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ANALYSIS OF THE PRE-INJECTION CONFIGURATION IN A MARINE ENGINE THROUGH SEVERAL MCDM TECHNIQUES

Summary

The present manuscript describes a computational model employed to characterize the performance and emissions of a commercial marine diesel engine. This model analyzes several pre-injection parameters, such as starting instant, quantity, and duration. The goal is to reduce nitrogen oxides (NO_x), as well as its effect on emissions and consumption. Since some of the parameters considered have opposite effects on the results, the present work proposes a MCDM (Multiple-Criteria Decision Making) methodology to determine the most adequate pre-injection configuration. An important issue in MCDM models is the data normalization process. This operation is necessary to convert the available data into a non-dimensional common scale, thus allowing ranking and rating alternatives. It is important to select a suitable normalization technique, and several methods exist in the literature. This work considers five well-known normalization procedures: *linear max*, *linear max-min*, *linear sum*, *vector*, and *logarithmic* normalization. As to the solution technique, the study considers three MCDM models: WSM (Weighted Sum Method), WPM (Weighted Product Method) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). The linear max, linear sum, vector, and logarithmic normalization procedures brought the same result: -22º CA ATDC pre-injection starting instant, 25% pre-injection quantity and 1-2º CA pre-injection duration. Nevertheless, the linear max min normalization procedure provided a result, which is different from the others and not recommended.

Key words: marine diesel engine; CFD; emissions; consumption

1. Introduction

Global pollution is currently reaching an alarming rate. In the marine field, marine engines are relevant sources of particulate matter (PM), NO_x, and other undesirable substances such as SO_x, CO_2, CO, HC, etc. [1-6]. Among those substances, NO_x and SO_x are currently receiving special attention due to the increasingly strict limitations imposed by the IMO (International Maritime Organization) and other organisms [7-16]. In recent years, the need to reduce NO_x emissions led to several measures. Briefly, these can be divided into *primary*

measures (which focus on the engine performance) and *secondary measures* (which focus on removing NO_x from the exhaust gases). Most of primary measures are of recent application. Among them, the present work focuses on modifying the injection system, particularly through pre-injection strategies. The main drawback of pre-injection policies (and most NO_x reduction methods in general), is that NO_x decreases at the expense of the increase in the emissions of other pollutants and/or overall fuel consumption. In accordance with this observation, it is crucially necessary to establish a formal procedure to select the most adequate pre-injection configuration. MCDM turns out to be a formal tool for handling decision problems involving conflicting criteria. Since its introduction in 1960, MCDM constitutes a continuously growing technique, employed in many fields. It is also referred to as MCDA (Multiple-Criteria Decision Analysis), MDDM (Multiple-Dimensions Decision Making), MODM (Multiple-Objective Decision Making), or MADM (Multiple-Attributes Decision Making).

The goal of MCDM is to find an appropriate compromise among conflicting criteria. In a nutshell, MCDM models consider different alternatives, criteria, and their corresponding weights. In most MCDM problems, criteria have different scales (e.g. consumption, emissions, mass, temperature...); for this reason, it is necessary to implement some procedures to normalize data and obtain a common non-dimensional scale. This allows the comparison of all data in order to provide a final score for each alternative. According to this, data normalization is a primary component of MCDM problems since it transforms the raw input data into numerical and comparable values. Several normalization methods have been proposed in the literature. Particularly, Jahan et al. [17] reviewed the state of the art about normalization techniques and identified. The effect of normalization procedures is still an open question and there is no consensus on an overall best method [18-19]. Consequently, the result may be different depending on the normalization technique employed [20]. As a matter of fact, several works compare different approaches [21-23]. Another important issue in MCDM models consists in the selection of the method. Several MCDM methods are available, and some authors affirm that choosing a MCDM method is a MCDM problem itself. In this regard, the so-called Pearson and Spearman correlations are useful to analyze the results deriving from different methods [24-26].

The present research aims at defining a pre-injection strategy to reduce the emission of NO_x in a commercial marine engine (the Wärtsilä 6L 46) using data form a CFD model which was built to collect data concerning SFC (Specific Fuel Consumption) and emissions of NO_x, CO, and HC using different pre-injection parameters.

The study uses data coming from 125 simulation cases carried out using different combinations of input parameters and employs MCDM techniques to define the most suitable alternative among them. It considers five normalization methods: *linear max* normalization, *linear max-min* normalization, *linear sum* normalization, *vector* normalization and *logarithmic* normalization. Moreover, the study compares the results of three different MCDM methods: WSM, WPM and TOPSIS.

