topography, altitude and curvatures, information about transport mission such as vehicle payload, vehicle configuration, etc. Several road data can be obtained by databases and external data services [2], [3] that can provide information about the current state of traffic, road works, weather or state of roads.

In the related literature several studies address the question of reducing fuel consumption or emissions. Gang et al. [4] use an improved genetic algorithm to solve the vehicle routing problem in a fuel-efficient way. In addition, Kuo [5] proposes a simulated annealing algorithm finding the vehicle routing with the lowest total fuel consumption taking in account HDV payloads. The payload problem associated with the fuel consumption is also considered by [6] and [7] that try to deliver as soon as possible the heaviest loads while satisfying storage constraints, fragility issues and priority policies. Finally, Yao et al. [8] propose a study that aims to find a solution to time-dependent vehicle routing problem with time windows by minimising fuel consumption. An ant colony algorithm is presented to solve the problem and the optimization of the departure time is introduced. However, the above cited studies do not consider data provided by the external data services, such as traffic conditions and weather forecast. Shahzada and Askar [9] describe a navigation system

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for mobile phones, which optimizes vehicle routing using road and traffic conditions and GPS coordinates. However, the authors minimize the duration time of the transport route.

Unlike the previous papers, our objective is offering a cloud platform for the fleet management companies to optimize the HDV routes by employing additional information as road topography, altitude or slope, traffic and weather conditions. Such cloud computing system not only minimizes the fuel consumptions or other important emissions, but improves the route planning avoiding incidents, bad weather conditions or slowdowns. Moreover, the cloud structure can be used by HDV on-board systems to calibrate engine and power train parameters on the basis of the choice of the optimal route and velocity profiles. In order to calculate the velocity profiles, the cloud system uses an optimization model proposed by Hellström et al. [10] but extends it, considering not only slope information but also curvature, traffic and weather conditions.

Summing up, the proposed cloud computing system is composed by: *i*) a Data Management Architecture devoted to data storage and data integration/fusion; *ii*) a Cloud Optimizer that finds the HDV optimal route and calculates velocity profiles to follow.

The remainder of this paper is organised as follows. In Section II the whole system architecture is presented, while Section 3 describes in detail the data management architecture. Moreover, Section 4 introduces the Cloud Optimizer and its sub-components. Finally, in Section 5 some case studies show the efficiency of the proposed system and Section 6 draws the conclusions and future works.

II. System Architecture

The system architecture presented in this work consists of a set of software components distributed in two different optimization modules that work in a coordinated fashion under the name of Global Optimizer (Fig. 1): the Cloud Computing Optimizer and the On-board Optimizer.

This paper focuses on the functionalities of the Cloud Computing Optimizer, which performs the route planning optimization task in a cloud-based environment. In the cloud system data from external sources (i.e., traffic, weather, maps and topography), mission related data (i.e., waypoints, payload, driver) and real-time data provided by the truck on-board system (i.e., position, speed, consumption, environmental sensors) are ingested and processed.

Cloud computing [11] is a model which enables on-demand access to a shared resource pool through the network. These highly configurable resources can be easily accessed and released, on a dynamic basis, with a minimum management effort and a limited interaction with the service provider.

Cloud computing solutions came with characteristics of high availability, scalability and performances [12] representing a very profitable opportunity for industrial sector and allowing to reduce effort, time and costs of development, distribution and management. Furthermore, the use of services and infrastructures provided by third party, let SME to make their investment which a level of flexibility e to rapidly adapt to market's evolutions and business opportunities. Cloud computing solutions are usually classified in three service models [13], as reported in Fig. 2:

- *Infrastructure as a Service (IaaS)*: the service provider delivers the complete framework of servers, routers, storage, hardware and virtualization software; the user is responsible of operating system, middleware, runtime and applications.
- *Platform as a Service (PaaS)*: the service provider delivers the whole hardware and software chain which includes networking and runtime functionalities; the user is responsible for data and application management.
- *Software as a Service (SaaS)*: the service provider delivers the whole service, including applications and data; the user just uses of service's functionalities.

