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Inference of steady-state non-road engine exhaust emissions values from non-stabilized data

Author, co-author list (Do NOT enter this information. It will be pulled from participant tab in MyTechZone)
Affiliation (Do NOT enter this information. It will be pulled from participant tab in MyTechZone)

ABSTRACT

This paper describes attempts to determine stabilized emissions of non-road engines without waiting for stable emissions values to be reached, with the goal to shorten laboratory testing time and/or to use real-world, in-service data featuring limited segments of steady-state operating conditions. The emissions from non-road engines are often evaluated and reported in steady-state operating conditions. Many larger engines are tested in the field, due to impracticality of dynamometer testing, resulting in practical limits for testing time at constant operating conditions. With lower fractions of elemental carbon (black soot) in the particulate matter and increased deployment of catalytic aftertreatment devices, longer times are required for reaching stable values. This work seeks to infer stabilized emissions values from limited length segments of unsteady but converging data. Theoretical consideration of thermal factors and storage of material in the exhaust system, and emissions data obtained in a laboratory and on a locomotive engine tested in the field, suggest that the instantaneous emissions in steady-state conditions tend to follow the exponential function y(t) = y(steady) + [y(initial)-y(steady)]*exp(-const.*t) describing both mixing and Newton's law of cooling. Several pathways of non-linear iterative regression has been investigated, generally leading to consistent results, albeit many individual segments of data yield inconsistent or no solution. It appears that when multiple segments of data longer than approximately two minutes are available, there is a high chance at arriving at a plausible steady state value of emissions concentrations. In such case, steady state emissions can be derived from not fully stabilized data, such as from real-world operation of, for example, diesel locomotives, or from large engines tested in a laboratory. With large engines, this can possibly yield considerable savings in testing expenses and improved emissions data. The findings are preliminary, and as of now, interpretation of data requires some skill.

INTRODUCTION

Exhaust emissions from internal combustion engines are one of the main sources of air pollution in most metropolitan areas. Nitrogen oxides (NO_x) and particulate matter (PM) are currently of highest concern. The particles are mostly on the order of tens of nanometers in diameter [1], a size that coincides with maximum efficiency of deposition in human lungs [2,3]. As the human bodies do not seem to have efficient defense against such particles, many such particles penetrate into the bloodstream, causing a widespread damage to the body [4]. Significant resources have therefore been devoted to reducing emissions of new engines, as well as of the existing fleet. These efforts have been first directed mostly towards engines in on-road vehicles, and are gradually expanding to engines in construction equipment, ferries, ships, locomotives, and various other mobile machinery, summarily termed off-road or non-road engines.

To assess the benefits of any emissions reduction strategy, actual in-use emissions of the engines in question must be reasonably known. While the emissions of on-road vehicles can be readily assessed using a chassis dynamometer, whether in a laboratory or transportable [5], there is no practical laboratory test for an in-use locomotive engine. Not only many of these engines are relatively large and engine dynamometers of sufficient capacity are scarce: The removal of an engine and its transport and installation in a test laboratory is a time and resource consuming task. Therefore, in-use measurement on such engines are often performed using on-board monitoring systems [6], or, in case of a stationary field test, using mobile laboratories transported to site.

For diesel-electric locomotives, the emissions are measured mostly during operation of the engine at discrete power levels during a stationary test, where the generated electric power is not used to propel the locomotive, but diverted into a load bank. A mobile laboratory [7-8] or on-board monitoring systems [9] are then used to measure emissions.

This approach was found not to be feasible for measurement of emissions of motorized rail cars and locomotives at Czech Railways, where many motorized cars use mechanical or hydraulic transmission of power, and thus cannot be adequately loaded during a stationary test. Also, particle emissions from in-use locomotives depended on the engine operating history and did not reach stable levels during allocated load bank time [10]. Measurements have been therefore carried out during regular operation of the trains using a portable, on-board monitoring system [11] mounted inside the tested railcar or locomotive [12].

The goal of this work was to determine steady state emissions at each discrete power level ("notch") from the measured data. As the utilization and sequencing of notches varied greatly among different lines and train weights, the data was aggregated over multiple runs, totaling over one thousand kilometers accumulated on different types of tracks with different train compositions [12]. It was found that the emissions during each window of steady-state operation were not always stable, but in some cases, consistently drifted at a gradually decreasing rate. The aim of the efforts reported on in this paper was to develop means to infer steady-state values from experimental data subject to drift.

Two major categories of theoretical reasons for drifting emission values have been identified. The first category are gradual changes in the temperatures of the combustion chamber inner surfaces and other parts and media (summarily engine thermal changes) associated with the transition into a different power regime. Associated with this are gradual changes in the temperatures of the working surfaces of catalytic aftertreatment devices (aftertreatment thermal changes). The second category are storage, or deposition and reentrainment, of particles, semi-volatile organics, and other compounds; deposition and reentrainment has been found to be a potentially important source of artefacts in emissions measurements [13]. The effects are complex and non-linear, however, the most common function describing both thermal changes and storage-equilibrium-mixing phenomenae is that of Newton's law of cooling,

$$Y(t) = Y_{steady} + (Y_{steady} - Y_{init}) * K_1 * \exp(-K_2 * t) \qquad (1)$$

where $Y(t)$ is the actual value of temperature or concentration at a time t, Y_{steady} is the stabilized steady-state value, Y_{init} is the initial value, and K_1, K_2 are constants. For practical purposes, $K_1 = 1$.

The relationship (1) is explored for determination of Y_{steady} using two approaches. The first is a regression of one of more segments of a continuous series of experimental data. This regression, lacking an analytical solution, is attempted using two iterative approaches. The second is aggregation of multiple segments, each with a different Y_{init}, into one data set, which is then evaluated for the likely value of Y_{steady}.

The goal of this effort is to find a steady-state value (Y_{steady}) from experimental data which converges towards, but has not reached, this steady value.

This work is motivated by the desires (1) to shorten the time an engine, typically a larger one, needs to be operated at each test point, in order to expedite the test and to reduce the engine downtime, the laboratory bench time, and fuel consumption, and (2) to obtain steady-state values from real-world in-service measurements, where the engine does not remain at constant operating conditions for long enough for the emissions data to stabilize, which is a typical case for, for example, many commuter train locomotives.

EXPERIMENTAL

Two sets of experimental data are discussed here. The first is a large set of exhaust emissions measurements on a CKD 749 series diesel-electric locomotive with a K 6 S 310 DR, six-cylinder, 163-liter, 1500 hp turbocharged diesel engine. The data was collected using a portable, on-board emissions monitoring system during regular line-haul duty on two different routes, a Prague-Tanvald hilly route with a 297-ton train and a Prague-Ceske Budejovice mostly flat route with a 160-ton train. (Train weights are subject to approximately 10 tons uncertainty due to changes in fuel level and passenger loads.)