2. Methodology

The first part of this section describes the engine and the corresponding CFD analysis. The second part shows the MCDM models, and the normalization techniques employed.

2.1 Engine characteristics and CFD model

The marine engine Wärtsilä 6L 46 is a four-stroke diesel engine with 6 in-line cylinders. Each cylinder has 2 inlet and 2 exhaust valves. Previous works [27-33] describe the CFD model and its validation with experimental results.

The characterization of the pressure inside the cylinder of the engine employed the MALIN 6000 performance analyzer. It is a portable pressure transducer that can be connected to the bleed valve, located at the engine head. The characterization of the emissions of NO_x, CO, HC and CO_2 used the Gasboard-3000 series gas analyzers.

In order to characterize data at different loads, the engine operated two hours at different setups (25%, 35%, 50%, 75% and 100% load). Eight tests for each load condition have been performed.

The free software OpenFOAM was used for the CFD computations. A new solver was programmed using C++ language. The solver has the following characteristics:

- it solves the equations of conservation of mass, momentum, and energy in the domain,
- for the temporal evolution, it adopts a simple backward Euler scheme, using a constant time step corresponding to 0.1° CA,
- the spatial discretization uses a second order scheme,
- the PISO algorithm implements the pressure-velocity coupling,
- the employed turbulence model is k-ε,
- the fuel heat-up and evaporation is computed by the Dukowicz model [34],
- the fuel droplet and breakup is computed by the Kelvin-Helmoltz and Rayleigh-Taylor model [35],
- the combustion, NO_x formation, and NO_x reduction are modeled through the schemes developed by Ra and Reitz [36], Yang *et al.* [37], and Miller and Glarborg [38], respectively.

Figure 1 shows the mesh employed for the computational simulations. Fig. 1(a) represents the 3D mesh at TDC (top dead center) position, while Figs. 1(b) and 1(c) a cross section at BDC (bottom dead center) and TDC positions, respectively. The alternative cylinder movement was imposed to the mesh, as well as the opening-closing movement of the valves. This mesh is composed by 50125 elements at TDC and 802527 at BDC, and it is composed by hexahedrons and tetrahedrons.
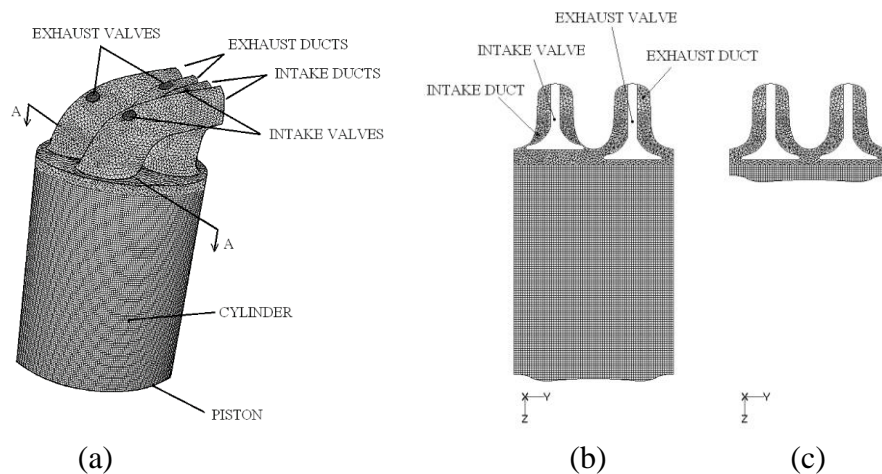

(a)   (b)   (c)

Figure 1. (a) 3D mesh at BDC; (b) AA section at BDC; (c) AA section at TDC.

Several mesh sizes have been considered in order to analyze their effects on the results. Table 1 summarizes the results obtained from three meshes of different sizes. The table shows the number of elements of these meshes at BDC and the error between experimental and numerical results regarding pressure and emissions of NO_x, CO, HC and CO_2. Since the results obtained with the meshes 2 and 3 were similar, the mesh 2 was selected for the computations carried out on the present work.

Table 1 Mesh independence test results.