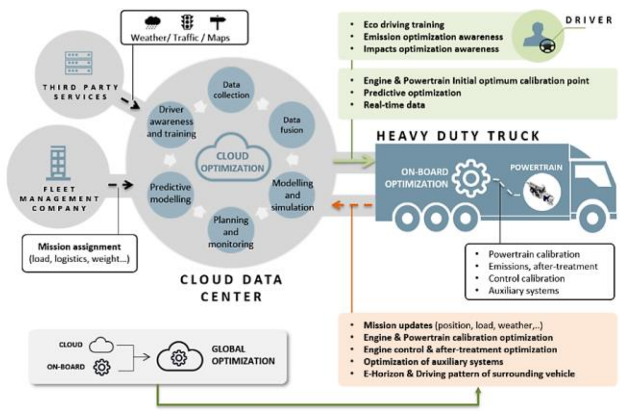

Fig. 1. *Global Optimizer*

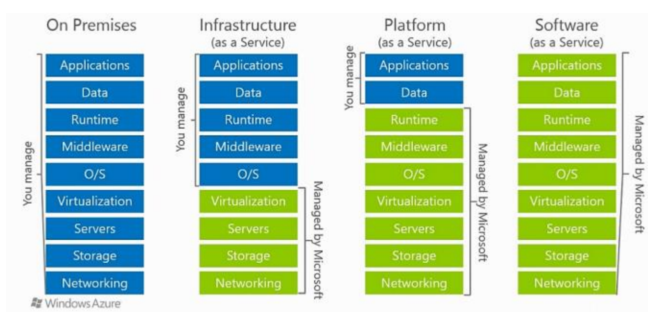

Fig. 2. *Cloud Computing Models*

The Cloud Computing Optimizer architecture (see Fig. 3) benefits of the PaaS model, resident on the Microsoft Azure public cloud, which gives the possibility to exploit existing building blocks and cloud applications flexibility. This platform consists of two main blocks:

- the Data Management Architecture
- the Cloud Optimizer.

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In the next Section III and IV, the functionalities of these two system components will be explicated and their roles in the scope of the overall solution will be detailed.

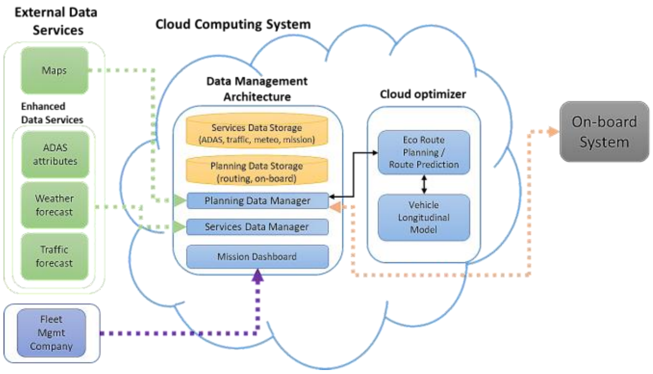

Fig. 3. *Cloud Computing System*

III. Data Management Architecture

The system architecture here described is structured to work with big datasets coming from external sources and in real-time from the trucks. These data are large and heterogeneous sets characterized by what in the Big Data domain is called the "3 Vs Model" [14, 15]: Volume (Gigabyte per data collection), Velocity (number of data collection systems and products around the world) and Variety (different formats). The main components forming the data management architecture are:

- The *Data Storage* components, to collect all the raw data from external sources and trucks;
- The *Business Logic* component, to ingest, integrate and fuse the datasets.

A. Data Storage

The Data Storage is the repository that collects the vast amount of raw data in native format (structured, un-structured, semi-structured) coming from the external data sources and the trucks. It is divided in two main sub-components:

a) *The Services Data Storage* (SDS), which is responsible for the storage of data from external sources and mission data. This is a shared area across different modules that store raw (not processed) system information coming from different data sources, such as ADAS data, traffic forecasting data, weather forecasting data, mission and truck data. Such data are stored into the database in order to help the system to plan the best route, perform useful evaluation a posteriori, assess the mission performance and demonstrate to external users (e.g. authorities) the effectiveness of the system.

b) *The Planning Data Storage* (PDS), responsible for the storage of the computed best routes data and data from the truck. This is a shared area across different modules, which store information, including best routes calculated by the system and truck on-board data received from the On-board system.

Both the sub-components operate on-line, supported by the Business Logic components, and offline in case of big data stored and need for analytical processing.

