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ANALYSIS OF THE PRE-INJECTION SYSTEM OF A MARINE DIESEL ENGINE THROUGH MULTIPLE-CRITERIA DECISION-MAKING AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The present work proposes several pre-injection patterns to reduce nitrogen oxides in the Wärtsilä 6L 46 marine engine. A numerical model was carried out to characterise the emissions and consumption of the engine. Several pre-injection quantities, durations, and starting instants were analysed. It was found that oxides of nitrogen can be noticeably reduced but at the expense of increasing consumption as well as other emissions such as carbon monoxide and hydrocarbons. According to this, a multiple-criteria decision-making (MCDM) model was established to select the most appropriate parameters. Besides, an artificial neural network (ANN) was developed to complement the results and analyse a huge quantity of alternatives. This hybrid MCDM-ANN methodology proposed in the present work constitutes a useful tool to design new marine engines.

Keywords: Marine engine,emissions,consumption,artificial neural networks,multi-criteria decision making,computational fluid dynamics

INTRODUCTION

The maritime industry is currently facing a crucial time regarding emission control, and engines have to deal with ever increasing legislative emission requirements. Special attention has been paid to NO_x emissions from marine engines mainly due to legislation imposed by the IMO (International Maritime Organization) through the MARPOL convention. The International Convention for the Prevention of Pollution from Ships (MARPOL) is the main international convention covering prevention of pollution of the marine environment by ships. It was adopted on 2nd November 1973 and has been updated through the years. Regarding air pollution, limits are established in annex VI “Prevention of air pollution from ships”. Several works have been published to characterise NO_x emissions from marine engines [1-4], and both primary and secondary NO_x reduction measures have been developed in recent years. Primary measures focus on reducing NO_x during the combustion phase, while secondary measures reduce NO_x in the exhaust gas through after-treatment devices. Both primary and secondary measures were summarised in recent reviews about emission reduction technologies for marine engines [5-7].

Engine experiments are usually expensive and time-consuming. In order to solve this issue, artificial neural networks (ANNs) have demonstrated the ability to reduce the experimentation cost and time. ANNs are computing systems inspired by the biological neural networks that constitute human brains. Such systems progressively improve their performance by a process called learning. They are able to learn complex non-linear and multivariable relationships between parameters and model nonlinear problems. The objective is to create a predictive model for the objects or phenomena under investigation. ANNs have demonstrated great progress in recent years, and have been applied in many fields such as engineering, medical diagnosis, economics, etc. Regarding internal combustion engines, ANNs have been employed to predict different characteristics like performance, combustion, emissions, etc. in both compression-ignition and spark ignition engines [8]. Regarding compression-ignition engines, one can refer to the work of Kowalski [9], who characterised NO_x and fuel consumption from 15 and 16 inputs, respectively. Celik and Arcaklioglu [10] predicted the consumption, fuel–air equivalence ratio, and EGT, using as inputs the engine power, engine speed, and water temperature. Siami-Irdemoosa and Dindarloo [11] predicted the fuel consumption using the loading time, idle time to load, empty travel time, payload, idled empty time, and loaded travel time as inputs. Bietresato *et al.* [12] predicted the consumption and torque using the exhaust gas temperature and motor oil temperature as inputs. Goudarzi *et al.* [13] predicted the exhaust valve temperature using two temperatures at different points of the seat. Arcaklioğlu and Çelıkten [14] predicted the power, consumption and emissions using the injection pressure, throttle position, and speed as inputs. Nikzadfar and Shamekhi [15] used 10 engine inputs to predict consumption, torque, NO_x, and soot. Besides these works about diesel engines, other analysis can be found in the literature applied to compression-ignition engines using alternative fuels such as biodiesel [16-18], butanol [19], bioethanol [20], ethanol [21], different dual-fuel configurations [22-29], etc.