Mesh	1	2	3
Number of elements	501,769	802,527	1,264,873
Pressure error (%)	4.2	4.1	4.1
NO_x error (%)	5.1	4.9	4.9
CO error (%)	8.1	7.9	7.9
HC error (%)	6.5	6.4	6.4
CO_2 error (%)	4.7	4.6	4.6

Figs. 2 and 3 show the correspondence between experimental and numerical results . These figures illustrate the emissions, consumption and pressure obtained both numerically and experimentally. As it can be seen, the CFD model shows a good agreement in SFC, HC, CO, and CO_2 with respect to experimental results. Regarding NO_x emissions, the values obtained numerically are higher than the experimental ones for all engine loads. The main reason is that compression ignition engines, as opposed to spark ignition engines, operate under lean conditions. Most NO_x formation kinetic models are based on NO thermal mechanism, which becomes significant at high temperatures, and for that reason they are not able to properly model locally lean, low-temperature regions which are typical in compression ignition engines and less common in spark ignition engines [39, 40]. Nevertheless, the numerical model predicts the NO_x trend with an average error of 4.9%, and it is thus considered appropriate for the present work.
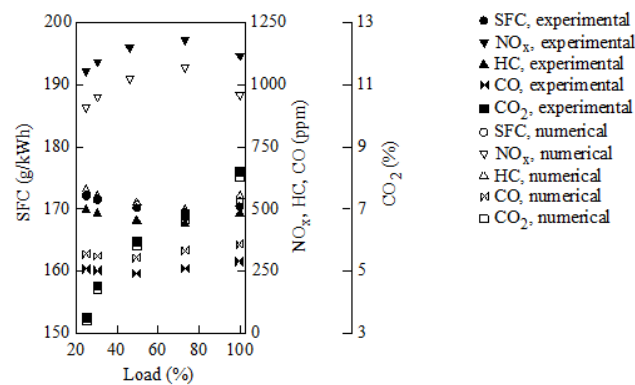

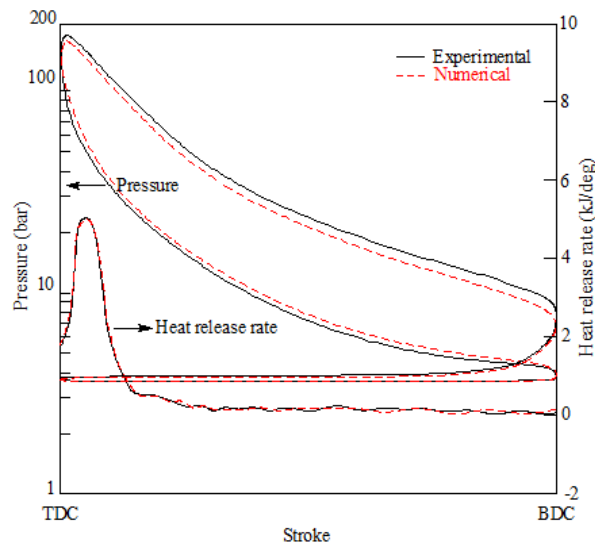**Fig. 2** Emissions and consumption at 20 to 100% load.

Fig. 3 In-cylinder pressure at 100% load.

2.2 MCDM analysis

The CFD model described in the previous section was employed to generate the data necessary to carry out the MCDM approach. 125 cases were analyzed, and they are schematically illustrated in Fig. 4. As can be seen, five pre-injection quantities (Q) were employed: 5%, 10%, 15%, 20%, and 25%; five pre-injection durations (D): 1º CA (Crank Angle), 2º CA, 3º CA, 4º CA, and 5º CA; and five pre-injection starting instants (S): -22º CA ATDC (Crank Angle After Top Dead Center), -21º CA ATDC, -20º CA ATDC, -19º CA ATDC, and -18º CA ATDC. These data ranges were chosen in order to define an appropriate engine performance. Pre-injection quantities higher than 25% and pre-injection starting instants before -22º are not recommended [32].
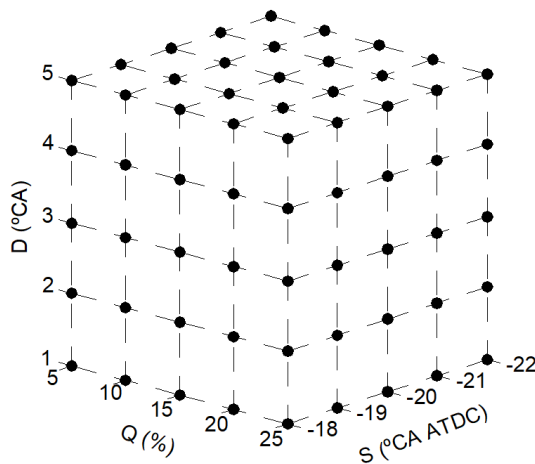

Fig. 4 Cases analyzed.

Taking into account the 125 simulations performed, and the four criteria considered: SFC, NOx, CO, and HC, , a $m \times n$ data matrix can be constituted with $m = 125$ rows and n = 4 columns, as shown in Eq. (1). This matrix is highlighted in red color in Table 2. To simplify, this table

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only exhibits the first, second and last alternative (row). The case number and corresponding pre-injection starting angle, quantity and duration are also shown in this table.

$$DM = \begin{pmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{pmatrix} \qquad (1)$$

Table 2 Decision matrix.