B. Business Logic

The Business Logic component operates several different types of operations on data from external sources such as ingestion, cleaning, transformation, processing, fusion and integration. This component includes two main sub-components:

a) *the Service Data Manager (SDM),* which has the objective to retrieve data from external services, then to store them to the Data Storage components in order to guarantee to have always the most recent data available;

b) *the Planning Data Manager (PDM),* which is the principal interface regarding both the flow of structured planning data and the communication as data transferred with the on-board system. The main functionality of this sub-component is the Data Fusion, which performs the Extract, Transform and Load process that is responsible for extract the relevant data from the source transform it to the required formats and then load the data into a data staging area.

IV. Cloud Optimizer

In this section the role and the structure of the second block of the Cloud Computing system (i.e., the Cloud Optimizer) is described. The aim of the Cloud Optimizer component is to determine the optimal route that an HDV has to follow, in order to reach its destination minimizing the fuel consumption and optimizing the route velocity profiles. The Cloud Optimizer component calculates the "best route" considering all relevant criteria for an efficient truck routing, such as weather forecast, traffic conditions, fuel consumption and emissions of air pollutants, road slopes, load factor. To this aim, the Cloud Optimizer is connected to the PDM which provides the transport mission data including the information of the External Data Services. More in detail, the transport mission data are released by the Fleet Management Company, transmitted from the Mission Dashboard component to the SDM and stored to the data storage components. These data include truck departure, destination and waypoints, maximum mission duration time and load factor. Moreover, weather forecast, traffic conditions as well as 2D topography and altitude are provided to the cloud system by the External Data Services. The Cloud Optimizer and the PDM components exchange information when the Fleet Management Company creates a new mission.

The operational scenario or sequence of events that occur in the use of the Cloud Optimizer can be described through a general two phase's scenario: i) Pre-mission phase; ii) In-mission phase. In the Pre-mission phase, the system computes the best route, optimizes the velocity profiles and sends them to the truck driver before the mission begins. In the In-mission phase, the best route is monitored by real-time traffic data collection: if incidents or severe slowdowns occur, the Cloud Optimizer re-calculates the best route based on the truck GPS coordinates. The Cloud Optimizer is divided into two sub-components:

- Eco Route Planner (ERP);
- Vehicle Longitudinal Model (VLM).

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Each sub-component is devoted to performing the following specific actions:

- The ERP performs two important tasks: 1) selecting a route network that links the transport departure, waypoints and destination; 2) determining the best route with minimum fuel consumption and the optimal velocity profiles.
- The VLM calculates the fuel consumption and the respective emissions of air pollutants for each route of the network selected by the ERP.

A. *Eco-Route Planner*

In this section, a detailed description of the ERP in the Pre-mission phase is presented. The ERP is activated by the PDM when a new transport mission is released by the fleet management company. The ERP receives by the PDM the truck departure, destination, waypoints and 2D Maps. Based on these data, the ERP selects the route network that will be used to determine the best route and monitor the transport mission.

First, two routes are calculated:

Route 1. the fastest route from the departure to destination by passing from the waypoints and respecting the mission duration time;
Route 2. an alternative route that respects the constraint of the maximum arrival time.

Second, the *route network* including all the possible routes connecting the origin to the destination is built by the following steps.

Step 1. Starting from Route 1 the crossing roads are determined.
Step 2. The alternative routes connecting each crossing road with the destination and not coinciding with Route 1 are selected.
Step 3. If some alternative routes have a road portion in common, then only one of them is considered.

After completing the three steps, the selected route network is obtained and can be described by a graph G(V,E), where V is the set of crossing roads and E is the set of the roads connecting them. At this point the first task of the ERP ends.

Now, the selected route network has to be evaluated by the VLM. In other words, the VLM has to calculate the optimal velocity profiles by minimizing the fuel consumption and emissions for each road of the network on the basis of truck model, traffic and weather conditions, altitude and curvature (the next subsection will describe in detail the behaviour of the VLM). The output of the VLM, presented by the table of Fig. 4, allows associating the value of fuel consumption and emission of air pollutants to each street (edge) of the route network.

Hence, a cost is associated to each edge of graph G(V,E). Such weighted graph represents the input for the second task of the ERP that determines the optimal route.

