

# Optimal Driving Profiles in Railway Systems based on Data Envelopment Analysis

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Abstract: The present study focuses on the development of a dynamically re-configurable Information Communication Technology (ICT) infrastructure to support the sustainable development of railway network. Once data have been collected, the extracted knowledge is used to develop a set of applications that can improve the energy efficient operation of railway systems. A typical example includes the identification of the optimal driving profiles in terms of energy consumption. In the present study, this is achieved through the adoption of an optimization framework based on Data Envelopment Analysis (DEA). The performance of the proposed scheme is evaluated based on actual data collected at an operation tramway system. Preliminary results illustrate that when the proposed method is applied, a 10% reduction in the overall power consumption can be achieved.

## 1 INTRODUCTION

The present study focuses on the identification of the optimal driving profiles on tramway systems. To achieve this, an experimental campaign has been

carried out to measure various parameters from an operational tramway system. Data for this study was collected via a dynamically re-configurable Information Communication Technology (ICT) infrastructure to facilitate both the operation and the

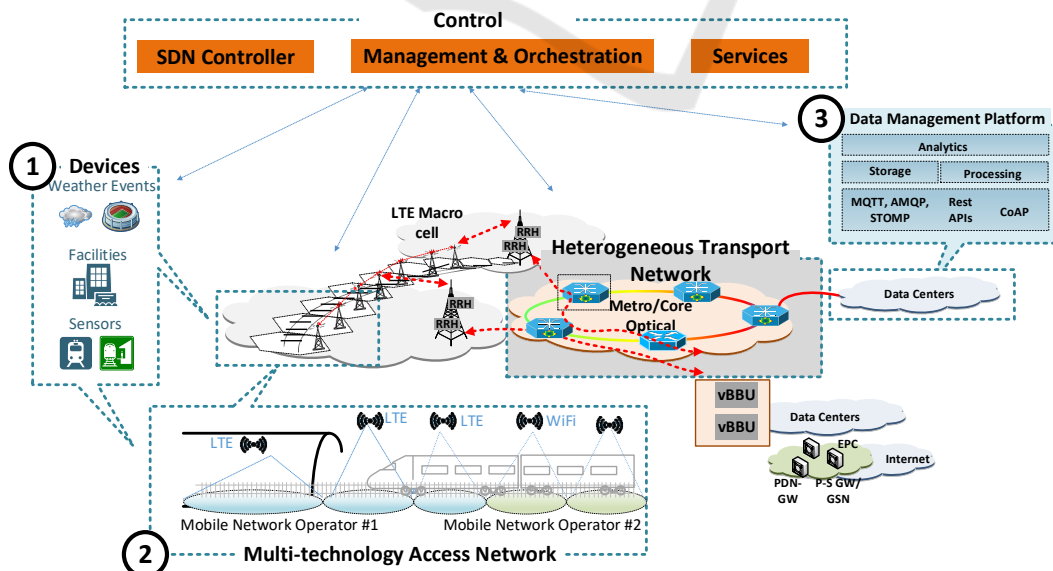


Figure 1: Converged Heterogeneous Network and Compute Infrastructures supporting railway services: Use case where data are collected from various devices (1) are transmitted over a 5G network (2) to the cloud-based data management platform (3).

end-user services supported by the railway network. Despite the recent progress in railway smart metering solutions and the implementation of several experimental trials, optimal operation of the ICT network supporting the power grid remains an unsolved challenge, even in the case where monitoring is limited to the rolling stock. The same holds for the interoperability between different heterogeneous network segments, which are currently static and unaware of each other. As a result, Railway System Operators (RSOs) are faced with a number of options for building their ICT networks but are limited by their inability to dynamically reconfigure the network infrastructure according to their operational and business needs and the lack of benchmarking information between possible solutions.