Primary measures that are commonly employed to reduce NO_x in engines involve multiple evaluation objectives which conflict with each other, *i.e.*, the improvement on one objective such as NO_x reduction sacrifices others such as emissions and/or consumption. Taking this into account, some researchers have developed multi-criteria decision-making (MCDM) models to complement ANN analyses. Prediction studies focused on ANN used together with MCDM can be found in some studies in the literature, applied to different aspects such as supplier selection for industries, failure estimations, machine selection, maintenance, etc. In these analyses, an MCDM is formulated, and ANNs are used to learn the relation among the criteria and alternatives and rank the alternatives. In engine engineering, hybrid MCDM-ANN methods can be found in the work of Tasdemir *et al.* [30], who analysed hydrocarbon emission, consumption, torque, and power using intake valve advancement and speed as inputs; Martínez-Morales *et al.* [31], who analysed NO_x emissions from the injection timing, torque, intake pressure, speed, ignition point, and throttle data; Etghani *et al.* [32], who developed a model to maximise the power and minimise the consumption and CO, CO_2, NO_x, and PM; Majumber *et al.* [33], who optimised the performance and emission parameters in a diesel engine using hydrogen in dual-fuel mode, etc.

The present work proposes a hybrid MCDM-ANN model to analyse the pre-injection pattern in the Wärtsilä 6L 46 marine engine. The data were obtained through a CFD (computational fluid dynamics) model previously validated with experimental data. A pre-injection system was proposed to reduce NO_x emissions and the developed model was developed to analyse the most appropriate injection pattern. The effects of the pre-injection starting instant (S), quantity (Q), and duration (D) were studied.

METHODOLOGY

This section first describes the engine analysed and the corresponding CFD analysis employed to obtain the data samples necessary to train, learn and test the ANN. After that, the MCDM and ANN methodologies are addressed.

ENGINE ANALYSED AND CFD ANALYSIS

As indicated above, the present work analyses the commercial marine engine Wärtsilä 6L 46. This is a four-stroke engine with 6 in-line cylinders, and each cylinder has 2 inlet and 2 exhaust valves. The CFD analysis and validation with experimental results was developed in previous works [22-27]. The simulations were realised using the open software OpenFOAM. Turbulence was treated through the k-ε model. The fuel heat-up and evaporation was treated through the Dukowicz [34] model and the fuel droplet breakup through the Kelvin–Helmholtz and Rayleigh–Taylor [35] model. As a combustion model, Ra and Reitz's kinetic scheme [36], based on 131 reactions and 41 species, was employed. As the NO_x formation model, Yang *et al.*'s kinetic scheme [37], based on 43 reactions and 20 species, was employed. As the NO_x reduction model, Miller and Glarborg's kinetic scheme [38], based on 131 reactions and 24 species, was employed.

A comparison between the numerical and experimental results is illustrated in Figs. 1 and 2. Fig. 1 shows the emissions and SFC (specific fuel consumption) obtained numerically and experimentally at several loads, and Fig. 2 shows the in-cylinder pressure and heat release rate obtained numerically and experimentally at 100% load. As can be seen, both figures show a reasonable correspondence between the numerical and experimental results.