The on-board monitoring system, designed and constructed by the author, was mounted inside the engine compartment of the locomotive. The locomotive has engineer cabins on both ends, connected by an isle through the engine compartment. The monitoring system was mounted at the end of the other isle, where it did not interfere with the operation of the locomotive. The choices for exhaust sampling were severely limited by the presence of 3 kV direct current traction lines in Prague and 25 kV alternating current traction lines in and near Ceske Budejovice. As the stack was directly under the traction lines, minimalistic approach had to be used.

The exhaust was sampled into three ¼" diameter copper tubing, two for measurement and one spare, inserted about 2' (60 cm) into the stack, bent around the stack rim, and secured to the stack and to the metal structural elements of the locomotive roof by baling wire. The tubes transitioned into conductive ¼" diameter sample lines. One line was used by the online on-board monitoring system. Concentrations of nitrogen monoxide (NO), carbon monoxide (CO) and carbon dioxide (CO_2) were measured online with a pair of modified, optimized and tuned BAR-97 grade analyzers, utilizing non-dispersive infra-red analyzers (HC, CO, CO_2) and electrochemical cells (NO). As the engine did not have any aftertreatment devices, the volumetric concentrations of total nitrogen oxides (NO_x) were assumed to be identical to those of NO. Concentrations of particulate matter were measured online with a forward scattering integrating nephelometer, which, for a given engine and a given setup, tends to provide output proportional to particle mass concentration. Exhaust flow was calculated from intake air flow computed from engine design and operating parameters. All data was synchronized to adjust for measurement delay of the analyzers, and instantaneous mass emissions were computed by multiplying corresponding values of exhaust flow and concentrations [11,14]. Instantaneous power transmitted from a direct-current generator powered by the locomotive diesel engine to the direct-current traction motors and engine rpm were obtained from analog signals available at the locomotive, which were recorded using a PC-based data acquisition system.

Particulate mass emissions were measured during selected steady-state operating points with a portable gravimetric sampling system, utilizing the second line. Sampling was done on 47 mm diameter PallFlex T60A20 (Pall Life Sciences) filters, which were conditioned and weighted twice prior and several times after the measurement, following standard procedures for gravimetric measurement, with added equilibration time and repeated weighings after the collection. Other measured parameters not relevant to this study are not reported on.

For the purposes of evaluating regression techniques, a second set of data was used, which was chosen from a wealth of tests run on a 120-hp, four-cylinder Zetor 1505 tractor engine powered by biofuels and tested on an engine dynamometer [15]. When this engine was powered by heated rapeseed oil and operated at lower loads, most of the particulate matter comprised of semi-volatile organics, which were subject to deposition in the exhaust system and subsequent reentrainment, with deposition and reentrainment affected significantly by exhaust flow and exhaust gas temperature. During these tests, measurements were performed both by laboratory and on-board instrumentation. The on-board instrument was used to provide online particulate measurements, and its readings were compared with standard laboratory instruments: Hydrocarbons were measured with a heated flame ionization detector, CO and CO_2 with non-dispersive infra-red spectrometers, total nitrogen oxides by a chemiluminescence analyzer, and total particulate mass by gravimetric method using a partial flow dilution tunnel and 47 mm PallFlex T60A20 filters.

The typical approach in reporting on-road emissions data is to determine exhaust flow and concentrations of respective pollutants, to obtain instantaneous emission rates by multiplying the flow by the corresponding concentrations, and to integrate such values over some pre-determined route. The totals per route can then be divided by the route distance, by the total engine brake work, or by the total fuel consumed, obtaining values per km, kWh, or kg of fuel. The focus of this work is the drift, or unsteadiness, of concentrations of pollutants in the exhaust gases, under the conditions where the engine rpm and load, power output, and exhaust flow are steady, and are considered constant. For this reason, and for simplicity, concentration data are given throughout this paper, rather than mass flow rates, or brake-specific emissions, of each pollutant.

RESULTS AND DISCUSSION

The instantaneous locomotive emissions were correlated, after synchronization of both sets of data due to measurement delays, against instantaneous generator output. These correlations have been done separately for the hilly Prague-Tanvald route with a five-car, 297-ton train (high-load route) and for the relatively flat Prague-Ceske Budejovice route with a two-car, 160-ton train (low-load route), as these were obtained at different days. The mass concentrations of PM are given in Figure 1 (left) for the high-load route and (right) for the low-load route. These plots of concentration on the vertical axis and generator power on the horizontal axis, with each point representing one second of data, were then compared against and interpreted using the real-time data. It is apparent that most data is in the form of "clouds", with highest aggregations of points in the horizontal direction around the target power level for each notch (idle and notch 1,2,…,8). Similar aggregation can be observed in the horizontal direction, although here the data is in many cases more spread. Other points correspond primarily to transitions among notches. Similar plots are given for NO_x in Figure 2 (left) for the high-load route and (right) for the low-load route, and for CO_2, for both routes, in Figure 3. (Note that the CO_2 concentrations do not increase substantially from notch 4 to notch 8. The additional power is derived not from lower excess air ratio, but from increased flow of both air and fuel through higher rpm and higher turbocharger boost pressure. NO_x concentrations decrease from notch 4 to notch 8, primarily due to injection timing strategy chosen to avoid smoke at intermediate notches.)

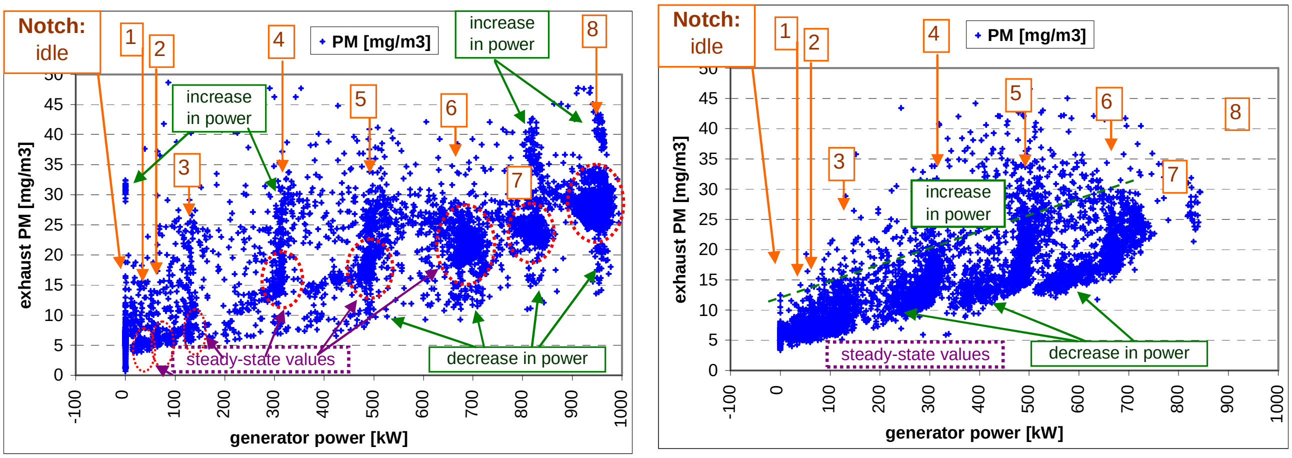

Figure 1: Particulate matter mass (PM) concentrations in exhaust gases of a diesel-electric locomotive as a function of generator power output: Aggregate data (left) over a high-load route run with a five-car train and (right) over a low-load route, mostly flat line traversed with a two-car train.