In response to these challenges we propose a smart metering system that monitors the energy flows of the whole railway systems and identifies the optimal performance/cost trade-offs on the fly. This is achieved through the deployment of an advanced open Operational Data Management (ODM) platform that comprises the following core elements Anastasopoulos (2018):

- a) A heterogeneous secure and resilient telecommunication platform, consisting of both wireless (e.g. Long Term Evolution – LTE, WiFi, Satellite) and wireline (e.g. optical) systems converging energy and telecom services. This infrastructure is used to interconnect a plethora of monitoring devices and end-users to the Operational Control Center (OCC).
- b) A platform that relies on a hybrid data storage and processing mechanism combining state-of-the art open source SQL/Non-SQL databases as well as batch and stream processing engines. Based on the characteristics of the collected data and the selected applications, data are dynamically forwarded to the most suitable storage/processing platform. A high-level view of this process is shown in Figure 1.

Once information has been collected, the extracted knowledge is used to support a set of applications that can improve the energy efficient operation of railway systems. A typical example includes the identification of the optimal driving profiles in terms of energy consumption. In the present study, this is achieved through the adoption of an optimization framework based on Data Envelopment Analysis (DEA). The performance of the proposed scheme is evaluated based on actual data collected from an operational tramway system. The rest of the paper is organized as follows. Section 2

outlines the objectives of the proposed study, Section 3 gives a brief overview of the state of the art on the subject, the research methodology along with a description of the proposed scheme is provided in Section 4. Finally, Section 5 concludes the paper.

## 2 OUTLINE OF OBJECTIVES

The main objective of this study is to improve the energy efficient operation of tramway systems through the identification of the optimal driving profiles. To achieve this, a smart metering system has been deployed monitoring energy, kinematic and environmental parameters of an operational tramway system based on sensing equipment installed both on-board and at the trackside. Once data have been collected and stored at the ODM system, an optimization framework based on DEA has been developed allowing the identification of the optimal driving styles. The objective of this approach is to identify driving styles that minimize the consumed energy subject to set of constraints related to scheduling, capacity and environmental conditions.

## 3 STATE OF THE ART

The problem of identifying optimal driving styles in railway systems has been extensively studied over the last years and a plethora of solutions have been proposed. These include offline techniques based on *Integer Linear Programming* (Gallo, 2015), schemes exploiting analytical kinematic equations and online algorithms using Machine Learning techniques (Zhang, 2019). Another approach relies on the Dynamic Programming Optimization Method proposed in (Mensing, 2011). Other studies minimize energy using Particle Swarm Optimization for a catenary-free mass transit system (Chang, 1997).

In this work, a different approach compared to the state-of-the art is adopted based on DEA. DEA can be effectively applied to the railway sector to improve service efficiency. Based on DEA, a linear programming model can be developed that can identify driving styles which can produce more output (i.e. transfer a larger number of passengers in shorter times) with less input requirements (i.e. power consumption).

Table 1: Sample of the collected dataset.

Timestamp	External Temp	Speed	Current HVAC C2	Voltage (catenary)	Current (Ventilation)	Voltage HVAC	Total Energy Pantograph
	°C	km/h	A	V	A	V	kWh
1442729913	10.8	43	15.6	892	38.7	449.32	37.0573402
1442729914	10.8	40.8	15.6	891	37.9	449.28	37.00736674
1442729915	10.7	38.9	15.6	869	38.2	449.55	36.95579201
1442729916	10.7	36.9	15.6	874	38.2	449.64	36.90263086
1442729917	10.8	35.1	15.6	855	39.5	449.73	36.85689206

## 4 METHODOLOGY

### 4.1 Data Collection Process

To improve energy efficient operation of railway systems, initially, an ODM platform has been deployed enabling data collection and processing of information obtained from a variety of sensors and devices. This platform comprises a *communication segment* that relies on a set of optical and wireless network technologies to interconnect a variety of end-devices and compute resources. Through this approach, data obtained from various sources (monitoring devices, users and social media) can be dynamically and in real-time directed to the OCC for processing. The wireless technologies comprise cellular WiFi, LiFi and LTE networks to provide the on-board and on-board to trackside connectivity. For the trackside to the OCC segment, information is transferred over an optical network. The overall solution is shown in Figure 1. As mentioned above, this platform is used to monitor a variety of parameters. An indicative sample of the collected measurements is provided in **Table 1**. This dataset includes information related to the geographic location of the rolling stock, on-board CO<sub>2</sub> levels that is used to estimate the number of passengers, internal and external temperature that is important for the evaluation of the Heating Ventilation and Air-conditioning system's (HVAC) performance, kinematic parameters (including acceleration and speed) etc.

