Prediction of PM Emissions During Transient Operation of Marine Diesel Engines Using Artificial Neural Networks

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Abstract. Many internal combustion engine emission limits are already prescribed for land transport. Stricter regulations are also expected for international shipping in the future. The International Maritime Organisation (IMO), a subdivision of the UN, has been negotiating for years on direct regulation of particulate emissions from ships. Therefore, in addition to exhaust aftertreatment systems, internal engine and operational measures are also of interest. This article focuses on an operational measure. A new type of assistance software is presented, which shows the nautical ship officer the environmentally relevant consequences of his actions already during manoeuvre planning and later during its execution. The well-known "black flag" on the funnel of a ship is usually the result of transient engine operation. A corresponding assistance software is dependent on a model of transient engine operation including the resulting particle emissions. Over decades, the reaction kinetics for the formation and oxidation of soot have been investigated. Such physical models are to be preferred, provided they meet the quality criteria and the calculation time requirements. At present, however, no model exists which describes the emissions of particulate matters (PM) in transient operation and can make predictions for several minutes within a few milliseconds. An alternative to physical modelling is data-based modelling. The shorter computing time is a major advantage here. On the other hand, there is a great need for training (measurement) data. Two different approaches of Artificial Neural Networks (ANN) were investigated for their applicability to the special case of PM emission prediction under transient engine operating conditions. The advantages and disadvantages of both approaches are discussed in the paper. The results were examined for their applicability in the Maritime Simulation Centre in Warnemünde (MSCW).

Introduction

Emissions of particulate matters (PM) from the combustion process of a marine diesel engine consist of organic and inorganic components. While their generation is relatively low in stationary ship operation, the PM load of the exhaust gas mass flow in transient operation assumes comparably high values (Figure 1).
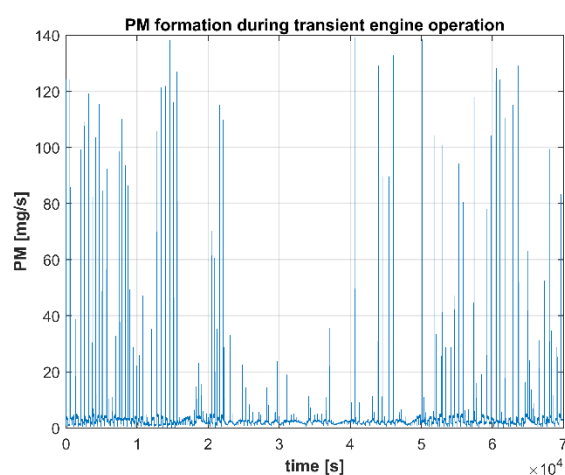

Figure 1: Measurement data from a marine diesel engine with various load changes: Peaks of PM emission are relatively high compared to the stationary PM level.

Even the stationary characteristic map, in which the particle load is shown as a function of engine speed and torque, shows strong non-linearities depending on the engine (Figure 2). The transient operation, however, contains even more non-linearities, which shall be represented by a model.

Over decades, the reaction kinetics for the formation and oxidation of soot have been investigated. Such physical models are to be preferred, provided they meet the quality criteria and the calculation time requirements. At present, however, no model exists which describes the emissions of PM in transient operation and can make predictions for several minutes within a few milliseconds of time. An alternative to physical modelling is data-based modelling. Two different approaches have been selected, to study the specific problem of simulation and prediction of PM. Both use Artificial Neural Networks (ANN).
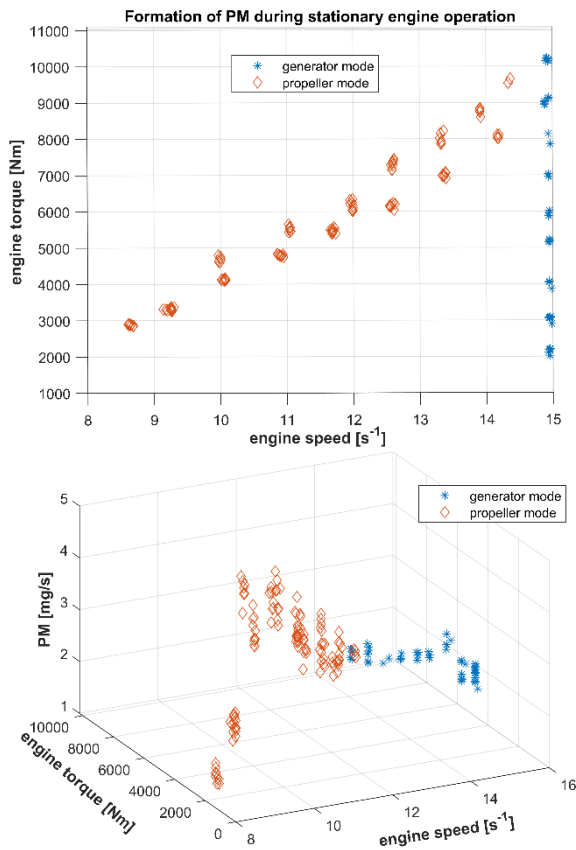
Figure 2: Measurement data from stationary load points from a marine diesel engine. Upper figure: top view of the engine map with generator mode (blue stars) and two times propeller mode with 100% resp. 85% nominal power (orange diamonds). Lower figure: Map display of PM over engine speed and torque.