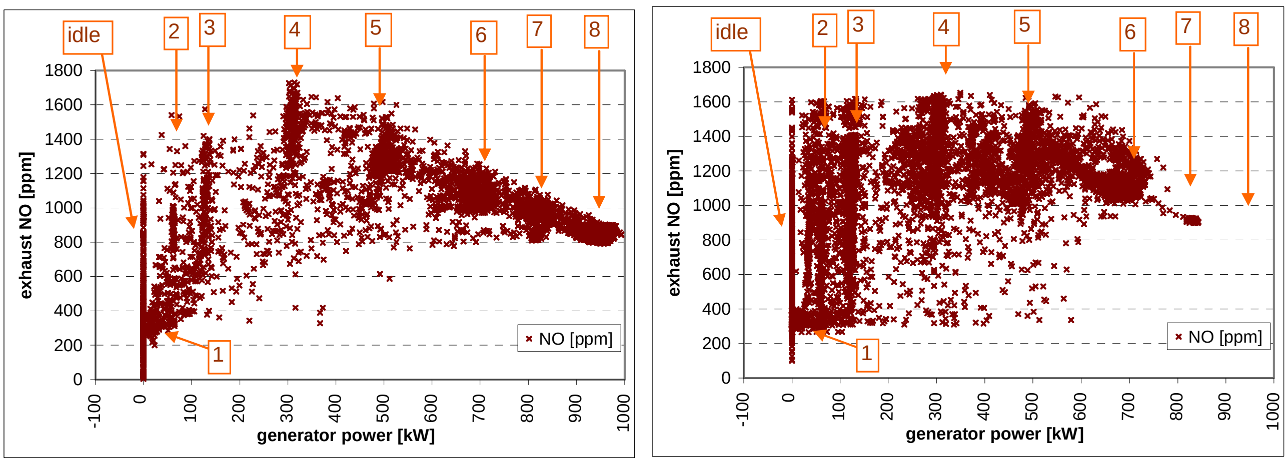

Figure 2: Nitrogen oxides (NO_x) concentrations in exhaust gases of a diesel-electric locomotive as a function of generator power output: Aggregate data (left) over a high-load route run with a five-car train and (right) over a low-load route, mostly flat line traversed with a two-car train.

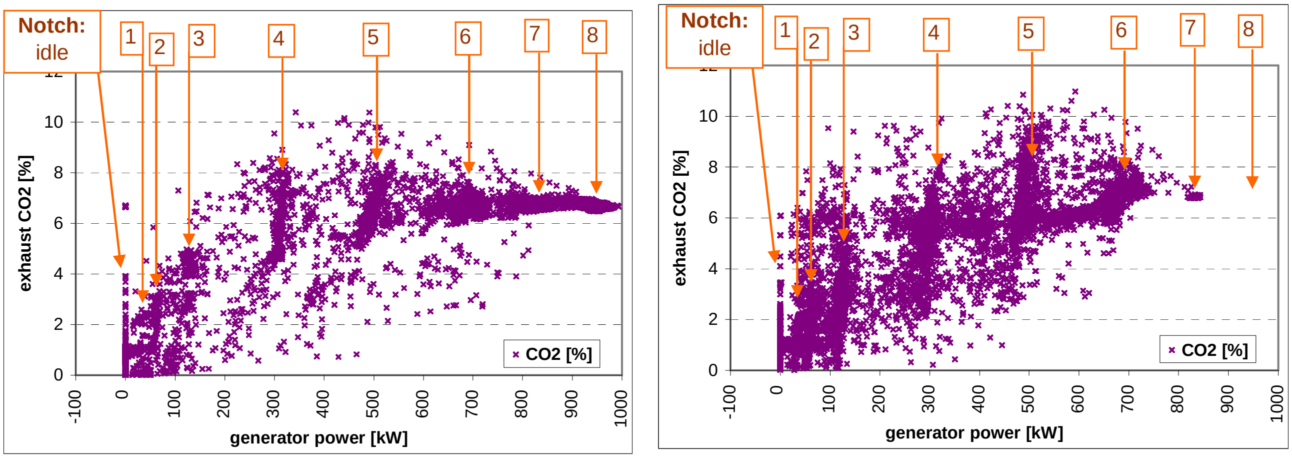

Figure 3: Carbon dioxide (CO_2) concentrations in exhaust gases of a diesel-electric locomotive as a function of generator power output: Aggregate data (left) over a high-load route run with a five-car train and (right) over a low-load route, mostly flat line traversed with a two-car train.

It is apparent that the high-load route favors higher loads while lower notches are rarely selected, while the low-load route has only one occurrence of notch 7 and totally avoids notch 8.

The data shown in Figures 1-3 has been binned according to notch, and sorted by the nominal value of NO_x and PM concentrations. For the purposes of binning, "notch" is represented by the actual power level, not by the selection of the train engineer. Therefore, for example, data binned as notch 5 also includes onsets of acceleration from notch 5 to notch 6 (or higher), but does not include the bulk of the transition from notch 4 (or lower) into notch 5.

These concentrations are plotted in upper graphs of Figure 4 (left) for notch 8 (full load) and (right) for notch 5 (intermediate load). In case of notch 8, the bulk of the NO_x and PM concentrations lies in a relatively narrow range, less than 10% of the nominal value, with tails of the distribution containing lower and higher values. For notch 5 operation, similar distribution is apparent in Figure 8 for NO_x data, but not for the PM data, where the higher concentration "tail" comprises of, depending on the interpretation, tens of percent to about one half of the data. This is consistent with observations apparent from Figures 1-3. This difference stems from the different periods for which the locomotive was consecutively operated in that notch.

From first-hand observations of the train engineer, it has been learned that notch 8 was used with the five-car train for accelerations and for higher speed hill climbs of a duration of one to several minutes. Notch 5 was used as an intermediate load during parts of accelerations of the lighter two-car train to moderate speeds, to maintain cruising speed, and during lower speed hill climbs on curved railroads along river gorges. It was often either selected as a part of a sequence during acceleration of lighter trains, or interleaved with lower or higher notches during cruise. The duration of each separate utilization of notch 5 was therefore shorter, often tens of seconds; this also accounts for higher transients.