The smart metering solution also comprises an *Information Technology* (IT) segment that is responsible for the storage and processing of the measurements. Storage is accommodated by hybrid mechanism combining state-of-the-art open source SQL/NoSQL databases while processing is executing based on Apache Spark. Using purposely developed algorithms, knowledge can be extracted from the

dataset which can assist railway system operators to identify optimal train driving and scheduling profiles.

### 4.2 Model Description

In the present study, identification of the optimal driving profiles is performed using DEA. DEA is a very powerful service management and benchmarking technique originally developed by Chames, Cooper and Rhodes (1978) to evaluate non-profit and public sector organizations. This is achieved by measuring the productive efficiency of the construction elements of these organizations, namely, decision-making units (DMUs). DEA can measure how efficiently a DMU uses the resources available to generate a set of outputs. The performance of DMUs is assessed using the concept of efficiency or productivity defined as a ratio of total outputs to total inputs. Note that efficiencies estimated using DEA are relative, that is, relative to the best performing DMU or DMUs (if multiple DMUs are the most efficient). The most efficient DMU is assigned an efficiency score of 1, and the performance of other DMUs vary between 0 and 1 relative to the best performance.

To apply DEA in railway environments, driving styles are treated as DMUs. Now, let  $S$  be the set of driving styles extracted from the dataset with  $\mathbf{X}_i, i \in S$ , being the vector of inputs of style  $i$ , with  $N$  elements  $x_{ij}, j \in N$ . Let  $\mathbf{Y}_i, i \in S$  be corresponding vector of outputs with size  $M$  ( $\mathbf{Y}_i = [y_{i1}, y_{i2}, \dots, y_{iM}]$ ). Let also  $\mathbf{X}_0 = [x_{01}, \dots, x_{0N}]$  be the inputs of the driving style that we want to evaluate and  $\mathbf{Y}_k = [y_{01}, \dots, y_{0M}]$  the output vector. Introducing parameter  $\lambda_i$  indicating the weight given to driving style  $i$  in its attempt to dominate Style 0, the measure of efficiency  $\theta$  of Style 0 is determined through the solution of the following optimization problem:

Table 2: Sample of 10 routes used for the identification of the optimal driving profiles.

StyleID	Inter-station Travelling Time (sec)	Total Energy (KW)	HVAC (KW)	CO2 (Average ppm)	Temperature °C
1	73	3139.2726	44.872627	47.979189	11.301351
2	77	2665.796	47.293833	38.555385	13.503846
3	73	4601.6475	29.122982	42.172973	14.404054
4	74	3397.467	45.642488	41.707368	14.797368
5	73	3146.8157	44.755127	45.322297	14.97973
6	77	3549.4091	307.04326	42.435443	15.134177
7	78	3334.6836	48.084032	42.387342	14.173418
8	75	3090.6305	45.894299	54.406974	13.892105
9	68	4883.8277	41.379654	46.720725	13.031884

$$\begin{aligned} & \text{Min } \theta & 44.872627\lambda_1 + 47.293833\lambda_2 + 291.22982\lambda_3 \\ & & \leq 44.872627 \quad (3.4) \\ \text{Subject to} & & 73\lambda_1 + 77\lambda_2 + 73\lambda_3 \leq 73 \quad (3.5) \\ & \sum_{i \in S} \lambda_i x_{ij} \leq \theta x_{0j}, \forall j \in N \quad (1) & \lambda_1, \lambda_2, \lambda_3 \geq 0 \\ & \sum_{i \in S} \lambda_i y_{ij} \geq y_{0j}, \forall j \in M \quad (2) & \\ & \lambda_i \geq 0 \forall i \in S & \end{aligned}$$

Constraint (1) limits the inputs of all other driving styles below the inputs used by the reference model 0, while equation (2) selects the driving styles that outperform style 0. The above problem is solved for all driving styles to identify the most efficient one.