1 ANN for prediction of dynamic, non-linear processes

There are many possibilities to generate data-based models. The main criteria for the present case study is that such a model must be able to deal with multi-dimensional input. This requirement is based on the assumption that for dynamic modelling, several past values are needed in order to predict the future behaviour of the system.

The current level of PM emissions depends on various factors, e.g. on the current engine speed as well as on the fuel injection. There are also other influencing aspects as e.g. the operation time of the engine and the system's internal temperatures. However, for the use in an assistance software, the two factors mentioned above should be sufficient for this study, in particular because the other operating parameters are by default not accessible at all or only to a limited extent on board sea-going

ships.

The selected architecture of ANN is a feed-forward multi-layer perceptron (MLP) network which means that the links between input, hidden and output layers are unidirectional without feedback between those multiple layers. Hidden neurons as well as the output neuron consist of two types of parameters to be adjusted during the model training: the synaptic weights which are multiplied by the neuron's input and the so called threshold of each neuron's activation function. For the second approach described here below, additional filter coefficients are to be adapted.

1.1 ANN with external dynamics

The expression external dynamics was coined by [1] and describes that the historical values, describing the dynamics, act as input values on the ANN. How many historical values are needed, can be taken from the dynamics of the output value in a first step, in a second step the best fitting number can be determined by a k-fold cross-validation. The following two aspects are important:

1. The curves of the input values should clearly indicate a single output value. If the uniqueness is not guaranteed, further past values have to be added.
2. Not more historical values than necessary should be included, because otherwise the number of hidden neurons has to be increased as well and thus also the number of parameters to be estimated.

1.2 ANN with internal dynamics

Black box systems, like the ANN with external dynamics, are not or only very difficult to interpret. With a large number of input variables, interpretability becomes even more difficult and the number of parameters to be estimated becomes even larger. To counteract these disadvantages, an ANN with internal dynamics is presented and discussed in [2], [3] and [4]. The internal dynamics uses an ARMA filter [5], which creates a memory effect. Such a filter is integrated in every neuron of the hidden layer as well as in the output neuron. Thus, the input space shall be limited to the current input values and at the same time reduce the number of necessary neurons. In contrast to this, the 5 coefficients of the ARMA filter have to be applied additionally for each neuron.

2 Measurement data

2.1 Test bed engine

As already mentioned in the introduction, no data from a theoretical model could be used for the investigations, which is why measurement data from the engine test bench (Table 1) was used directly.

	MAN B&W 6L23/30
Type	medium speed 4-stroke marine diesel engine
Bore	225 mm
Stroke	300 mm
Rated output	960 kW
Rated speed	900 min^{-1}
Compression ratio	13.5:1
Fuel injection system	unit injector system
Load	water vortex brake

Table 1: Specification of the used engine test bench MAN B&W 6L23/30

The engine allowed test runs on the generator curve as well as on the propeller curve. In generator mode, the controller is set so that the engine speed should remain constant despite changing load. In propeller mode, load and speed change, which corresponds to the operation of a fixed pitch propeller ship.

2.2 Data series

Over a period of six days various load changes were systematically carried out as shown in Figure 1. The first approx. 25000 seconds concern the transient operation on the propeller curve with a nominal power of 100%. The following measurements refer to the generator mode, while from second 43000 on the propeller mode was repeated, but with a nominal power of 85% (see Figure 2). For the training of the two different ANNs, the individual load cycles were strung together in such a way that no discontinuities appear in the data. A smoothing of the data was deliberately avoided, as this would have resulted in the loss of important information.

