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Prediction of soot loading onto a DPF using Artificial Neural Networks

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I. Introduction

- Diesel exhaust particulate matter (PM) is composed of a solid carbon fraction (soot) and a soluble organic fraction (SOF).
- PM (mainly composed of soot) has a mutagenic action associated with adverse health and environment effects including lung cancers, asthma and increased mortality rate [1].
- Increasing concerns about these effects lead to stringent new emissions standards (from 0.14 g/km for Euro 1 to 0.005 g/km for Euro 6) which motivated the development of PM control technologies such as a diesel oxidation catalyst (DOC) in combination with a diesel particulate filter (DPF).
- Real-time modelling of soot emissions is an interesting way to estimate the efficiency of PM control technologies.
- Soot formation is an highly complex process, difficult to describe mathematically. Empirical and semi-empirical models are easier to implement but are generally limited to specific operating conditions and are not able to generalize accurately [2].

Fig 1: Image of the tested DAF truck, from [3]

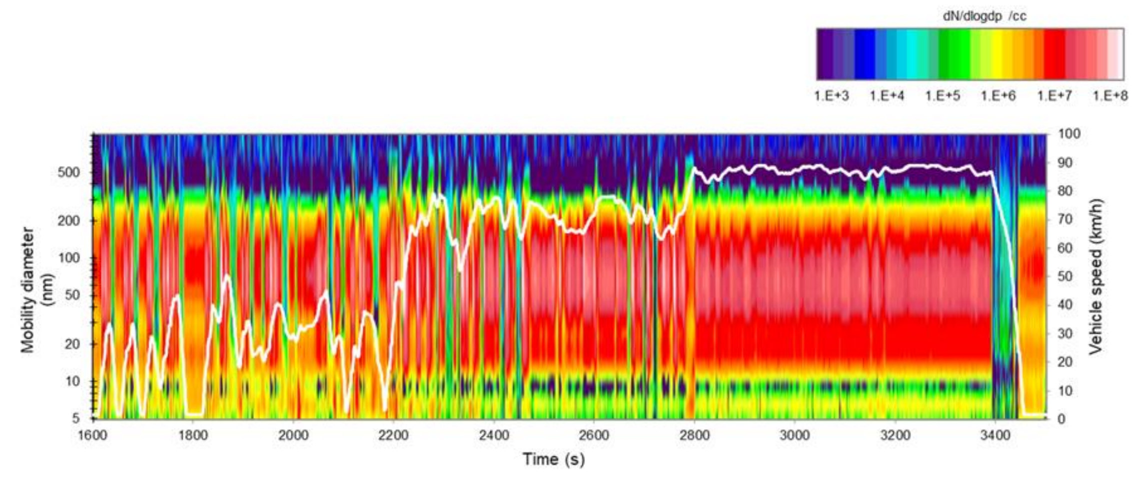


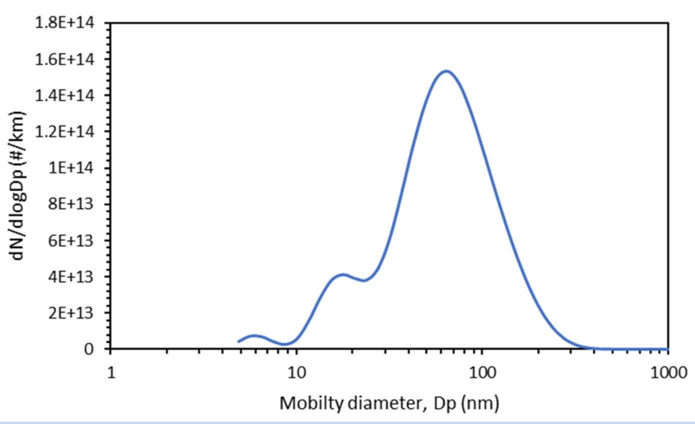
Fig 2: Vehicle Speed and particle size distribution as a function of time, from [3]

- This poster has two objectives:
  1. Compare two different methodologies to compute mass
  2. Use neural networks to predict Geometric Mean Diameter (GMD), Geometric Standard Deviation (GSD) and total number (N) which will be used to predict mass.

II. Material and methods

1. Data description

- 2 Euro 5 heavy-duty diesel vehicles equipped with Selective Catalytic Reduction (SCR) but without DPF [3].
- 1 Hz measurements of particles size distribution from a Cambustion DMS500
- 1 Hz On-Board Diagnostics (OBD) data, including vehicle speed, engine torque, engine speed and engine load are used as an input to the ANN
- Various operating conditions (steady-state and transient) are covered.