In the present study, the optimal driving styles have been calculated taking as inputs parameters related to the in-cabin CO2 levels, the external temperature, the total driving time between adjacent stations, the total power consumption as measured by the pantograph and the power consumed by the HVAC system. An indicative sample of the parameters characterizing the driving styles is provided in Table 2, while the corresponding linear programming (LP) formulation considering only the first two styles is given below:

#### LP for evaluating Style 1:

$$\begin{aligned} & \text{min } \theta \\ \text{subject to} & & 47.979189\lambda_1 + 38.555385\lambda_2 + 42.172973\lambda_3 \\ & & \geq 47.979189\theta \quad (3.1) \\ & 11.301351 \lambda_1 + 13.503846\lambda_2 + 14.404054\lambda_3 \\ & & \leq 11.301351\theta \quad (3.2) \\ & 3139.2726\lambda_1 + 2665.796\lambda_2 + 4601.6475\lambda_3 \\ & & \leq 3139.2726 \quad (3.3) \end{aligned}$$

#### LP for evaluating Style 2:

$$\begin{aligned} & \text{min } \theta \\ \text{subject to} & & 47.979189\lambda_1 + 38.555385\lambda_2 + 42.172973\lambda_3 \\ & & \geq 38.555385\theta \quad (4.1) \\ & 11.301351 \lambda_1 + 13.503846\lambda_2 + 14.404054\lambda_3 \\ & & \leq 13.503846\theta \quad (4.2) \\ & 3139.2726\lambda_1 + 2665.796\lambda_2 + 4601.6475\lambda_3 \\ & & \leq 2665.796 \quad (4.3) \\ & 44.872627\lambda_1 + 47.293833\lambda_2 + 291.22982\lambda_3 \\ & & \leq 47.293833 \quad (4.4) \\ & 73\lambda_1 + 77\lambda_2 + 73\lambda_3 \leq 77 \quad (4.5) \\ & \lambda_1, \lambda_2, \lambda_3 \geq 0 \end{aligned}$$

### 4.3 Results

Solving the LP model for the styles shown in Table 2, the efficiency scores can be readily determined. The relevant results are provided in Table 3.

A preliminary set of results indicating the driving styles obtained when the DEA approach is adopted is shown in Figure 2. When the system is optimized for energy efficiency (green curve) the obtained driving style is smooth. On the other hand, when the system is optimized for shorter travelling times a higher average speed and steeper acceleration levels are