Alternative (i)	S (ºCA ATDC)	Q (%)	D (ºCA)	Criterion (j)			
				j = 1	j = 2	j = 3	j = 4
				SFC (g/kWh)	NOx (g/kWh)	CO (g/kWh)	HC (g/kWh)
1	-22	5	1	190.9	7.38	4.65	5.72
2	-22	5	2	189.0	7.83	4.67	5.73
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
125	-18	25	5	174.5	10.86	4.88	5.92
Minimum value				173.4	3.70	4.57	5.60
Maximum value				206.3	11.79	5.02	6.12

An important aspect in MCDM methods is the definition of the weight of each criterion. This refers to the degree of importance of each criterion. Instead of objective methods, subjective ones are recommended to establish the criteria weights, since experts in the field can directly define them. Objective weighting criteria methods are only recommended when there is no agreement between the experts or when the objectivity is extremely important [27, 41]. According to this, this study considers two main requirements: consumption and emissions. Equal importance has been assigned to consumption and emissions, *i.e*., 50% each. Regarding emissions, the importance of NOx, CO and HC was also distributed equally, *i.e*., 33.3% for each one. To summarize, Table 3 shows these values in per-unit basis. Logically, each column in Table 3 sums to 1 for the requirements. Regarding sub-requirements, the value of the part of the column corresponding to SFC is 1 and the part of the column corresponding to emissions sums to 1. The weight of each criterion is obtained by multiplying the weight of the requirement by the weight of the sub-requirement, leading to 0.5, 0.167, 0.167, and 0.167 for SFC, NOx, CO, and HC, respectively. These weights also sum to 1.

Table 3 Criteria weights, per unit basis.

Requirement (α)	Sub-requirement (β)
SFC (0.5)	SFC (1)
Emissions (0.5)	NOx (0.333) CO (0.333) HC (0.333)

Another important step consists on normalizing the decision matrix. The normalization process eliminates the units of each criterion to work in dimensionless form. Normalization

converts the different measurable values into comparable similar ones, and the normalized decision matrix is a $m \times n$ matrix given by Eq. (2), whereby each V_{ij} element is the normalized value of X_{ij}. As mentioned above, many normalization techniques are available in the literature. The most employed ones, which will be compared in the present work, are listed in Table 4. This table shows the expressions used to normalize each term of the decision matrix, both for beneficial and non-beneficial criteria. Beneficial and non-beneficial terms refer to criteria for which a higher greater value is preferable or not, respectively. In the present work, all considered criteria are non-beneficial since the goal is to reduce SFC, NO_x, CO, and HC as much as possible. Table 4 shows the normalization criteria used in this study: $X_{j,min}$ and $X_{j,max}$ are the minimum and maximum grades of the alternatives for each criterion j.

$$NDM = \begin{pmatrix} V_{11} & \cdots & V_{1n} \\ \vdots & \ddots & \vdots \\ V_{m1} & \cdots & V_{mn} \end{pmatrix} \tag{2}$$

Table 4 Normalization methods employed in the present work.

Normalization technique	Criteria	Expression
Linear max normalization	Beneficial	$V_{ij} = \dfrac{X_{ij}}{X_{j,\max}}$
	Non-beneficial	$V_{ij} = 1 - \dfrac{X_{ij}}{X_{j,\max}}$
Linear max-min normalization	Beneficial	$V_{ij} = \dfrac{X_{ij} - X_{j,\min}}{X_{j,\max} - X_{j,\min}}$
	Non-beneficial	$V_{ij} = \dfrac{X_{j,\max} - X_{ij}}{X_{j,\max} - X_{j,\min}}$
Linear sum normalization	Beneficial	$V_{ij} = \dfrac{X_{ij}}{\sum\limits_{i=1}^{m} X_{ij}}$
	Non-beneficial	$V_{ij} = \dfrac{1/X_{ij}}{\sum\limits_{i=1}^{m} (1/X_{ij})}$
Vector normalization	Beneficial	$V_{ij} = \dfrac{X_{ij}}{\sqrt{\sum\limits_{i=1}^{m} X_{ij}^2}}$
	Non-beneficial	$V_{ij} = 1 - \dfrac{X_{ij}}{\sqrt{\sum\limits_{i=1}^{m} X_{ij}^2}}$
Logarithmic normalization	Beneficial	$V_{ij} = \dfrac{\ln(X_{ij})}{\ln\left(\prod\limits_{i=1}^{m} X_{ij}\right)}$
	Non-beneficial	$V_{ij} = \dfrac{1 - \dfrac{\ln(X_{ij})}{\ln\left(\prod\limits_{i=1}^{m} X_{ij}\right)}}{m-1}$

Once the decision matrix is normalized, the adequacy index corresponding to each i-th alternative, AI_i, was computed through the three procedures described below.