The derivative of the functions plotted in the lower graphs of Figure 4, computed as a rolling average of 15 consecutive differences between each two adjacent measured concentrations, is plotted in the bottom graphs in Figure 4 (left) for notch 8 and (right) for notch 5. It is apparent that this derivative has a minimum in the mid-range of the measured concentrations for NO_x and PM for notch 8 and for NO_x for notch 5, while lying relatively low in the range of measured concentrations of PM for notch 5. This is consistent with visual interpretation of the real-time data as well as with overall experience with diesel emissions: Operation at notch 5 is relatively more transient, and PM emissions of a diesel engine tend to be more affected by engine operating dynamics and engine operating history than NO_x emissions.

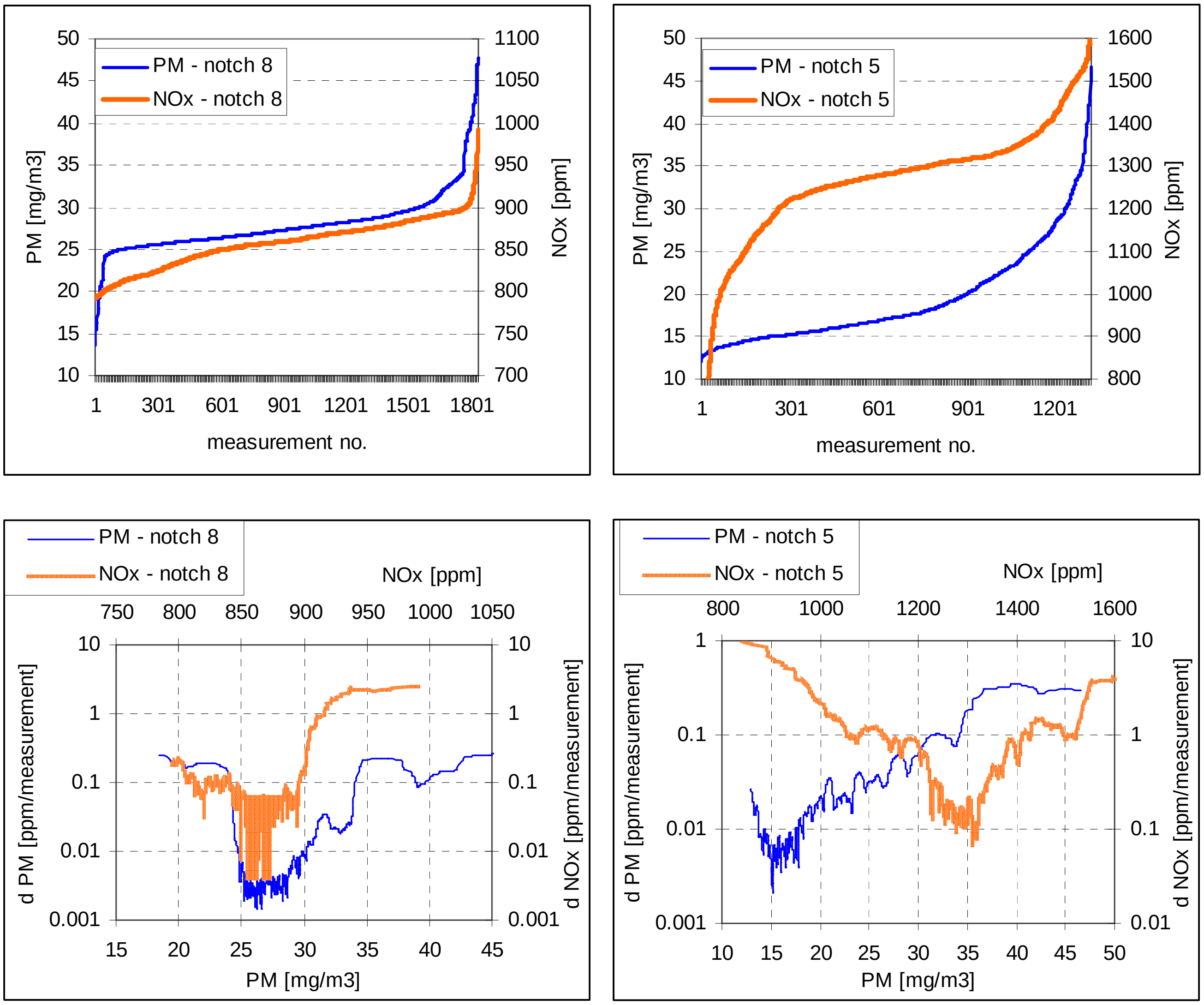

Figure 4: Top graphs show PM and NO_x concentrations during all occurrences of operation of a diesel-electric locomotive (left) at notch 8 and (right) at notch 5, aggregated over all test runs, sorted by and plotted as a function of the measured concentration value. Bottom graphs show derivatives (rolling average of each 15 consecutive numerical values) of PM and NO_x concentrations plotted in the upper graphs.

Segments of data from longer, uninterrupted operation at each notch were extracted as separate series and were subjected to regression analysis. Equation (1), following the Newton's cooling law, was used as the regression equation.

If the stabilized value is known, such as in many cases of heat transfer calculations, the transient value can be readily expressed as the difference between actual and stabilized value, and the equation transcribed as

$$Y(t)-Y_{steady} = (Y_{init} - Y_{steady}) * \exp(-K * t) \qquad (2)$$

Equation (2) can be then linearized by taking the logarithm of both sides and substituting $X(t) = \ln(Y(t)-Y_{steady})$, yielding

$$X(t) = -K * t + [\ln(y_{init} - y_{steady})] \qquad (3)$$

which can be readily resolved for constants K and $[\ln(y_{init} - y_{steady})]$ using linear regression of a general function $y = ax + b$.

Here, however, with the stabilized emission value, analogous to the "temperature of surroundings" in Newton's cooling law, not only being unknown, but, in this case, being the very goal of the quest, no analytical solution for this regression has been identified.

Alternative approaches have therefore been used:

1. The data have been uploaded into an online Non-linear least square regression solver [16].

2. Practical limits of the constants of the equation (1) have been set by a qualified guess, and within these limits, different combinations were tried by Monte-Carlo simulation [17,18]. Each such set was further optimized by an improvised implementation of a "greedy search" algorithm [19] in Microsoft Excel, until maximum correlation between a curve fitted using each set of constants and actual experimental data has been obtained. R^2, square of Pearson's correlation coefficient, was used as the correlation metric.

3. A nominal value for the stabilized concentration, Y_{steady}, was selected, reducing the problem to linearized equation (2), for which analytical solution has been found using the linear regression / linear estimate tool of Microsoft Excel, and correlation between actual experimental data and a curve fitted based on the computed regression coefficients and on the chosen nominal value was computed. R^2, square of Pearson's correlation coefficient, was used as the correlation metric. This calculation was repeated for all nominal values lying in a reasonable range, with the aim to identify the value resulting in the highest correlation. Additionally, the nominal value for Y_{steady} was searched for using Microsoft Excel "solver" feature, with varying results.