Roads	Traffic Condition			Weather Condition		Fuel consumption/CO2	Velocity Profile
	Low	Medium	High	Good	Bad	M	V_k
Street 1	X			X		Value [Kg]/Value [Kg]	V_k with k= 1, ... ,s_f
Street 2	X				X	Value [Kg]/Value [Kg]	V_k with k= 1, ... ,s_f
....	....	......	.....	......	......	......	....
Street n			X		X	Value [Kg]/Value [Kg]	V_k with k= 1, ... ,s_f

Fig. 4. *Table of fuel consumption in the route network*

Indeed, the ERP computes the path that minimizes the total cost represented by the fuel consumption and pollutant emissions. In the related literature, the Dijkstra or A* are efficient algorithms to perform the proposed optimization [16], [17]. Obviously, the best route is composed by a subset of the streets of the table shown in Fig. 4 and the optimal velocity profiles are in the last table column. Finally, the best route and the optimal velocity profile are sent to the PDM that transmits them to the truck driver.

The In-Mission phase becomes essential when the truck begins its transport mission: the traffic and weather conditions of the route network and, in particular, of the best route are constantly monitored. If necessary, the calculation procedure for the best route is activated again. However, the new mission departure is represented by the GPS coordinates provided by sensors equipped on the truck. In particular, when a new calculation procedure is activated, the PDM start to exchange data with the Cloud Optimizer. The GPS coordinates of the truck and the information about incidents, congestion durations, bad weather conditions derived respectively by truck sensors and External Data Services are the new main data that the ERP and the VLM will analyse in order to calculate the best route and the new velocity profiles.

B. *Vehicle Longitudinal Model*

Once the ERP determines the route network, estimated values about emissions of air pollutants and fuel consumption are necessary. The VLM mostly uses the truck longitudinal model introduced by Hellström et al. [10]. Such model optimizes the velocity trajectory with respect to a criterion formulation that weighs trip time and fuel consumption.

More in detail, the street is divided in sections, each section is discretized in n intervals of length h. The generic interval k with k=1,...,n is modeled as follows:

$$\frac{(v_{k+1}-v_k)}{h} = \frac{1}{v_k}\frac{1}{J_l+mr_w^2+\eta(g)i(g)^2J_e}\Big(i(g)\eta(g)T_e(v_k,u_f)+ \\ -T_b(u_b)-r_w\big(F_a(v_k)+F_r(s)+F_g(s)\big)\Big) \quad (1)$$

where the used parameters and variables are the following:

$(v_{k+1}-v_k)$	speed variation between interval k+1 and k
J_l	wheel inertia
r_w	wheel radius
m	truck mass
$\eta(g)$	gear efficiency

$i(g)$	conversion ratio the transmission
J_e	engine inertia
T_e	engine torque
T_b	brake torque
F_a	air drag force
F_r	rolling resistance force
F_g	gravitational force
u_f	fueling level
u_b	braking rate
s	slope

In the model the state vector is $x_k = [v_k \ \ g]^T$, where v_k is current speed and g is the engaged gear. Moreover, the control vector is denoted by $u_k = [u_f \ u_b]$. The fueling level is assumed to be bounded by the relation $0 \leq u_f \leq u_{f,max}(\omega_e)$, where ω_e is the engine speed (rad/s).

The vehicle velocity is bounded inside the interval $v_{min} \leq v_k \leq v_{max}$, where v_{max} is the maximum possible velocity taking into account traffic condition, weather conditions and road topography (curvature and slopes).

The objective is minimizing the energy and time required for a given transport mission. The fundamental trade off when studying minimization of energy required for a transport mission is between the fuel use and the trip time. The fuel use on a trip from $S = S_0$ to $S = S_f$ is denoted by M and is calculated as follows:

$$M = \int_{S_0}^{S_f} \frac{n_{cylinder}}{2\pi n_r r_w} v u_f, \ g \neq 0 \qquad (2)$$

where $n_{cylinder}$ is the number of cylinders and n_r is the number of the crankshaft revolutions per cycle. On the contrary, the trip time is denoted by T and is defined by the following relation:

$$T = \int_{S_0}^{S_f} \frac{dS}{v} \qquad (3)$$

The cost function is evaluated as follows [10]:

$$Cost = M + \beta T \qquad (4)$$

where β is a scalar factor which can be tuned to receive the desired trade off respecting the mission duration time.