3 Practical Implementation

3.1 Experiments with a small selection of data

For reasons of better comparision of the two approaches only a selection of the measurement data will be taken in a first approach. Figure 3 shows the selected data which are extracted from the entire measurements. They originate from the measurement data around time 25000 s in Figure 1. This involves the following load changes: from 90% to 100% power, then down to 20% and up to 60%. During these three load changes the system waits for the transient settling to a steady state, but the last load change increases from 60 to 90 and shortly afterwards already to 100% power.
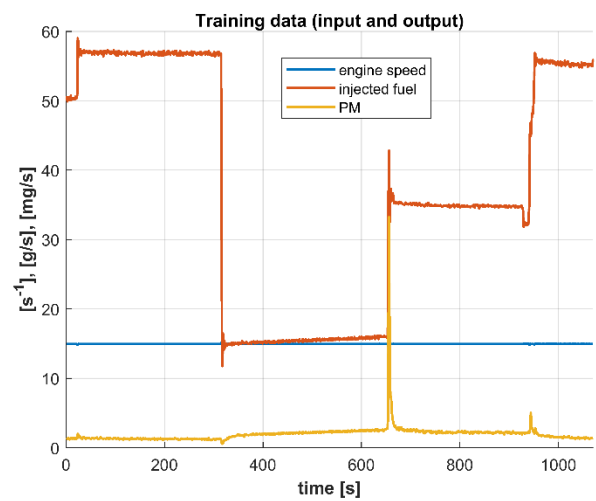

Figure 3: Four load changes of different character in generator mode to compare the two approaches.

These four resp. five load changes refer to the engine mode called generator mode which corresponds to the operation of a ship with controllable pitch propeller. Therefore, only the changes in fuel consumption influence the formation of PM, unless there is a temporary reduction of engine speed during a load change.

3.2 General remarks

The synaptic weights as well as the thresholds start with a randomly determined start value. According to experience, one can adjust the start values within a more suitable and limited range. Due to the uncertainty and by using the random function repeatability is missing. Each new try for model training can lead to a totally different output. By using a k-fold cross-validation statistics upon the selection of the adjustable parameters can be provided. Besides the model parameters (synaptic weights

and thresholds) these are e.g. the number of hidden neurons, training epochs, the learning rate as well as the number of delays when working with external dynamics resp. the filter coefficients when applying the approach with internal dynamics.

ANN are known to need a lot of training data. This example does not satisfy this need for data. It is only intended to show that it is possible to represent the relationship between input and output variables by means of a suitably selected network architecture.

For these reasons, the findings shown here are only some of many, possibly even better results.

3.3 Example: ANN with external dynamics

Settings.
- Start values: randomize(1)
- Number of epochs: 2000
- Learning rate: 0.002
- Number of hidden neurons: 30
- Number of delays: 5

Result. The number of parameters to be adjusted amounts to 151. Figure 4 shows one possible result which looks promising.
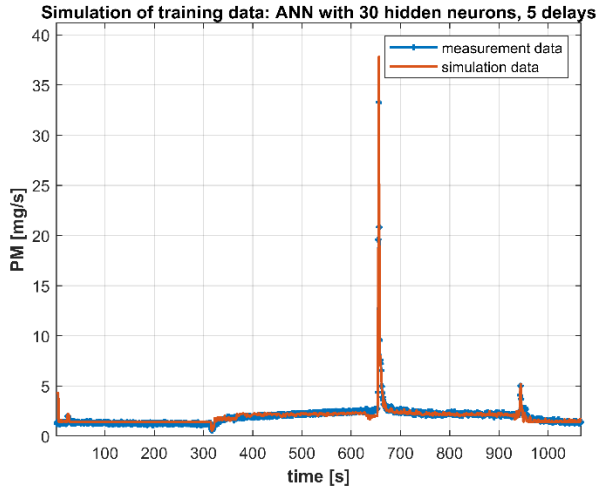

Figure 4: Simulation of training data after training the ANN

3.4 Example: ANN with internal dynamics

Settings.
- Start values of weights: randomize(0.01)
- Start values of filter coefficients: set by experience
- Number of epochs: 80
- Learning rate: 0.002