Selected segments of data from continuous operation at notch 8 are plotted in Figure 5 (left) for PM and (right) for NO_x. These segments were extracted from the high-load route (notch 8 was not used on the low-load route) and represent the longest sections with uninterrupted operation at notch 8. It is apparent that the PM concentrations decrease, while NO_x concentrations increase. This is consistent with the expected result of a transition to a higher load: PM are temporarily increased due to removal of the deposits from the exhaust system, and are converging towards a steady value. NO_x are temporarily suppressed by lower intake air temperature and/or engine working surfaces temperature, and are gradually increasing towards a steady value.

For each segment, a curve fit has been identified using a combination of the first two mentioned approaches has been plotted, along with the "winning" equation and correlation coefficient between fitted and experimental data.

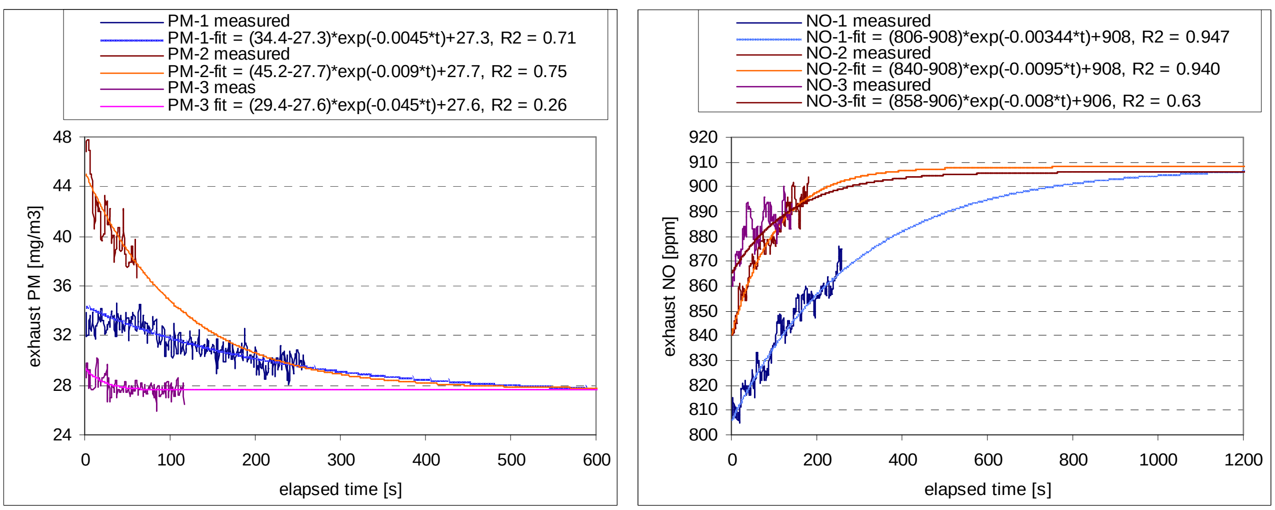

Figure 5: Monte-Carlo iterative regression of multiple continuous subsets of experimental data with fitted curves and predicted steady values for operation at notch 8: concentrations of (a) PM and (b) NO_x.

It appears that the stabilized concentrations determined from each data set were relatively consistent across all plotted segments. The correlation has been found to decrease with increasing stability of the data, which is consistent with inherencies of the correlation (there is no "trend" in stabilized data). This was, for example, the case for the set PM-3 in Figure 5.

The practical limit observed for such regression was the combination of the length of the data segment subjected to the regression and the noise level in the data. Generally, segments shorter than about two minutes were not useful and often yielded multiple "candidate" values. For this reason, only regression on longer segments of notch 8 data is reported on.

The steady concentrations of PM identified in Fig. 5, approximately 27.5 mg/m^3, appear to lie on the higher end of the "low-change" range apparent from upper graph in Fig. 4 and identified in lower graph of Fig. 4 as 25-28 mg/m^3. The steady concentrations of NO_x shown in Figure 5, 908 ppm, are somewhat above the "low-change" range of approximately 850-890 ppm in Figure 4.

It should be noted here that the segments subjected to regression were primarily from the early part of the test day, where the engine was additionally loaded with alternator for electric heating of the passenger cars, the use of which was highest in the early morning and diminished throughout the day; this additional load, on the order of tens to about one hundred kW, was not accounted for in the measurements.

Using the same data set, iterative regression has been performed using the third identified method – iteratively choosing the steady-state value, reducing the regression to a linear one, finding regression coefficients using a spreadsheet program (Microsoft Excel 2003), and observing the correlation between experimental and fitted data. The results of this effort for notch 8 are shown in Figure 6 (left) for PM and (right) for NO_x.

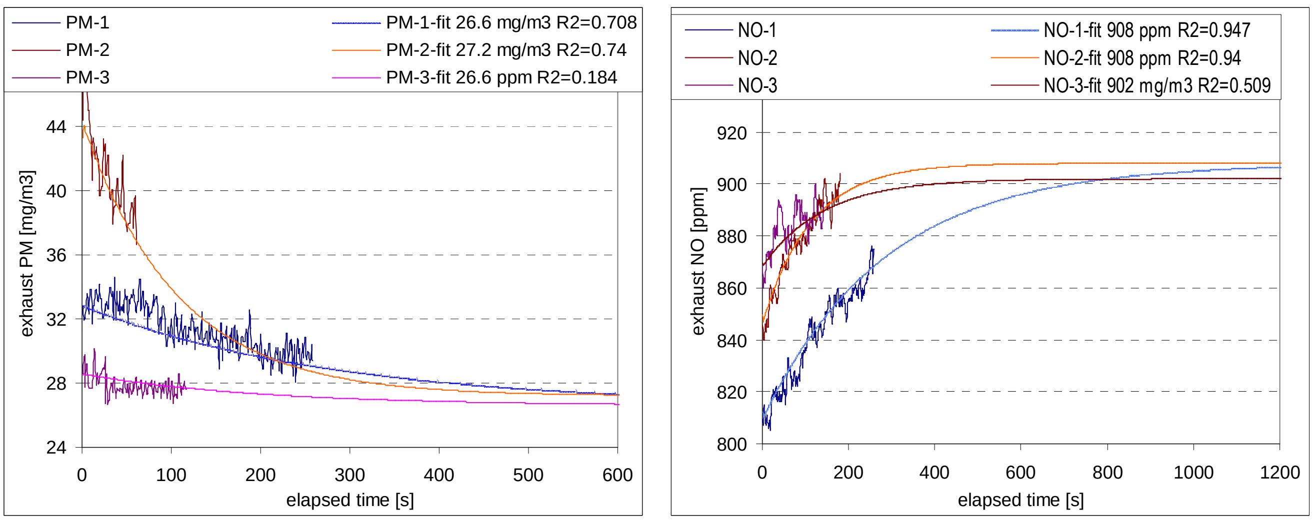

Figure 6: Iterative regression of multiple continuous subsets of experimental data with fitted curves and predicted steady values for operation at notch 8: concentrations of (left) PM and (right) NO_x. Regression was solved analytically for a user-supplied steady value and steady value yielding highest correlation between experimental and fitted data was selected.