Now, it is possible to generate (considering admissible velocities and gears for a truck) all the possible m_k states $x_{k,j}$ in a generic interval k with k=1,…,n and j=1,…, m_k, and calculate the value of u_f to pass from a state $x_{k,j}$ to the next one $x_{k+1,i}$.with i=1,…, m_{k+1}. We perform different trials to find the optimal distance h and evaluate the number of k points that are necessary to have good results. In our case we consider h=2 km.

Fig. 5 shows how the algorithm works: *i*) it is taken in account a route divided in n intervals of length 2 km; ii) each interval k is divided in m_k states $x_{k,j}$. In addition, each $x_{k,j}$ state is linked to all the following ones $x_{k+1,i}$ with i= 1,…,m_{k+1} by a weighted edge $u_{k\ i,j}$ (see Fig. 6) that represent the fuel consumption to perform the step k, k+1.

Once calculated all the states and the weights, the Dijkstra algorithm [18] determine the minimum path of the graph represented in Fig. 5: in this way the algorithm chooses the optimal velocities and the corresponding gears in each interval k that minimize the total cost (represented by the fuel consumption) for a section of length h. Repeating the same approach for all the sections of 2 km in a street, the velocity profiles and the corresponding gears for the whole street are obtained and reported in the table shown in Fig. 4.

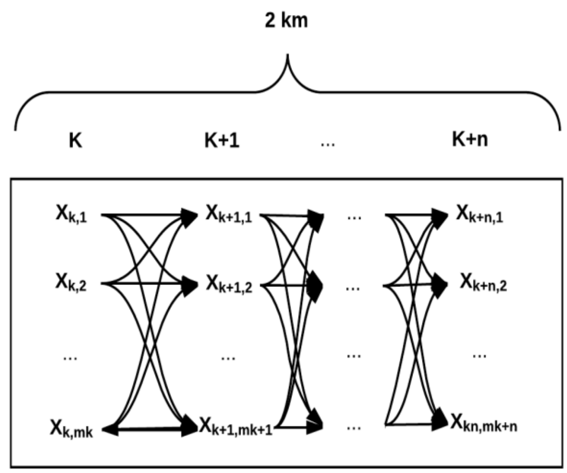

Fig. 5. *Look ahead steps scheme*

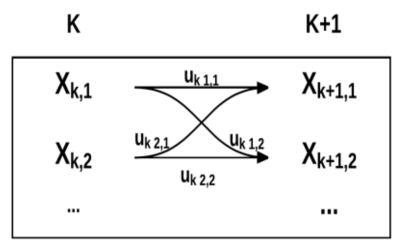

Fig. 6. *Fuel consumption cost associated to look ahead scheme*

V. CASE CTUDY AND RESULTS

This section presents some transport missions of different length in order to show how the proposed Cloud computing system is able to select the optimal routes from the emission point of view, by respecting the requested arrival times. To this aim we enlighten the differences between the fastest possible routes and the selected roads minimizing fuel consumption. Different tests based on three transport missions in Europe are considered:

A. *Bari – Santeramo (Short range)*
B. *Bari – Pescara (Medium range)*
C. *Rimini(Italy) – Vienna(Austria) (Long range)*

The performed tests are implemented by the External Data Services provided by PTV – xRoute [19] and GFS Model [20].

A. *Short range case study description*

The first mission loaded on PDM by fleet management company is Bari–Santeramo, two cities in the south of Italy. The maximum mission duration time established by the company is 1 hour and the payload is equal to 40 tons. The mission data are thus sent to the ERP that has to select the route network. In particular, the ERP initially calculates the fastest route (Route 1) and its sustainable alternative by PTV – xRoute [19]. Successively, the ERP builds the route network shown in Fig. 7.

Fig. 7. *Route Network: Bari – Santeramo*

The Route Network is thus sent to the VLM that calculates the fuel consumption, the air pollutants emissions and velocity profiles optimized taking in account traffic and weather conditions (provided by the External Data Service).