- Number of hidden neurons: 5
- Number of filter coefficients: 5

Result. The number of parameters to be adjusted amounts to 51. Figure 4 shows one possible result which looks rather worse than the former one. Training with more than 80 epochs led to worse results.
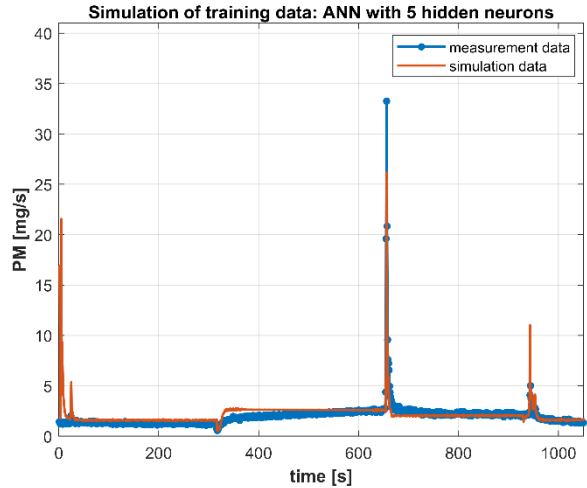

Figure 5: Simulation of training data after training the ANN

3.5 Discussion

Both approaches can reflect the trend in the relationship between input and output variables. Another common feature is the adaptation process at the beginning of the prediction: ANN with external dynamics first needs the specified number of historical values to make a prediction, whereas ANN with internal dynamics needs a few seconds to settle down, because the recursive values of the ARMA filter, the internal memory of the neurons, are not known at the beginning. If one considers the simulation of the four resp. five peaks, the ANN with external dynamics performs obviously better. On the other hand, the last load increase from 60 % to 90 and immediately to 100 % power is qualitatively better represented by the internal dynamics, in which two differentiated peaks are visible according to the measured data (see Figure 6).
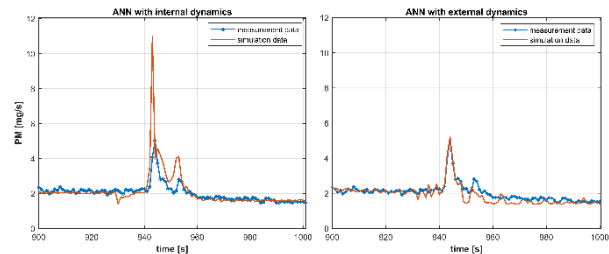

Figure 6: Load increases from 60% to 90% followed by 100%. Left side: simulation of ANN with internal dynamics. Right side: simulation of ANN with external dynamics.

Furthermore, there is also the possibility that an ANN with external dynamics provides relatively imprecise results if the optimization process gets stuck in a local optimum. Then, also negative PM values may be predicted – a result which has not yet been observed with the internal dynamics approach.

4 Results and Validation

The following section shows the application of a MLP ANN with external dynamics for larger measurement data sets. The measurements shown in Figure 1 have been carried out systematically. After the completion of these measurements, random commands were selected over a period of about 5000 s, covering the entire engine map. 75% of the systematically measured time series (up to second 52400) were used for training, the remaining systematic measurement points as well as the supplementary measurements were used for validation.

4.1 Neural Network training

Settings. The same setting as above (3.3) have been chosen for this example.

Training results. Figure 7 shows the measurement data on which the training is based (blue circles). The trained network with the 151 adapted parameters simulates the PM emissions (red line) based on the current input values of engine speed and consumption as well as their historical values.
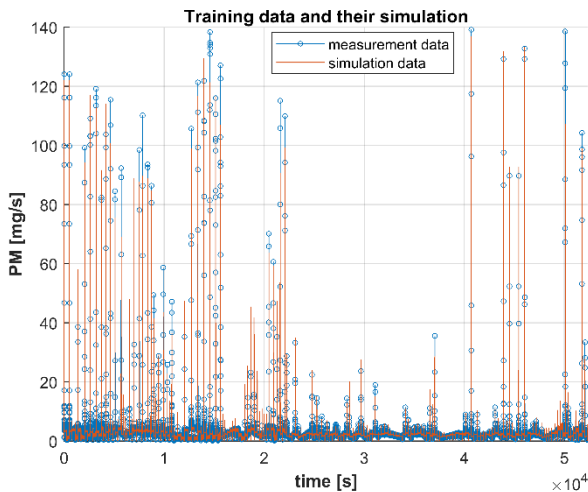