A notable problem with this approach was with data sets where the experimental data, which include random oscillations due to noise, lie on both sides of the chosen steady value, as this would require, in linearization of equation (2), computation of a logarithm of a negative number. Exclusion of such data, if present in larger quantities, was not deemed feasible as this would skew the data. In such cases, the series was truncated at the first occurrence of an "overshoot" – an experimental value lying on the opposite side of the steady value than the rest of the data encountered so far – and the regression was computed on the truncated series. The underlying logic here was that when the steady value is already well within the range of the experimental data, the measured values have converged sufficiently, and regression is no longer needed.

For further elucidation of the problem, data from a large set of tests on a Zetor 1505 engine powered by heated rapeseed oil have been considered. Such operation rarely yielded stabilized values of HC, CO and PM, owing to the deposition and reentrainment of semi-volatile organic matter in the combustion chamber and in the exhaust system.

The regression by the third method, analytical regression of a linearized eq. (2) with iteratively chosen steady value to yield highest correlation between experimental and modeled data, was applied on multiple runs of nominally 10-minute idle, of which first 30 s and last 30 s have been discarded as "transitional" period between adjacent test points, yielding 540 s segments. During idle, the combustion has gradually deteriorated, and the concentrations of HC and CO were gradually increasing while those of NO_x have been decreasing. As this "gradual deterioration" was not attributed to a single phenomenon, it was not readily clear that the same equation holds for the entire 10-minute period. Therefore, regression was performed on the entire 540 s, and then on segments 1-100 s, 101-250 s and 251-400 s. The results have been plotted in Fig. 7 for NO_x and in Fig. 8 for HC. In both figures, the experimental data along with an overall best fit line are plotted on the left, and the relationship between arbitrarily selected steady value and correlation between experimental and modeled data are plotted on the right. The dependency of the correlation on the chosen steady value was plotted for all sets subject to regression, that is, separately for 1-100 s, 101-250 s, 251-400 s, and 1-540 s segments.

For NO_x, shown in Figure 7, all segments except 251-400 s yield the best-fit steady value between 234 and 242 ppm, a sufficiently narrow range given approximately ±3% uncertainty in NO_x concentration measurement. For the segment 251-400 s, correlations are lower in this region, and do not yield maximum within a reasonable range of steady values. For HC, shown in Figure 8, iterative regression on the first 100 s yields maximum correlation below 315 ppm which is unrealistic, and remaining series yield maximum correlation between approximately 330 and 360 ppm.

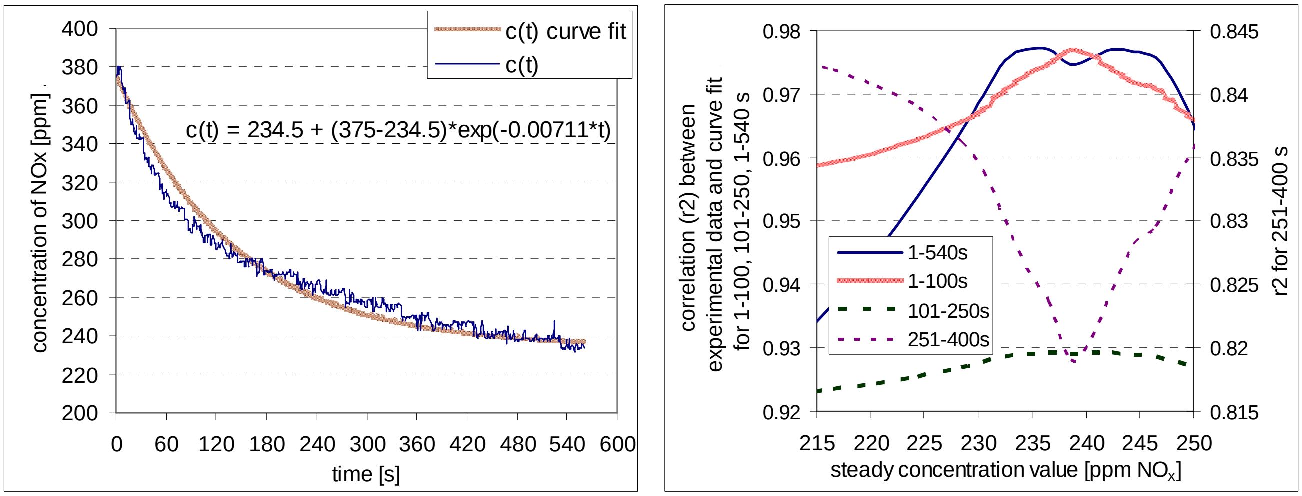

Figure 7: Iterative regression of concentrations of NO_x during idling of a Zetor 1505 tractor engine on heated rapeseed oil. Left: Experimental NO_x concentration data and overall best fit. Right: Correlation between experimental data and fitted curve obtained using regression of multiple segments of the same series, as a function of steady value for concentration of NO_x.

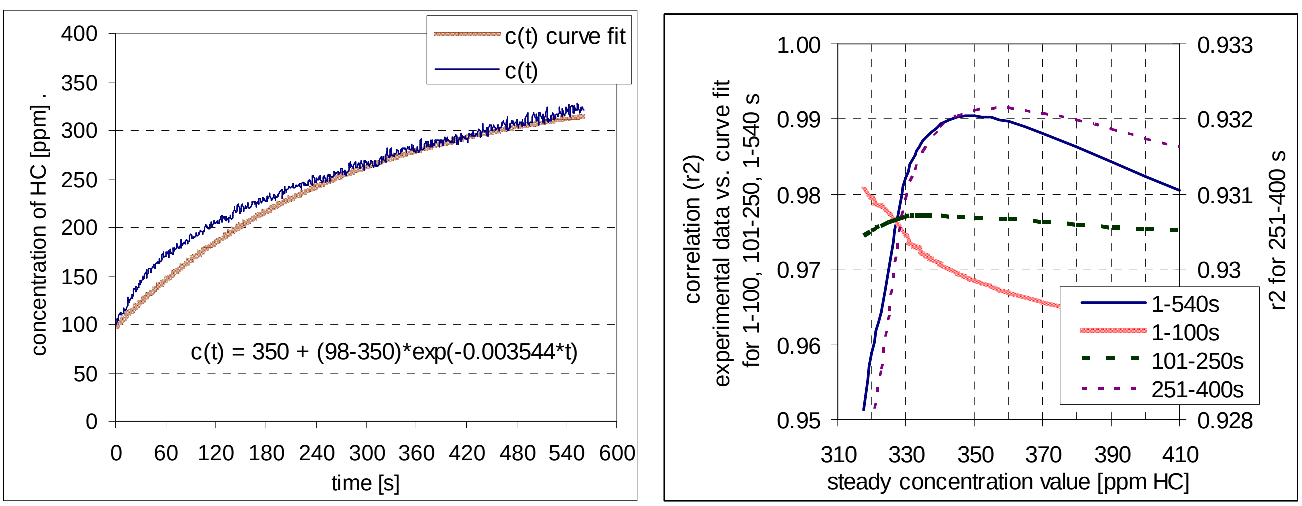

Figure 8: Iterative regression of concentrations of HC during idling of a Zetor 1505 tractor engine on heated rapeseed oil. Left: Experimental HC concentration data and overall best fit. Right: Correlation between experimental data and fitted curve obtained using regression of multiple segments of the same series, as a function of steady value for concentration of HC.