The fuel consumption is the parameter chosen to perform the optimization, hence the fuel consumption weighted cost is assigned to every edge of the Pre-calculated graph. This graph is sent to the ERP that generates the Eco- Route. In Fig. 8 the results are shown (Eco Route in green and fastest route in red) and in Table I a comparison between the fastest route and the Eco Route is reported.

The results confirm that the algorithm works correctly, while remaining within the time limits imposed by the fleet management company. It is possible to save the 8% of fuel.

Fig. 8. *Eco Route (green) and Fastest route (red): Bari – Santeramo*

	Comparison between eco route and fastest route: Bari - Santeramo		
	Distance [km]	***Fuel consumption [kg]***	***Duration [min]***
Fastest Route	57,9	13,83	52
Eco Route	43,6	12,72	55

TABLE I

B. Medium range case study description

The second mission loaded on PDM by fleet management company is Bari–Pescara. The maximum duration time requested by the feet company is 3 hours and 30 minutes while the payload is equal to 40 tons.

For this mission the architecture is programmed to perform the optimization taking in account the CO2 emissions and also in this case results are promising. The route network is shown in Fig. 9.

Fig. 9. *Route Network: Bari – Pescara*

The generated eco route and the fastest route are shown in Fig.10 and in Table II the comparison is reported.

Fig. 10. *Fastest Route (red) and Eco-Route (green):Bari – Pescara*

	Comparison between eco route and fastest route: Bari – Pescara		
	Distance [km]	***CO_{2}- emissions [kg]***	***Duration [h:mm]***
Fastest Route	315	202,18	3:03
Eco Route	305	197,94	3:05

TABLE II.

C. Long range case study description

The third mission loaded on PDM by fleet management company is Rimini (Italy) – Vienna(Austria). The maximum duration time requested by the feet company is 9 hours and 30 minutes while the payload is equal to 40 tons.

The optimization is done taking in account the CO2 emissions. The route network in shown in Fig.11. The generated eco route and the fastest route are shown in Fig.12 and the comparison is reported in Table III. It is apparent that also in this case the CO_2 emission is reduced of about 5%.

Fig. 11. *Route Network: Rimini-Vienna*

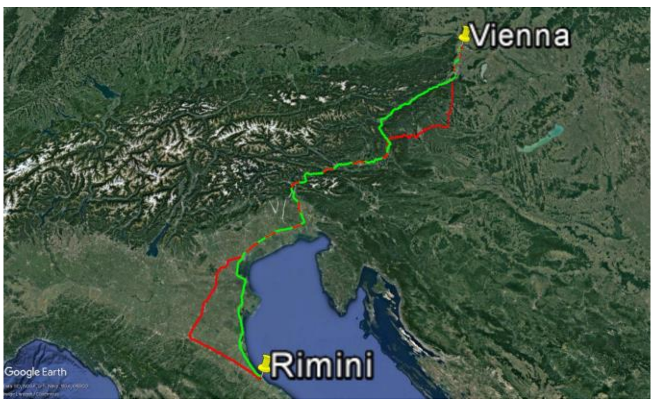

Fig. 12. *Eco – Route (green) and Fastest Route (red): Rimini - Vienna*

	Comparison between eco route and fastest route: Rimini - Vienna		
	Distance [km]	***CO_2 emission [kg]***	***Duration [h:mm]***
Fastest Route	833	591,04	8:31
Eco Route	788	559,53	9:02

TABLE III.

VI. CONCLUSIONS

This paper presents a Cloud Computing System to support the fleet management company in the choice of the routes to be performed by Heavy Duty Vehicles (HDV). In particular, the Cloud Computing System determines the best route and the optimal velocity profiles that an HDV has to run in order to minimize fuel consumptions and/or emissions of air pollutants. The optimization procedure is performed by the Cloud Optimizer that outputs the best route and the optimal velocity profiles on the basis of information provided by the fleet management company and external data services. Finally, some case studies show the efficiency of the proposed architecture, comparing the fastest routes and regular velocity profiles with the best route and the optimal velocity profiles determined by the Cloud Optimizer. The results show that in all the considered cases of different route lengths there is a saving of the fuel consumption or CO2 emission.

Future works will consider an on-board system that will collaborate with the cloud computing system to improve the efficiency of the proposed architecture. Indeed, the on-board system could improve the truck powertrain parameters based on the best route and obtain an additional reduction of fuel consumption.

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