Figure 7: Simulation of training data with a MLP ANN with external dynamics

Zooming out the section selected in (3.3), Figure 8

shows that this ANN also represents the course of the measurements relatively well. Due to the fact that the 30 hidden neurons also have to cover completely different, additional non-linearities, inaccuracies occur in some places.
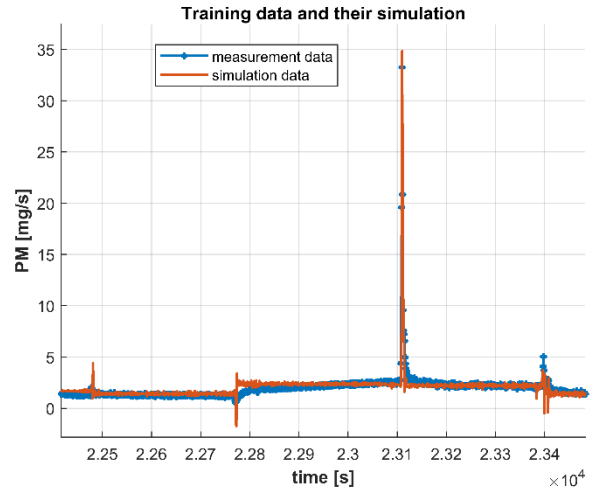

Figure 8: Zoom of above (Figure 4 and Figure 5) selected data, now simulated with the ANN trained with 75% of all measurement data.

4.2 Validation result

The validation result is presented in Figure 9. The PM peaks during transient engine operation tend to be mapped nearly correctly.
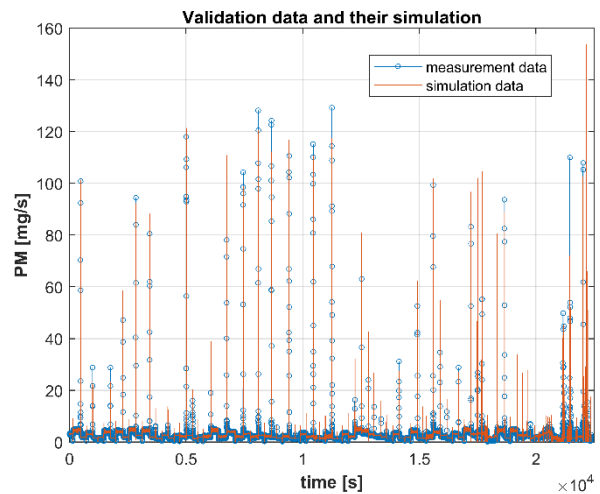

Figure 9: Simulation of validation data with a MLP ANN with external dynamics

The zoomed out section, shown in Figure 10, represents the stepwise ramp-up from 20% load on the propeller curve (85%) to 100% load in 10% steps. The stationary intermediate points are met relatively well.
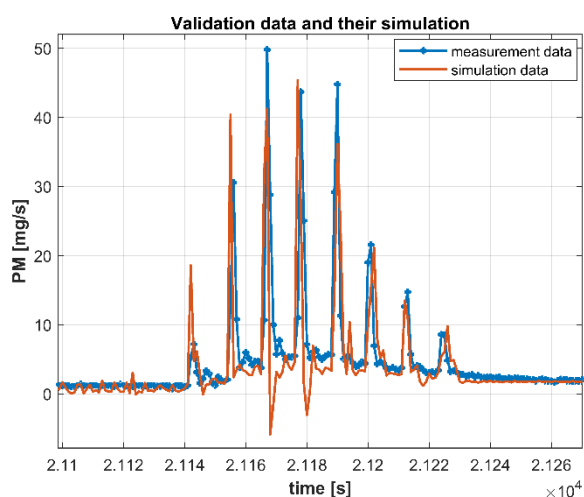
Figure 10: Zoom of validation data and simulation of a stepwise load increase in propeller mode (85%) from 20% to 100% power.