2.2.1 WSM procedure

This procedure is also knowns as SAW (Simple Additive Weighting) or WLC (Weighted Linear Combination). This method, proposed by Churchman and Ackoff in 1954 [42], is the oldest and most widely used MCDM approach. The adequacy index is given by Eq. (3), and after applying the normalization procedures described, the most appropriate alternative is the one corresponding to the maximum *AI*.

$$AI_i = \sum_{j=1}^{n} w_j V_{ij} \tag{3}$$

whereby w_j the weight of the *j*-th criterion.

2.2.2 WPM procedure

This procedure is also known as MEW (Multiplicative Exponential Weighting). This method is quite similar to WSM, and computes the adequacy index as [43]:

$$AI_i = \prod_{j=1}^{n} (V_{ij})^{w_j} \tag{4}$$

2.2.3 TOPSIS procedure

The TOPSIS method, introduced by Hwang and Yoon [44], determines the so called positive ideal solution and the negative ideal solution. By computing the Euclidean distance to these two alternatives, this method provides the solution that is closest to the best one and farthest to the worst one. The main steps of the TOPSIS procedure are the following ones:

Step 1: Determining the normalized decision matrix. Although the classical TOPSIS uses the vector normalization technique, the normalization techniques described above have been compared.

Step 2: Weighting the data, given by the following expression:

$$R_{ij} = w_j V_{ij} \tag{5}$$

Step 3: Determining the positive ideal solution and negative ideal solution:

$$S^+ = (R_{1j}^+, R_{2j}^+, ..., R_{mj}^+) \tag{6}$$

where $R_{ij}^+ = [\max(R_{ij}) \text{ if } j \in J^+; \min(R_{ij}) \text{ if } j \in J^-]$

$$S^- = (R_{1j}^-, R_{2j}^-, ..., R_{mj}^-) \tag{7}$$

where $R_{ij}^- = [\min(R_{ij}) \text{ if } j \in J^+; \max(R_{ij}) \text{ if } j \in J^-]$

Step 4: Calculating the Euclidean distance of each alternative. Eqs (8) and (9) give the distance from the positive ideal solution and negative ideal solution., respectively:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (R_{ij}^+ - S^+)^2} \tag{8}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (R_{ij}^- - S^-)^2} \tag{9}$$

Step 5: Calculating the relative closeness to the ideal solution:

$$C_i = \frac{D_i^+}{D_i^- + D_i^+} \tag{10}$$

Step 6: Ranking the alternatives according to the highest C_i. A value of $C_i = 1$ is the ideal solution and $C_i = 0$ is the worst solution.

3. Results and discussion

Tables 5 to 9 show the normalized matrixes using each of the described methods (*i.e.*: linear max, linear max-min, linear sum, vector and logarithmic normalization techniques, respectively). The expressions presented in Table 4 produce the normalized values. Since all criteria are non-beneficial, the expressions corresponding to non-beneficial criteria are considered. The minimum and maximum normalized values corresponding to each criterion are also shown at the end of each of the Tables 5-9. As can be seen, the linear max normalization technique provides normalized values between 0 (minimum value) and a number lower than 1 (maximum value). The linear max-min normalization provides a normalized matrix with data within the range [0 1], where 0 is the worst value and 1 the best one. The linear sum and logarithmic normalization techniques provide normalized values considerably smaller than the other ones, and finally the vector normalization technique provides normalized values close to 1.

Table 5 Normalized matrix using the linear max normalization technique.

Alternative (*i*)	S (ºCA ATDC)	Q (%)	D (ºCA)	Criterion (*j*)			
				j = 1, SFC	*j* = 2, NOx	*j* = 3, CO	*j* = 4, HC
1	-22	5	1	0.074593	0.374650	0.072703	0.066747
2	-22	5	2	0.083981	0.335886	0.068517	0.063859
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
125	-18	25	5	0.154040	0.079254	0.027977	0.033914
Minimum value				0	0	0	0
Maximum value				0.159514	0.686433	0.088126	0.085443

Table 6 Normalized matrix using the linear max min normalization technique.