- The truck was tested against a FIGE cycle, including a city, a rural and a motorway part defined by average speed of respectively 50, 72 and 88 km/h

Fig 3. : Distance specific particle size distribution over the combined FIGE cycle

2. Mass computation

- Soot mass is computed using the Integrated Particles Size Distribution (IPSD) Method and the Particle Number Mass Emission (FA method, see poster 22) [4]. Both methods are compared.

	IPSD method	FA method
Formula for M	$M = \sum_i \rho_{\mathrm{eff,i}} \cdot n_{\mathrm{i}} \cdot \left(\frac{4}{3}\pi \cdot \left(\frac{D_{\mathrm{p,i}}}{2}\right)^3\right)$ [6]	$M = N \cdot k_\alpha \cdot \rho_0 \cdot \frac{\pi}{6} \cdot k_{\mathrm{TEM}}^{3-2D_\alpha} \cdot GMD^{\varphi} \cdot e^{\frac{\varphi^2 \cdot \ln(\mathrm{GSD})^2}{2}}$ [4]
Effective density	$\rho_{\mathrm{eff,1}} = \rho_0 \cdot (\frac{D_{\mathrm{p}}}{D_{\mathrm{pp}}})^{D_{\mathrm{m}}-3}$[3] $\rho_{\mathrm{eff,2}} = 0.0758 \cdot D_{\mathrm{p}}{}^{D_{\mathrm{fm}}-3}$ [5] $\rho_{\mathrm{eff,3}} = 1.2378 \cdot e^{-0.0048 \cdot D_{\mathrm{p}}}$ [6]	$D_\alpha = 1.069$ $k_\alpha = 0.998$ $D_{\mathrm{TEM}} = 0.29$ $k_{\mathrm{TEM}} = 2.644 \cdot 10^{-6}$ $\varphi = 3D_{\mathrm{TEM}} + (1 - D_{\mathrm{TEM}}) \cdot 2D_\alpha$ [4]
Variables	Particle effective diameter (D_{p}), number of particles scanned per channel (n_{i})	Geometric Mean Diameter (GMD), Geometric Standard Deviation (GSD), total particles number (N)

3. Implementation of an LSTM neural network

- Long Short-Term Memory (LSTM) neural networks are designed to model temporal sequences and their long-range dependencies [7].
- Each node (memory cell) of the network is a complex unit able to memorize information for an extended number of time step.
- 3 logistic gates control the storage and the update of the cell state.

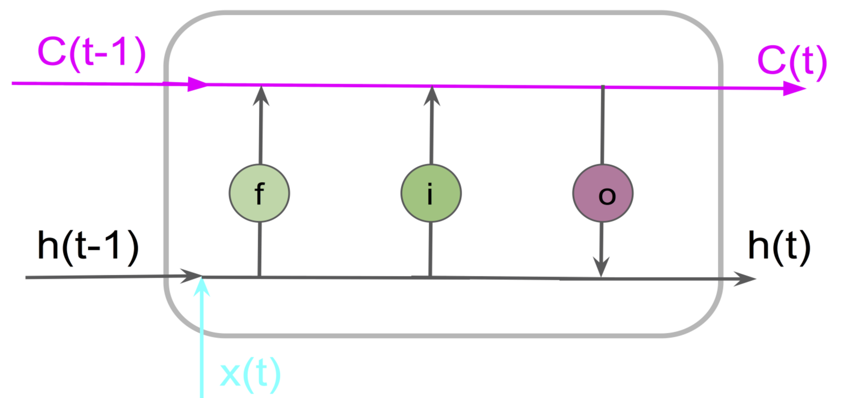


Fig 4: Schema of an LSTM, x(t) represent the input at time t, h(t-1) the prediction at time t-1, h(t) the prediction at time t, f the forget gate at time t, i the input gate at time t, o the output gate at time t and C(t) the cell state at time t. Adapted from [8].

- During the training procedure, the final error between the true output and predicted output is computed, propagated backward and the weights and biases are adapted to minimize the error.
- Trained for 76 epochs, until the error on the testing set (20% of input data) stops improving.

SUMMARY

- Inputs = vehicle speed, engine torque, engine speed and engine load
- Output = Geometric Mean Diameter (GMD), Geometric Standard Deviation (GSD) and particles total number (PN) every second
- GMD, GSD and PN are used to compute the soot's using the FA-method.

III. Results and discussion

1. Mass computation comparison

Table 1: Estimation of emissions using the IPSD method with two effective density estimation, the FA-method and the weigh of the filters.