The consistency of the predictions of the steady value has been next evaluated on multiple sets of concentrations of HC, CO and NO_x, measured during operation of a Zetor 1505 tractor engine at 1480 rpm and 225 Nm (50% load) on heated rapeseed oil. In all cases, idle or some lower load have preceeded. The concentration data for six segments of such operation is plotted in Figure 9 (left) as a function of time at 1480 rpm and 50% load. For each segment, regression has been performed by iteratively choosing the steady value and reducing the problem to a linear one which was analytically solved using a spreadsheet program. The correlation between measured and fitted data for each steady value is plotted as a function of the chosen steady value, for all six segments, in Figure 9 (right). Out of the six segments, one, series A, have yielded lower correlation than the rest. The maxima were, for each series, A – 31.5, B – 33.8, C – 35.1, D – 33.7, E – 33.5 and F – 37.9 ppm HC. Three of these six regression, B, D and E, yielded very consistent data (33.5, 33.7 and 33.8 ppm), and the overall variance within the six predicted values was 6%, which can be readily explained by the combination of test-to-test variances and measurement uncertainties (similar spread would be expected should the tests be carried to the point where steady values are reached).

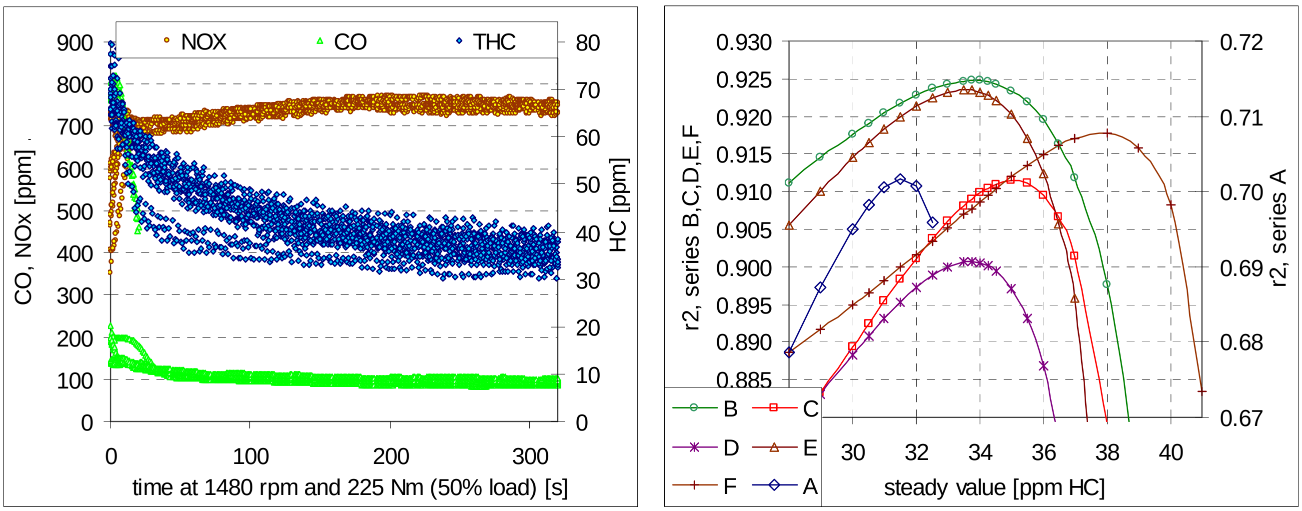

Figure 9: Left: Concentrations of HC, CO and NO_x during multiple occurrences of operation of a Zetor 1505 tractor engine on heated rapeseed oil at 1480 rpm and 225 Nm (50% load). Right: Correlation between measured HC concentrations and fitted curve obtained using regression of each data series, as a function of steady value for concentration of HC.

SUMMARY DISCUSSION

In this study, several segments of non-stabilized emissions data have been examined. The values have been reported as concentrations, as mass exhaust flow rates were generally comparable and their inclusion would yield another dimension to the problem.

For data where sufficient lengths of individual segments were available, regression of the data using Newton's cooling law equation was attempted using three iterative numerical approaches – online non-linear regression calculator, Monte Carlo simulation coupled with fine-tuning each solution using "greedy search", and iterative regression in a spreadsheet program, where analytical solution was found for a series of arbitrarily picked steady state values, until best correlation between experimental and fitted data was obtained. It appears that these approaches yielded, in general, comparable results (see Figures 5 and 6). This approach has, however, worked only if segments of data of sufficient length were available, with sufficient length being in this case on the order of approximately two minutes.

Further investigation on longer sets of laboratory data confirmed the general validity of the approach, however, it was discovered that the fit can be far from perfect, and that different segments of the same series, when subjected to regression, may yield different steady values, and in some cases, no steady values at all (see Figures 7 and 8). Similar experience has been gained with multiple sets of repeated measurements, where three out of six measurements yielded very consistent values, but the overall variance was about 6%

due to less exact fit of the other three sets. This suggests another condition: multiple sets of data need to be present, out of which a sufficient number of sets needs to yield consistent predictions of the steady value.

The condition of sufficient number of segments is relatively easy to fulfill during field measurements, as once the engine is instrumented, it can be tested for many hours without much additional expenses. The condition of sufficient segment length might be, however, harder to meet. In the example of locomotive data, the locomotive had to be operated with two different weight trains and on two different routes in order to sufficiently cover the entire engine operating range. And at most power levels, the length of the segments was too short to perform the regression described here.

For evaluation of short segments, data was binned by operating condition, sorted by numerical value, and in an attempt to find most consistently produced value, numerical derivative was taken, and data evaluated for its minimum. The underlying idea behind this approach is that the farther is the data from steady, the faster it changes, and on the contrary, the slower the change in the data, the closer it lies to the steady value. As apparent from Fig. 4, this most consistent value is not necessarily the mean or the median of the series. In case of PM for notch 5 (see Fig. 4), the most consistent values is towards the lower end of the range, due to short segments, where PM was often higher during accelerations. In case of notch 8, where steady values were also obtained using regression, the predictions were consistent for PM, and differed relatively by several percent for NO_x (850-890 ppm most consistent values vs. 902-908 ppm obtained from regressions).