Alternative (*i*)	S (ºCA ATDC)	Q (%)	D (ºCA)	Criterion (*j*)			
				j = 1, SFC	*j* = 2, NOx	*j* = 3, CO	*j* = 4, HC
1	-22	5	1	0.467628	0.545793	0.824986	0.781182
2	-22	5	2	0.526481	0.489321	0.777482	0.747387
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
125	-18	25	5	0.995682	0.115157	0.317462	0.336920
Minimum value				0	0	0	0
Maximum value				1	1	1	1

Table 7 Normalized matrix using the linear sum normalization technique.

Alternative (*i*)	S (ºCA ATDC)	Q (%)	D (ºCA)	Criterion (*j*)			
				j = 1, SFC	*j* = 2, NOₓ	*j* = 3, CO	*j* = 4, HC
1	-22	5	1	0.007682	0.009063	0.008159	0.008122
2	-22	5	2	0.007761	0.008534	0.008122	0.008097
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
125	-18	25	5	0.008404	0.006156	0.007783	0.007846
Minimum value				0.007109	0.005668	0.007566	0.007580
Maximum value				0.008459	0.018075	0.008297	0.008288

Table 8 Normalized matrix using the vector normalization technique.

Alternative (*i*)	S (ºCA ATDC)	Q (%)	D (ºCA)	Criterion (*j*)			
				j = 1, SFC	*j* = 2, NOₓ	*j* = 3, CO	*j* = 4, HC
1	-22	5	1	0.907106	0.926984	0.912349	0.911944
2	-22	5	2	0.908048	0.922458	0.911953	0.911671
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
125	-18	25	5	0.915081	0.892494	0.908121	0.908846
Minimum value				0.899618	0.883240	0.905476	0.905646
Maximum value				0.915630	0.963388	0.913806	0.913708

Table 9 Normalized matrix using the logarithmic normalization technique.

Alternative (*i*)	S (ºCA ATDC)	Q (%)	D (ºCA)	Criterion (*j*)			
				j = 1, SFC	*j* = 2, NOₓ	*j* = 3, CO	*j* = 4, HC
1	-22	5	1	0.007859	0.007895	0.007841	0.007865
2	-22	5	2	0.007860	0.007890	0.007840	0.007865
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
125	-18	25	5	0.007863	0.007862	0.007834	0.007861
Minimum value				0.007856	0.007855	0.007830	0.007857
Maximum value				0.007863	0.007954	0.007843	0.007868

The results show a strong dependency on the range of the normalized data. According to the expressions shown in Table 4 for the linear max-min method, the initial data are transformed into normalized values within the range [0 1]. Nevertheless, the other methods lead to a much narrower range of the normalized data. The variation of HC and CO emissions with the pre-injection starting instant and quantity is considerably small, as shown in Figs. 5 and 6, respectively. These figures represent the HC and CO emission against the pre-injection quantity and starting rate using 1º pre-injection duration. Other pre-injection durations provide similar results and thus are not presented here. As can be seen in Figs. 5 and 6, the variation of HC and CO is too small, and all normalization methods reflect this fact by providing close values in the normalized matrix, except for the linear max-min normalization. Since this method transforms the values corresponding to each criterion within the range [0 1], the importance of these small variations in CO and HC emissions is incremented, *i.e.*, small differences are always transformed to the range [0 1] independently of the initial data range, and thus small differences are extended. Nevertheless, the other normalization methods maintain the irrelevance of CO and HC during the normalization process and pay more attention to the variation of NO_x emissions and consumption with the pre-injection starting instant and quantity. The variation of NO_x and consumption with the pre-injection rate and starting angle is shown in Figs. 7 and 8, respectively. These figures underline an important dependence of NO_x and consumption on the pre-injection rate and starting angle.
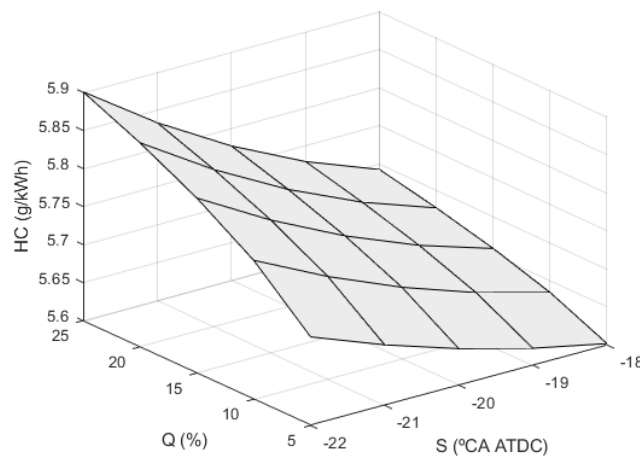