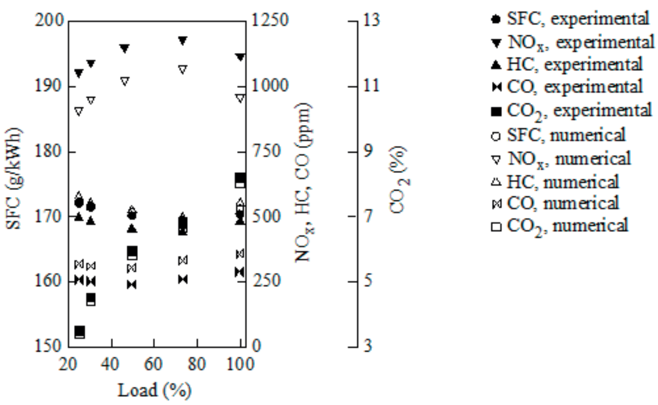

Fig. 1. SFC and emissions at different loads

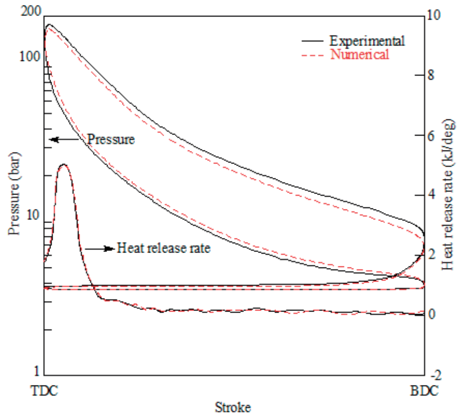

Fig. 2. In-cylinder pressure at 100% load

The data obtained through this CFD model were used as samples to train, validate and test the ANN. 180 cases were characterised through CFD using pre-injection quantities from 5 to 30%, starting instants from -23° to -18° CA ATDC (crank angle after top dead centre), and durations from 1 to 5° CA. All of these simulations were realised at 100% load and 500 rpm. Some of the results obtained for these 180 cases are illustrated in Figs. 3-6. These figures show the consumption, NO_x, CO and HC against the pre-injection quantity and starting angle using 1° injection duration, respectively. As can be seen in these figures, the NO_x emissions are reduced with increments of the pre-injection quantity and advances of the pre-injection starting instant. It is well known that NO_x is formed mainly due to the high temperatures reached during the combustion process. If these temperatures are reduced, the NO_x emissions are reduced too. Unfortunately, low combustion temperatures lead to lower power and thus higher consumption. Besides, lower combustion temperatures promote incomplete combustion, which is the main source of CO and HC emissions. According to these results, it can be seen that SFC, NO_x, CO and HC constitute conflicting criteria since none of the measures proposed in the present work are able to reduce all of them together.

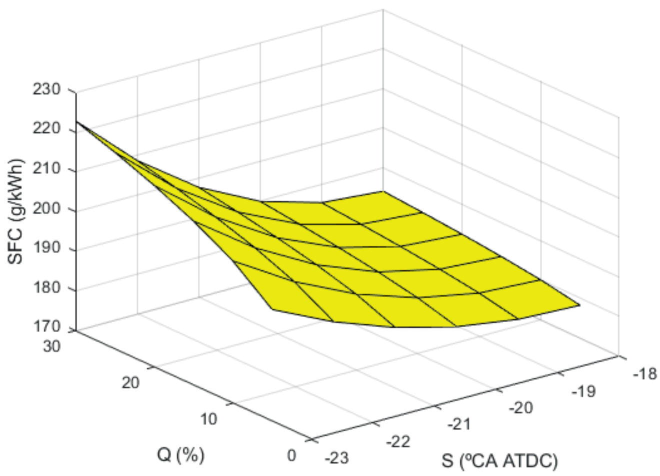

Fig. 3. Consumption against the pre-injection quantity and starting instant. 1° pre-injection duration

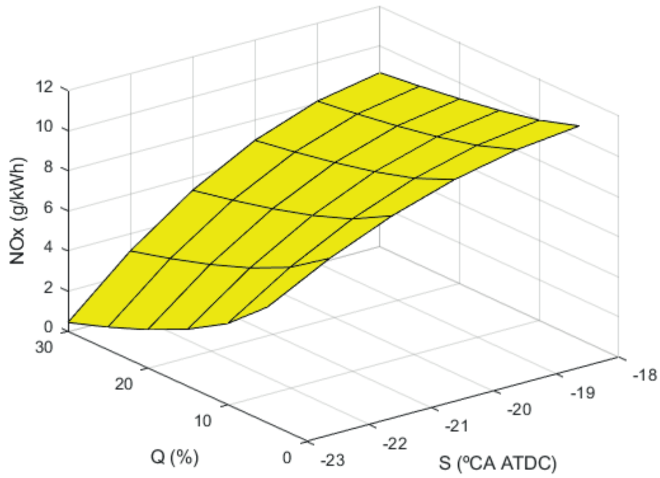

Fig. 4. NO_x emissions against the pre-injection quantity and starting instant. 1° pre-injection duration