5 Application

5.1 Assistance Software

The aim of the present investigations is to find a suitable method which can subsequently be integrated into an existing manoeuvre assistance system. This system called SAMMON (Simulation Augmented Maneouvring Design and Monitoring) [6] currently supports the navigational officer in planning manoeuvres in advance as well as in their execution. The basis for the prediction is a fast calculating mathematical ship model. Currently, ship movements can be predicted up to 24 minutes ahead. An extension of the engine module enables the prediction of fuel consumption and thus also of emissions. While in online operation the ship's motion and the prediction of its future path is an essential support, the extensions offer valuable possibilities to include environmental concerns in education and training as well as in the planning of manoeuvres on board.

5.2 Practical studies in the simulation centre

The Maritme Simulation Centre Warnemünde (MSCW) offers the possibility to conduct studies for the usefulness of the above mentioned assistance software. Not only the presence of a realistic 360° ship bridge, but also the closeness to nautical students and the direct contact to graduates who are working at sea facilitate the implementation of practical and meaningful tests. Such tests had been carried out as part of the MEmBran project funded by the German government (funding code 03SX423B). [7]

The results clearly showed that, thanks to the support software, the energy input into the water can be reduced: large rudder angles, which considerably increase the ship's resistance, became less, while the number of smaller rudder angles increased only slightly. Power at the propeller was measurably reduced thanks to the assistance software (Figure 11). These energetic improvements have not noticeably influenced the maneuvering time.
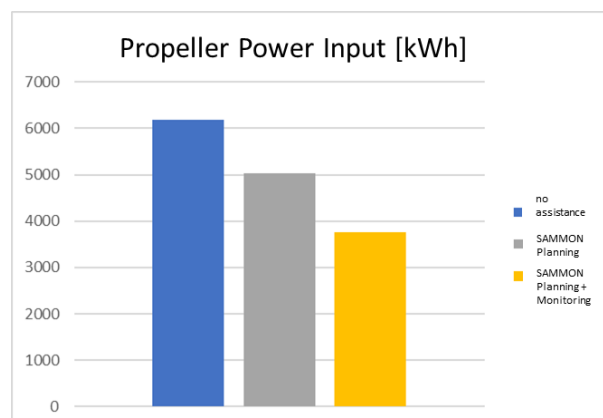

Figure 11: Comparison of the power input of the ship's propeller into the water as a mean value of all executed test scenarios: The blue bar shows the power induced without any assistance, the grey bar is the result of manoeuvres executed with a pre-planning and the yellow bar is the result of a pre-planned manoeuvre and an online monitoring during its execution.

Corresponding comparative studies for the software extended with emission data are still pending.

5.3 Comparison of different strategies

Figure 10 shows a stepwise load change from 20 to 100% in generator mode. The question arises whether this strategy is better in terms of time, energy and environment than a directly given command. With the help of the SAMMON assistance, this question would be answered in a very short time, provided that all necessary models of the ship and its sub-modules are available.

The following two figures illustrate a corresponding experiment. These are measured values from the test bench engine. The load is increased from 20 to 60% in propeller mode (100%). In Figure 12 the load is increased stepwise in 5 % steps, in Figure 13 the increase is initiated with a single command.

For the two strategies, PM emissions and time consumption are to be compared at the time when the same amount of energy has been delivered by the engine. In practice, this would mean that both vessels would have achieved the same manoeuvring target, but with different PM
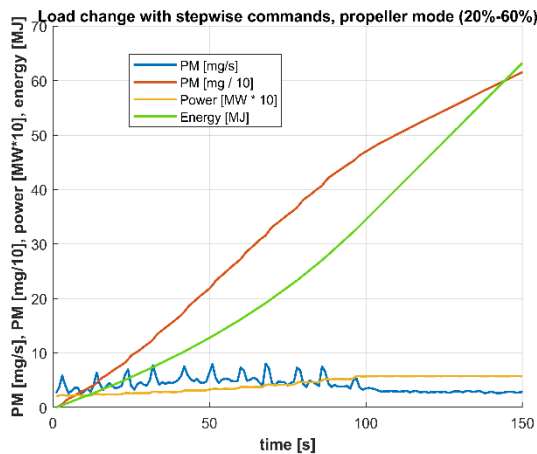
emissions and in different times.

Figure 12: Load change from 20 to 60% in 5% steps. Note the blue line is representing the formation of PM over time and the reddish line is the summation of PM. The power (yellow line) integration, the delivered energy, is illustrated by the green line.