IPDS - ρ_1	IPDS - ρ_2	IPDS - ρ_3	FA - method
0.025 g/km	0.033 g/km	0.042 g/km	0.031 g/km

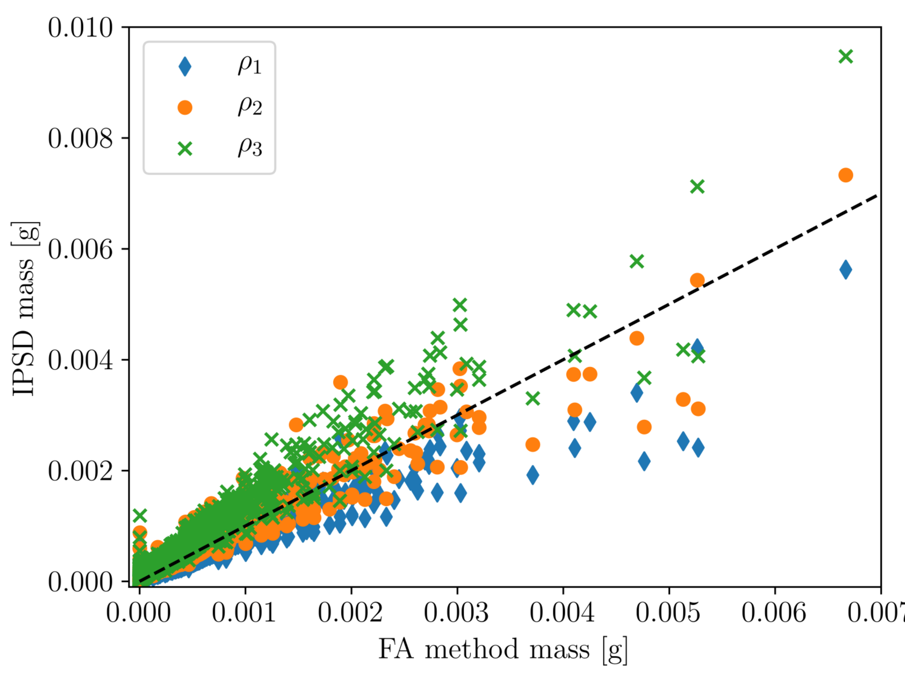
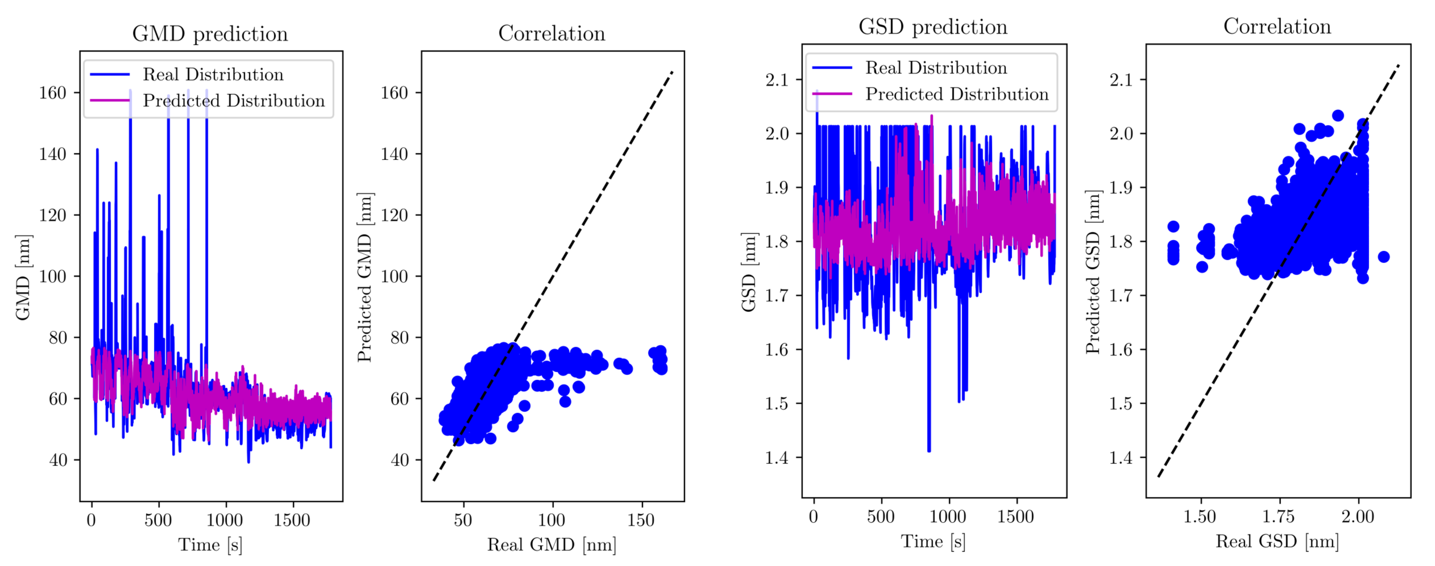


Fig 5. : IPSD mass estimation versus FA method mass estimation

The IPDS method is sensitive to the effective density. FA-method gives close estimations.