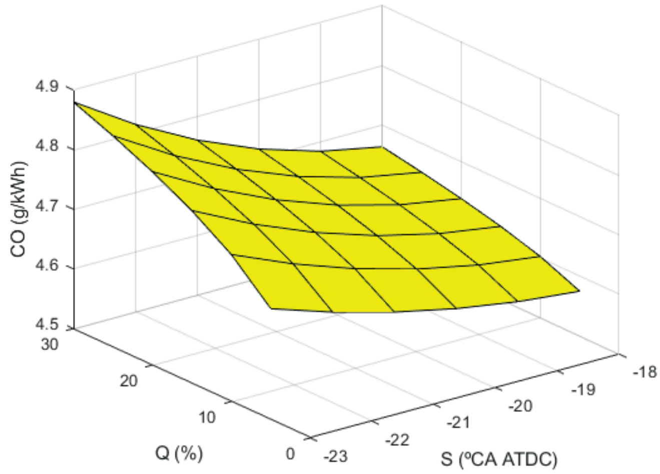

Fig. 5. CO emissions against the pre-injection quantity and starting instant. 1° pre-injection duration

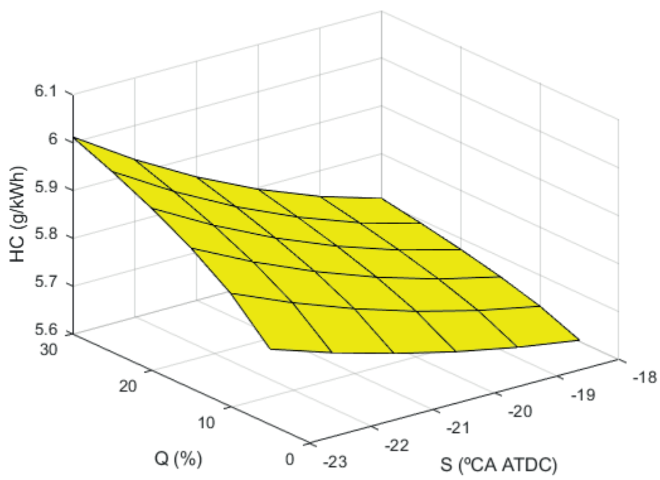

Fig. 6. HC emissions against the pre-injection quantity and starting instant. 1° pre-injection duration

MCDM ANALYSIS

Taking into account the 180 alternatives analysed through the CFD model and the four criteria considered (SFC, NO_x, CO, and HC), a 180 × 4 data matrix can be constituted with 180 rows and 4 columns. Each element X_{ij} indicates the performance of alternative *i* when it is evaluated in terms of the decision criterion *j*. This matrix is highlighted in red in Table 1. This table also shows the pre-injection starting instant, quantity, and duration corresponding to each alternative.

Tab. 1. Decision matrix

Case (*i*)	S (°CA ATDC)	C (%)	D (°CA)	Criterion (*j*)			
				j = 1 SFC (g/kWh)	*j* = 2 NO_x (g/kWh)	*j* = 3 CO (g/kWh)	*j* = 4 HC (g/kWh)
1	-23	5	1	198.2	5.79	4.69	5.76
2	-23	5	2	196.3	6.25	4.71	5.78
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
180	-18	25	5	174.5	10.86	4.88	5.92

An important issue in MCDM methods consists in establishing the criteria weights, *i.e.*, the degree of importance of each criterion. Although several objective methods can be found in the literature, subjective methods are recommended since these are directly defined by experts in the field [8, 33]. In the present work, two main requirements were considered, consumption and emissions. An importance of 20% was provided for consumption and 80% for emissions. Regarding emissions, the importance of NO_x, CO and HC was also distributed equally, *i.e.*, 33.3% for each one. To summarise, these values on a per-unit basis are shown in Table 2. Logically, each column in Table 1 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 too. 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, NO_x, CO, and HC, respectively. Logically, these weights also sum to 1. A sensitivity analysis of these criteria weights will be shown in the results section.