Figure 13: Load change from 20 to 60% with a single command. Note the blue line is representing the formation of PM over time and the reddish line is the summation of PM. The power (yellow line) integration, the delivered energy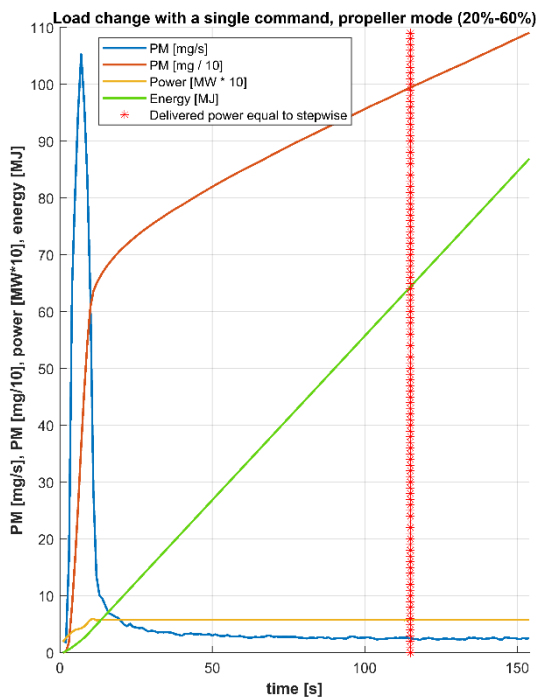, is illustrated by the green line. The red vertical line shows the stage at which the same manoeuvre objective was achieved as with the step-by-step strategy.

The step-by-step strategy (Figure 12) achieves stationary operation after 150 s. The energy delivered at that time is 64.4 MJ (green line). The 64.4 MJ is taken as the reference value. It is observed when the same value is reached in the direct command strategy. After 114 s this is the case (red vertical line in Figure 13). At that time, the same manoeuvre objective was achieved with both strategies. The direct strategy took only 76% of the time (114 s instead of 150 s), but has a 60% higher PM output than the stepwise strategy. (995 mg instead of 621 mg).

6 Potentials for Improving Training and Decision Making

Models to describe the emissions of PM in transient operation for purposes of predictions is a compelling need in today's shipping. While just 20, 30 years ago this need was rather underestimated and models allowing for detailed consideration of optimal engine operation to save fuel had priority. The impact of emissions on climate changed has changed the focus.

Development and imnplementation of assistance systems need to comprehensively address emissions as a consequence of navigational manoeuvres. Different manoeuvre strategies to safely arrive and berth a ship can be applied according to the prevailing environmental conditions and the actual ship status. The availability of models like those developed and researched here have the potetntial to improve traning of navigational officers and to integrate the concepts of green manoeuvring [8] into maritime education and training of cadets but also into professional development courses of experienced navigators.

Existing tools and manoeuvring assistance systems not only predicting the ship's path according to ordered and intended orders of engine(s), rudder(s), thrusters etc. are important for safety of navigation and the avoidance of groundings or allisions with pillars, jetties or berth constructions etc. However, such tools are increasingly required to also support bridge team's decision making in respect to minimize emissions. Especially when manoeuvring a ship, engine operates in transient modes where emissions are particularly high. Due to the absences of suitable models training and simulation exercises could not completely meet those requirements in the past [9]. Same is valid for assistance systems not taking into account such issues appropriately. Sopisticated models as investigated and tested here have great potential to contribute to substantial improvement in maritime education and training as well as in environmentally-friendly

ship operation by ships' crews as well.

IMO's concept of e-Navigation aims at enhanceing "berth to berth navigation and related services for safety and security at sea and protection of the marine environment." It is the authors' hope, that the studied models may contribute especially to the second mentioned aspect of the e-Navigation concept.

7 Summary and Outlook

This paper shows us how existing, data-based methods can be applied to the concrete problem of online predictions of PM emissions. Two model approaches, both of which use ANN, were programmed and trained on established optimisation procedures in order to use them for predictions. A successful validation depends very much on the amount and quality of the training data but also on the settings for start values and other framework conditions.

In general, both methods are able to represent the validation data, if not exactly then at least with the right trend, giving a valuable impression to the trainee about the consequences of his/her actions.

A third method still to be investigated, using a static ANN for stationary and an ARMA-filter for the transient part of PM exhaust gas, is one outcome of the presented studies and will be further persued.

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