2. LSTM modelling



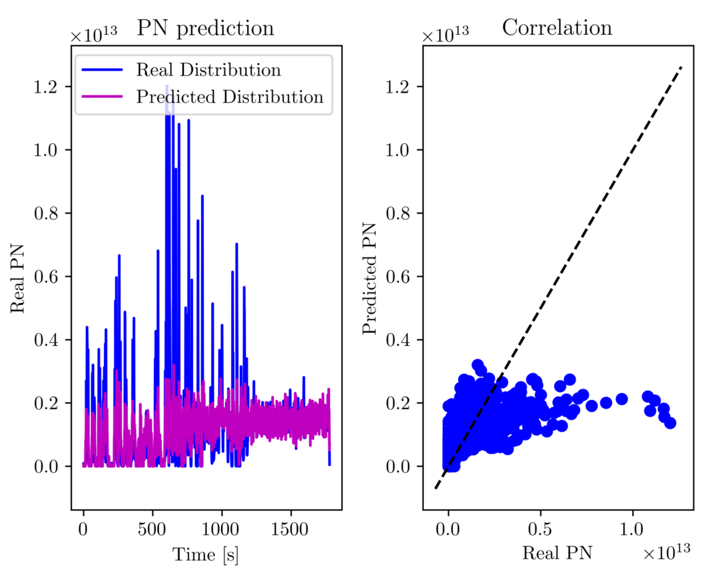


Fig. 6: PN, GMD and GSD prediction using an LSTM model

	Cumulative PN
Real	$2.12 \cdot 10^{15}$ km^{-1}
Prediction	$2.04 \cdot 10^{15}$ km^{-1}

-3.8 %

- The trends in GMD, GSD and N are well predicted (especially during the motorway part of the FIGE cycle) although the peaks are globally under predicted.
- Transient regime with short peaks that are difficult to predict.
- The input data is not sufficient to capture the highly complex and transient soot formation and therefore to accurately capture the peaks.

3. Predicted soot loading

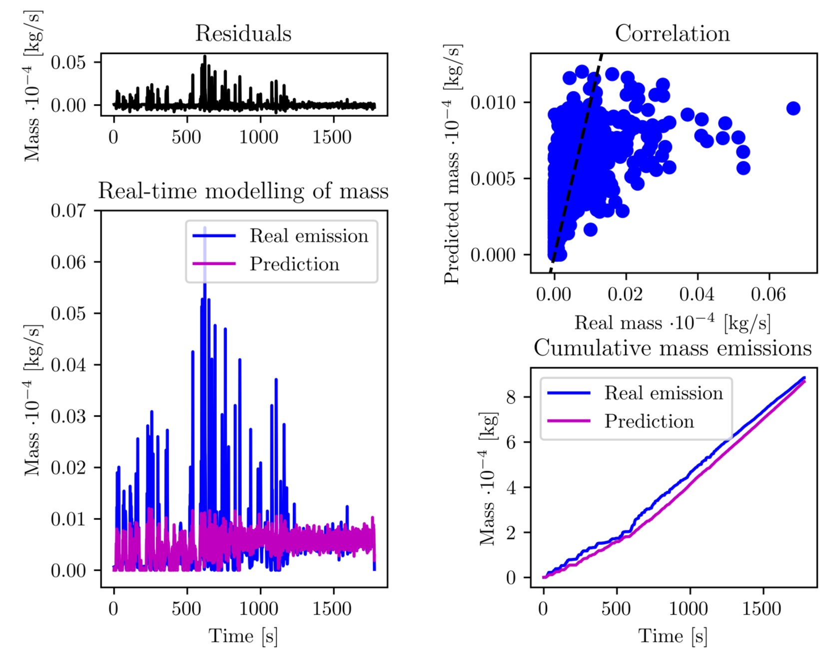


Fig. 7: Soot mass estimation from GMD, GSD and PN using the FA-method

	Cumulative PM
Real	0.030 g/km
Prediction	0.029 g/km

-2.0 %

- Peaks are not correctly predicted. An improvement of the prediction of N, GMD and GSD should allow to predict more accurately the peaks.
- Final soot emission estimate close to reality.

IV. References

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