Tab. 2. Criteria weights, per unit basis

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

Another important step consists in normalising the decision matrix. Normalisation is used to eliminate the units of each criterion so that all the criteria become dimensionless and to set the ratings of different alternatives into the same range. Normalisation changes the different measurable values into comparable similar ones. Many normalisation techniques are available in the literature. In the present work, the so- called linear max-min normalisation technique was employed, according to which each normalised value, V_{ij}, is given by:

$$V_{ij} = 1 - \frac{X_{ij}}{X_{j,\max}} \tag{1}$$

The adequacy index was computed by the WSM (weighted sum method), according to which the adequacy index is given by Eq. (2). This procedure is also called SAW (simple additive weighting) and WLC (weighted linear combination). Taking into account the normalisation procedure applied, the most appropriate alternative is the one corresponding to the maximum *AI*.

$$AI_i = \sum_{j=1}^{n} w_j V_{ij} \tag{2}$$

where *AI* is the adequacy index, w_j the weight of the *j*-th criterion, and *n* the number of criteria.

ANN ANALYSIS

ANNs are structures that model human intuition by simulating the physical process upon which intuition is based, *i.e.*, the process of biological learning. In the present work the ANN was employed to obtain the adequacy index (AI) from three inputs: pre-injection starting instant, quantity, and duration. The software Matlab 2021b was used to develop the analysis. The structure of the ANN employed is shown in Fig. 7. As can be seen in this figure, the ANN has three parallel layers. The first layer, *i.e.,* the input layer, contains the three independent variables: S, Q, and D. The second layer is the hidden layer that contains the so-called hidden nodes, and the third layer is the output layer, containing the dependent variable/s. In this problem, a single variable, AI, was employed. Regarding the number of hidden layers, the general recommendation is to employ a single layer for most problems [39] [40], and multi-layered structures are only recommended for complex problems since too many hidden layers may cause memorising instead of generalising. The number of neurons in the hidden layer was established by comparing ANNs with a number of hidden neurons between 3 and 15. A low number of neurons may lead to inaccuracy and a high number to over-fitting. In this case, it was found that the ANN with 12 neurons provided the lowest error and thus this structure was selected.

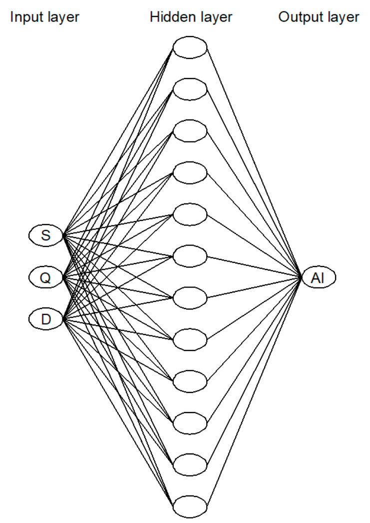

Fig. 7. ANN structure employed in the present work

As mentioned previously, 180 samples were employed and their data were obtained from CFD. 126 of these samples were used for learning, 27 for testing, and 27 for validation. Fig. 8 shows the regression results with respect to training, validation, testing, and all of them. This figure shows a satisfactory performance since R = 0.99966, very close to the optimum value of 1, indicating that the ANN provides an appropriate prediction accuracy.