The overall image obtain by this exercise is that steady values can be obtained using multiple methods which generally yield consistent results, however, many individual attempts yield no results or results inconsistent with the rest, leaving in the process some “art” dimension in the realm of interpretation of the data. No “preferred” approach among the possibilities described in the paper was identified.

SUMMARY/CONCLUSIONS

Analysis of experimental emissions data obtained on a diesel-electric locomotive under real-world operating conditions and on a tractor engine tested in a laboratory has shown that unsteady emissions data can be reasonably fitted with a Newton’s cooling law equation, which can be solved for steady state value. With this problem having no analytical solution, several pathways of non-linear iterative regression has been investigated, generally leading to consistent results, albeit many individual segments yield inconsistent or no solution. It appears that when multiple segments of data longer than approximately two minutes are available, there is a high chance at arriving at a plausible steady state value of emissions concentrations. In such case, steady state emissions can be derived from not fully stabilized data, such as from real-world operation of, for example, diesel locomotives, or from large engines tested in a laboratory. With large engines, this can possibly yield considerable savings in testing expenses and improved emissions data. As of now, however, interpretation of data requires some skill, and the technique is yet to be verified on large sets of data.

REFERENCES

1. Kittelson D. B., Watts W. F., Johnson, J. P., 2006. On-road and Laboratory Evaluation of Combustion Aerosols Part 1: Summary of Diesel Engine Results. J. Aerosol. Sci. 37, 913-930.
2. Gerde P., Muggenburg, B.A., Lundborg, M., Dahl, A.R., 2001. The rapid alveolar absorption of diesel soot-adsorbed benzo(a)pyrene: bioavailability, metabolism and dosimetry of an inhaled particle-borne carcinogen, Carcinogenesis 22, 741-749.
3. Alföldy B., Giechaskiel B., Hofmann W., Drossinos Y.: Size-distribution dependent lung deposition of diesel exhaust particles. Aerosol Science 40, 2009, 652-663.
4. Künzli, N, R Kaiser, R, Medina, S, Studnicka, M., Chanel, O., Filliger , P., Herry, M., Horak, F., Puybonnieux-Texier, V., Quénel, P., Schneider, J., Seethaler, R., Vergnaud, J.-C., Sommer, H., 2000. Public-health impact of outdoor and trafficrelated air pollution: a European assessment, The Lancet 356, 895-901.
5. Bata, R., Clark, N., Gautam, M., Howell, A. et al., "The First Transportable Heavy Duty Vehicle Emissions Testing Laboratory," SAE Technical Paper 912668, 1991, doi:10.4271/912668.
6. Ropkins K., Beebe J., Li H., Daham B., Tate J., Bell M., Andrews G.: Real-World Vehicle Exhaust Emissions Monitoring: Review and Critical Discussion. Critical Reviews in Environmental Science and Technology, 39, 2, 2009, 79-152.
7. Savant, A.A.; Nigam, A.; Miller, J.W.; Johnson, K.C.; Cocker, D.R. Regulated and Non-Regulated Emissions from In-Use Diesel-Electric Locomotives. Environ. Sci. Technol., 2007, 41 (17), 6074–6083. DOI: 10.1021/es061672d
8. Fritz, S.G. Evaluation of Biodiesel Fuel in an EMD GP38-2 Locomotive. Report by Southwest Research Institute for National Renewable Energy Laboratory, Golden, CO, contract no. DE-AC36-99-GO10337, document no. NREL/SR-510-33436, 2004. Online at http://www.nrel.gov/docs/fy04osti/33436.pdf

9. Frey, H.C., H.W. Choi, and K. Kim, "Measurement of the Energy Use and Emissions of Passenger Rail Locomotives Using a Portable Emission Measurement System," Paper 2009-A-243-AWMA, Proceedings, 102nd Annual Conference and Exhibition, Air & Waste Management Association, Detroit, Michigan, June 16-19, 2009.
10. Vojtisek-Lom, M.: Operating history artefacts of large engine particulate matter emissions measurement. Proceedings of the ASME 2012 Internal Combustion Engine Division Spring Technical Conference (ICES2012), May 6-9, 2012, Torino, Piemonte, Italy, paper no. ICES2012-81168.
11. Vojtisek-Lom M., Fenkl M., Dufek M., Mareš, J.: Off-cycle, real-world emissions of modern light-duty diesel vehicles. SAE Technical Paper 2009-24-0148, 2009.
12. Vojtisek-Lom M., Jirku J., Opava J., Fenkl M.: Measurement of exhaust emissions of railroad locomotives using an on-board system. Proceedings of 14th ETH Conference on Combustion Generated Nanoparticles, Zurich, Switzerland, 2.-4.8.2010.
13. Kittelson, D., Johnson, J.: Variability in Particle Emission Measurements in the Heavy Duty Transient Test. SAE Technical Paper 910738, 1991, doi:10.4271/910738.
14. Vojtisek-Lom, M., Cobb, J.T.: On-road light-duty vehicle emission measurements using a novel inexpensive on-board portable system. Presented at the 8th CRC On-road vehicle emissions workshop, San Diego, CA, April 20-22, 1998.
15. Vojtisek-Lom, M., Pechout, M., Blažek, J., Moc, L.; Hlavenka, T.: Effects of Current and Prior Operating Conditions on Particulate Matter Emissions from a Diesel Engine Operated on Heated Rapeseed Oil. SAE Technical Paper 2009-01-1913.
16. Pezullo, J.C.: Non-Linear Least Square Regression: Curve Fitter. Online at http://statpages.org/nonlin.html (accessed March 22, 2012).
17. Metropolis, N.: The Beginning of the Monte Carlo Method. Los Alamos Science, No. 15, 1987, p. 125-130. Online at http://jackman.stanford.edu/mcmc/metropolis1.pdf (accessed March 26, 2012).
18. Stiesh, G.: Modeling Engine Spray and Combustion Processes. Birkhauser, 2003, ISBN 3540006826.
19. Jones, L.K.: Local Greedy Approximation for Nonlinear Regression and Neural Network Training. The Annals of Statistics, 26, 5, 2000, 1375-1389.

CONTACT INFORMATION

Michal Vojtisek-Lom holds research appointments at the Czech Technical University of Prague (Department of Automobile, Internal Combustion Engine and Railway Engineering, Technicka 4, 166 07 Prague, Czech Republic, michal.vojtisek@fs.cvut.cz) and at the Technical University of Liberec (Department of Vehicles and Engines, Studentska 2, 461 17 Liberec, Czech Republic, michal.vojtisek@tul.cz).

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