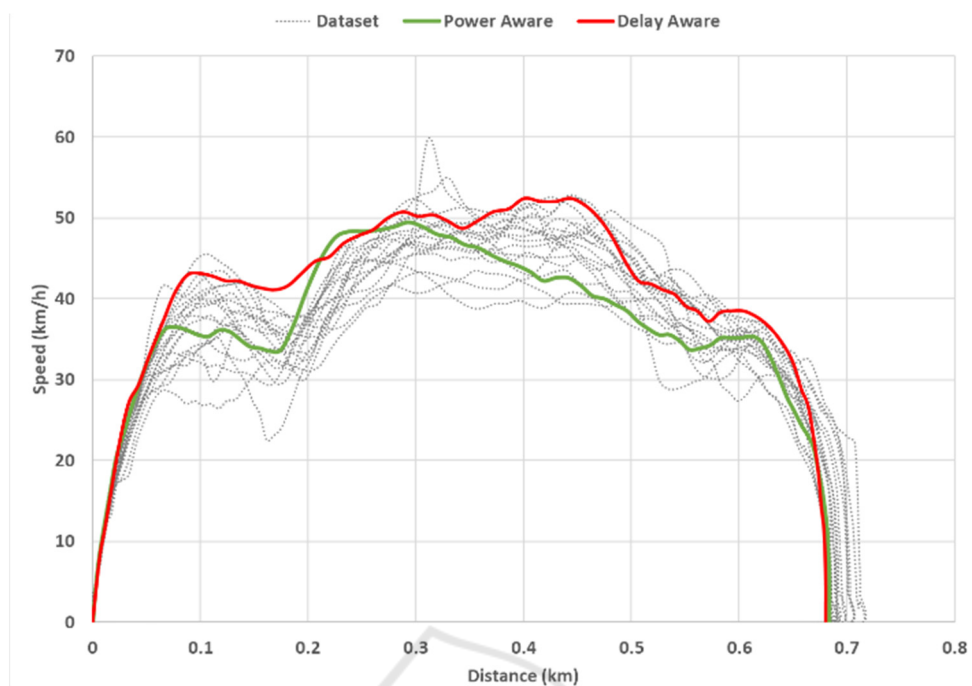


Figure 2: Tramway speed as a function KM distance for various driving profiles.

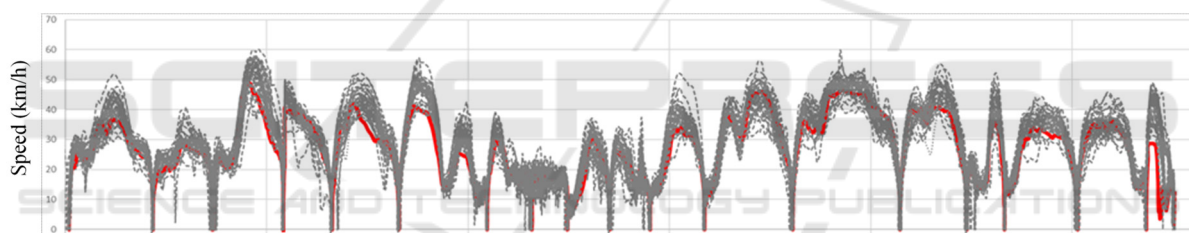


Figure 3: Optimal driving profile obtained when the DEA method is applied (red line) and comparison with styles obtained from measurements (grey lines).

Table 3: Efficiency scores for the driving styles shown in Table 2.

Style ID	Efficiency score
1	0.8099
2	0.7312
3	0.6887
4	0.6902
5	0.7649
6	0.6746
7	0.67
8	0.8975
9	0.819

observed. A similar set of results are shown in **Figure 3** where the optimal profile that minimizes the power consumption under end-to-end scheduling and passengers’ constraints is illustrated. When the proposed method is applied, a 10% reduction in the overall power consumption can be achieved.

In the method followed, the fastest routes were compared, those with the highest consumption and those with the slowest routes, respectively. In addition, the similar time routes were compared to each other to arrive at the above results. For example, we notice that routes 1 and 5 reach their destination at the same time and have almost the same consumption, total and ventilation. However, CO2 levels in the cabin are higher in the case of the first route, so more passengers are transferred. Therefore, it is reasonable to get the result that route 1 is more efficient than route 5. Additionally, we notice that route 8 is more efficient than route 1. Also, in these routes the



consumptions are similar, but we observe a considerable increase CO<sub>2</sub>. As a result, the tramway on route 8, with more passengers and lower consumption, arrived later to the station compared to route 1.

## 5 CONCLUSIONS

The present study proposed a modelling framework based on Data Envelopment Analysis that aims at identifying the optimal driving styles in terms of energy efficiency of an operational tramway system. To achieve this, in the first stage of the research, a data management platform has been deployed enabling collection and monitoring of energy, kinematic and environmental parameters. Preliminary results indicate that the proposed approach can reduce the energy consumption in railway systems by 10%. A main limitation of this approach is related to its increased computational complexity. To address this, in our future work the DEA method will be coupled with machine learning techniques to reduce the complexity of the ILP formulations.

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