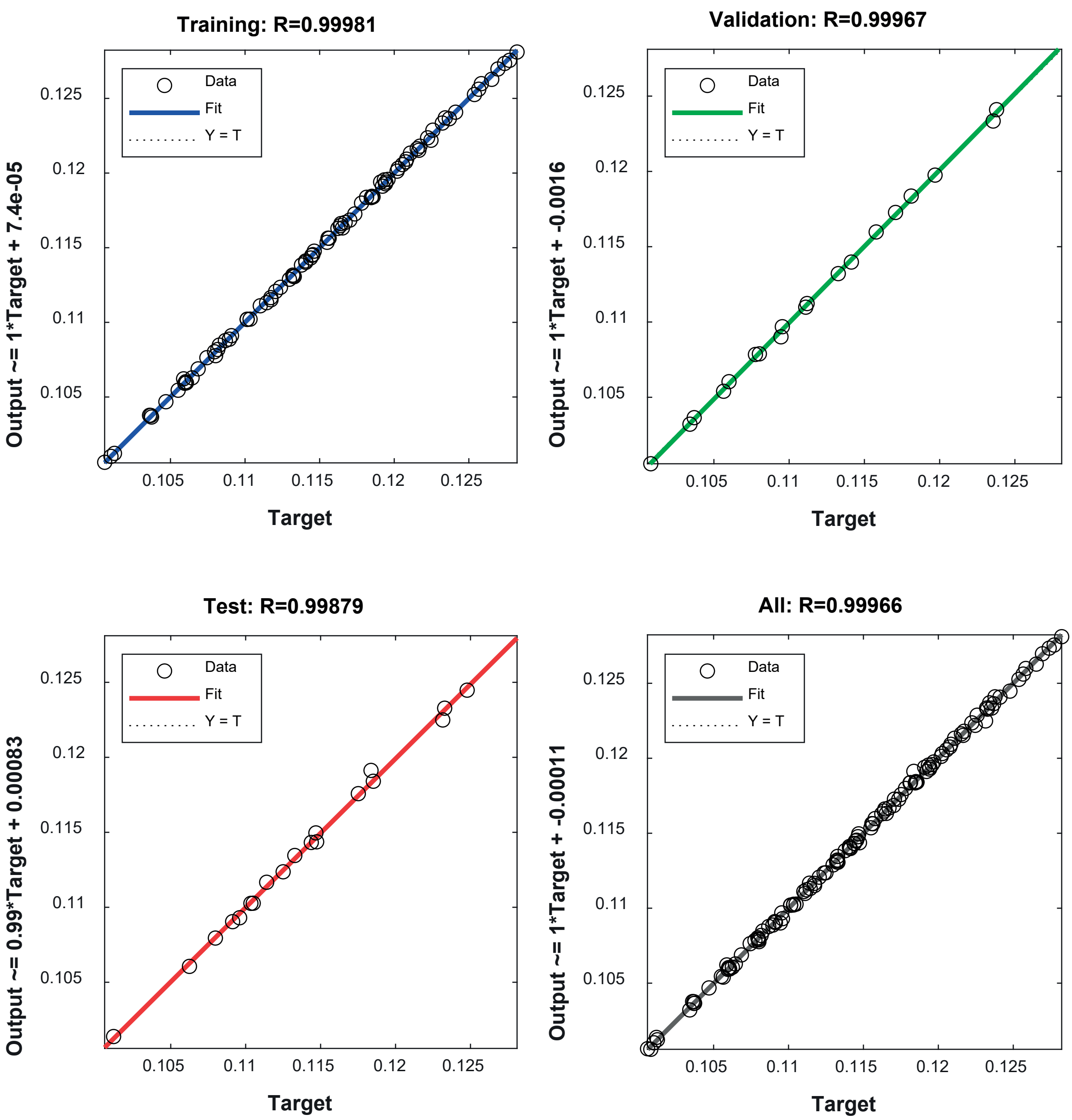

Fig. 8. Regression graphs of the ANN

RESULTS AND DISCUSSION

Fig. 9 shows the most appropriate option provided by the hybrid ANN-MCDM model, which corresponds to a -22.2° pre-injection starting instant, 25.4% quantity and 1° duration. This solution was obtained using the criteria weights shown in Table 2. It is useful to perform a sensitivity analysis of the criteria weights. According to this, Table 3 shows the most appropriate option under different weights of the consumption. In this analysis, the emissions were assigned equally with the remaining weight. As can be seen, as more importance is provided to the consumption, a lower pre-injection rate and more retarded starting instants are obtained since these effects reduce consumption. It is worth mentioning that some of the results obtained in Table 3 are not recommended in practical application despite the significant NO_x reductions obtained. A 30.5% pre-injection quantity is too high for an appropriate performance of the engine. Besides, a -23.1° starting instant is too early since the combustion must be produced after TDC. Regarding the injection duration, injections shorter than 1° were not analysed since some injectors are not able to provide these short injections.

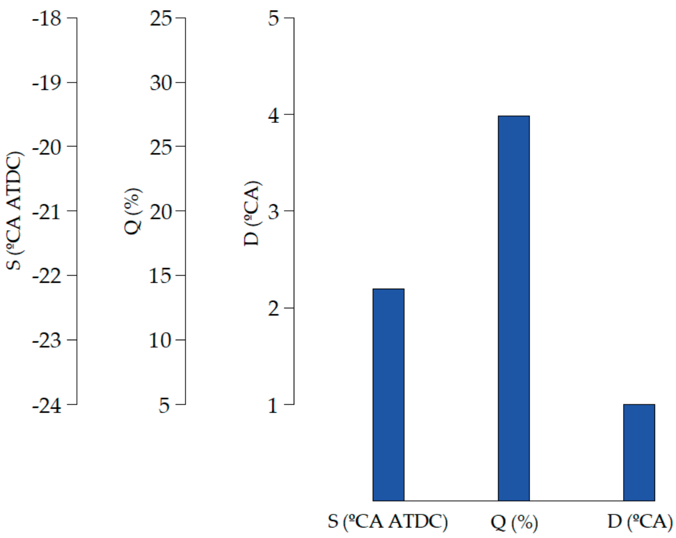

Fig. 9. Most appropriate option according to the MCDM model alone

Tab. 3. Most appropriate option under several criteria weights for the consumption according to the hybrid MCDM-ANN model

α_{SFC}	S (°)	Q (%)	D (°)
40	-23.1	28.3	1.5
45	-22.8	27.1	1.2
50	-22.2	25.4	1
55	-20.9	23.2	1
60	-18.5	19.8	1

CONCLUSIONS

This paper proposes a hybrid MCDM-ANN model to select the most suitable pre-injection pattern in the Wärtsila 6L 46 marine engine. The purpose is to reduce emissions and consumption as much as possible. The motivation comes from the ever stricter legislation, especially IMO MARPOL. The pre-injection quantity, starting instant, and duration were analysed. Since these measures have conflicting criteria on emissions and consumption, the hybrid MCDM-ANN developed in the present work model provides a tool to facilitate the selection for decision makers. The pre-injection quantity, starting instant, and duration were selected as input data for the ANN model, while the adequacy index was selected as the output data. The model is fast in application and allows the user to vary the input parameters in order to show their effects on the results.

This work provides useful information for marine engine designers. MCDM tools are becoming necessary to select between conflicting criteria, and ANN allows a huge quantity of alternatives to be analysed. Once the ANN is trained, it can be used for predicting solutions, in this case the adequacy index of each alternative. Manufacturers can find in the present study an assessment tool for designing their engines. The proposed model is applicable for a wide variety of multi-attribute decision-making problems and can be used for future ranking or selection. Future studies will focus on analysing more pollutant reduction measurements and other marine engines.

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