Fig. 5 HC emissions against the pre-injection quantity and starting instant. Pre-injection duration 1ºCA.
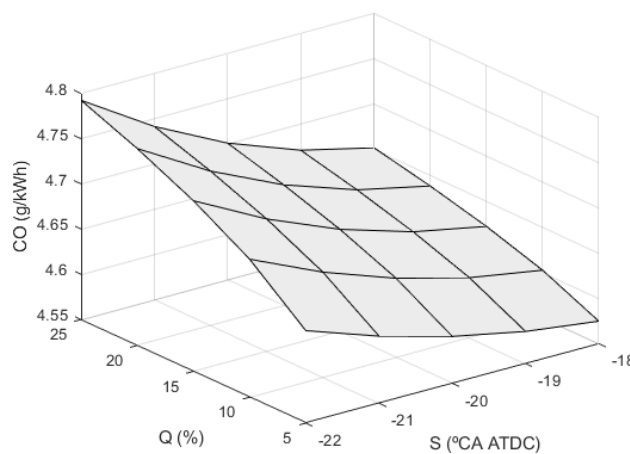

Fig. 6 CO emissions against the pre-injection quantity and starting instant. Pre-injection duration 1ºCA.
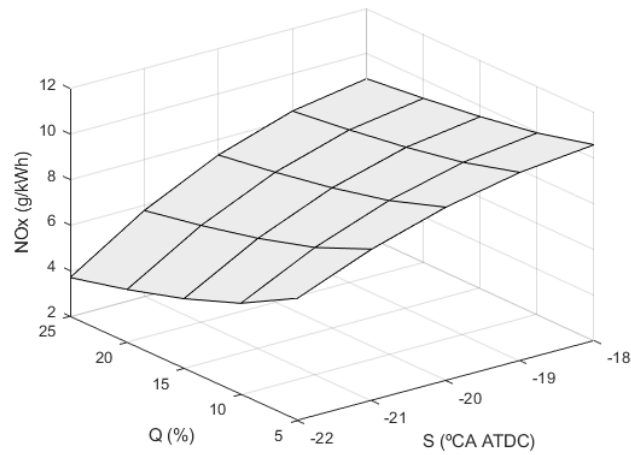
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Fig. 7 NO$_x$ emissions against the pre-injection quantity and starting instant. Pre-injection duration 1ºCA.
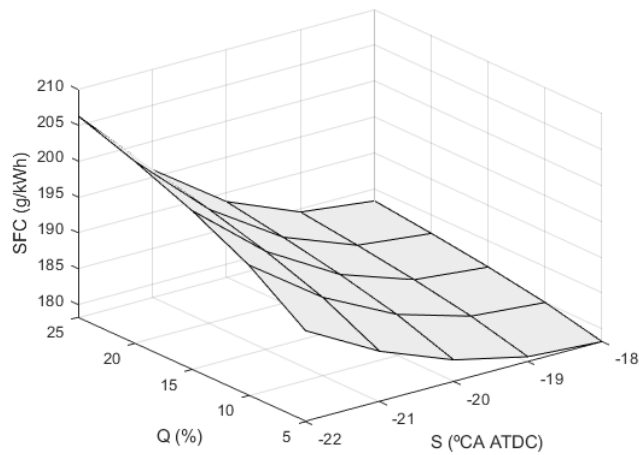

Fig. 8 Consumption against the pre-injection quantity and starting instant. Pre-injection duration 1ºCA.

Table 10 shows the highest adequacy index using the different normalizations methods analyzed in the present work. As can be seen, the linear max, linear sum, vector and logarithmic normalization methods provide practically the same result, which corresponds to -22º pre-injection starting instant, 25% pre-injection quantity and 1º (WSM and WPM) or 2º (TOPSIS) pre-injection duration. Nevertheless, the linear max-min normalization method provides the alternative corresponding to -18º pre-injection starting instant, 5% pre-injection quantity, and 2º pre-injection duration.

Table 10 Most appropriate pre-injection pattern using different normalization methods.

Normalization method	S (º CA ATDC)	Q (%)	D (%)
Linear max	-22	25	1-2
Linear max-min	-18	5	2
Linear sum	-22	25	1-2
Vector	-22	25	1-2
Logarithmic	-22	25	1-2

The linear max-min normalization method provides a different result since, as mentioned above, it transforms the negligible variations of CO and HC into significant values. According to this, this normalization technique leads to a solution with small CO and HC emissions. This alternative is a compromise between the four criteria analysed (NO_x, SFC, CO, and HC), providing more relevance to CO and HC than these really have. This alternative leads to a small contribution of pre-injection, with a 5% quantity, due to the increment of SFC, CO, and HC with the pre-injection quantity. Besides, this solution does not lead to important pre-injection advancements also due to the SFC, CO, and HC penalty. Since a 5% pre-injection quantity leads to excessive NO_x emissions, this solution is not recommended due to the current legislation about NO_x emissions.

On the other hand, the alternative obtained by the other normalization techniques provides significant NO_x reductions with a small increment of SFC in comparison with the case without pre-injection. This solution proposes a high pre-injection percentage (*i.e.* 25%) due to the effect on NO_x reduction. As shown in Fig. 5, advancing the pre-injection starting instant also leads to important NO_x reductions, resulting in -22º as pre-injection starting instant. Regarding pre-injection duration, low values emerge since short injections provide important NO_x reductions. NO_x is mainly caused by the high temperatures that are reached during the combustion process [45]. In order to reduce NO_x efficiently, the fuel must be rigorously injected at the optimum instant and thus under short injections.

4. Conclusions

The following conclusions may be drawn from the present work:
- Due to the important emissions of NO_x produced in the marine field, the present work analyses a NO_x reduction policy in a commercial marine diesel engine. The measure proposed is a pre-injection system. Besides NO_x, the objective is to maintain SFC and emissions of CO and HC as low as possible. It is worth mentioning that PM emissions should also be included in this model. These were not included due to the difficulties to accurately predict these emissions through CFD.
- A total of 125 alternatives with different values of the pre-injection starting instant, quantity and duration were analyzed.
- Since the pre-injection starting instant, quantity and duration are conflicting criteria, a MCDM methodology was employed to determine the most suitable pre-injection configuration.
- An important step in MCDM is the normalization process. Many normalization methods can be found in the literature, and the five most employed ones were compared in the present work: linear max normalization, linear max-min normalization, linear sum normalization, vector normalization and logarithmic normalization.
- 3 MCDM approaches were compared: WSM, WPM, and TOPSIS.
- It was found that linear max, linear sum, vector, and logarithmic normalization methods provided practically the same result as most appropriate pre-injection pattern: -22º CA ATDC pre-injection starting instant, 25% pre-injection quantity, and 1º (WSM and WPM) or 2º (TOPSIS) pre-injection duration due to the important NO_x reductions with a low SFC penalty. Nevertheless, the linear max-min normalization technique provided a very different result: -18º CA ATDC pre-injection starting instant, 5% pre-injection quantity, and 2º pre-injection duration. The reason of the discrepancy between the max-min normalization technique and the other normalization techniques lies in the range of the normalized values. The variation of CO and HC emissions in the 125 cases is practically irrelevant, but the linear max-min normalization technique increments the importance of these pollutants since it

converts its values into the range [0 1]. On the other hand, the other normalization methods maintain the irrelevance of the variations of CO and HC and thus lead to another optimal configuration.

- Among the limiting aspects of MCDM methods, it is worth mentioning that, even if they provide a formal tool for decision making problems, subjectivity is not removed, due to the procedure to stablish the weights. In fact, different MCDM methods and different normalization procedures lead to different results, which means that there is no universal method suitable for all problems.

Nomenclature

AI	Adequacy index
α	Requirement
β	Sub-requirement
C	Relative closeness to the ideal solution
D	Pre-injection duration
D^+	Euclidean distance from the positive ideal solution
D^-	Euclidean distance from the negative ideal solution
DM	Decision matrix
i	Alternative
j	Criterion
m	Number of alternatives
n	Number of criteria
NDM	Normalized decision matrix
Q	Pre-injection quantity
R	Weighted normalized data
S	Pre-injection starting instant
S^+	Positive ideal solution
S^-	Negative ideal solution
V	Normalized data
w	Weight
X	Data

Abbreviations

ATDC	After Top Dead Center
BDC	Bottom Dead Center
CA	Crank angle
CFD	Computational Fluid Dynamics
CO	Carbon monoxide
CO_2	Carbon dioxide
HC	Hydrocarbons
IMO	International Maritime Organization
MADM	Multi-Attributes Decision Making
MEW	Multiplicative Exponential Weighting

MCDA	Multiple-Criteria Decision Analysis
MCDM	Multiple-Criteria Decision Making
MDDM	Multiple-Dimensions Decision Making
MODM	Multiple-Objective Decision Making
NO_x	Nitrogen oxides
PM	Particulate matter
SFC	Specific Fuel Consumption
SO_x	Sulphur oxides
TDC	Top Dead Center
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
WSM	Weighted Sum Method
WPM	Weighted Product Method

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