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# Contribution Based on Neurons Networks for the Prediction of Greenhouse Gas Emissions in a Handling Port

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**Abstract:** Greenhouse gases emitted by ships and port handling equipment contribute enormously to the climate change, which is why our reflection in this paper focusses on its quantification. This study is performed to predict the amount of greenhouse gases during the unloading and loading operations of ships at the quayside in a seaport. After developing a model whose resolution allowed us to obtain a solid database, we performed a simulation using the Levenberg-Marquart algorithm using artificial neural networks. The results allowed us to determine the performance of our machine-learning model.

**Key words:** Greenhouse gas emissions, artificial neural networks.

## Introduction

The reality of climate degradation is rarely contested in view of the various climatic disasters. Storms are very frequent and destructive (Pascal Boniface, 2023). The acceleration of policies to reduce emissions from maritime transport now appears as a new factor to be taken into account by shipping companies.

They must combine this reduction with their economic objectives of seeking profits and market shares.

In recent years, several studies have reported that maritime transport is a major contributor to climate change (Ubeda et al., 2011).

Innovations in ship diesel engines have allowed the use of heavy fuel oil instead of diesel. Ships equipped with diesel engines have gradually replaced steam ships.

For several decades, artificial intelligence methods have shown interesting potential for solving optimisation problems. In an environment increasingly threatened by the effects of climate change, the contribution of prediction algorithms would be a very crucial asset for production players.

The predictions included in it enable proactive action by taking corrective measures before problems become critical, thereby improving service availability (Chaoyun et al., 2019).

Alexandre Lacoste et al. (2019) provided the machine learning emissions calculator, which relies on self-declaration. This tool is able to estimate the carbon footprint of a computation performed by a graphics processing unit, taking into account the types of hardware, and the usage time. However, the increase in computationally intensive artificial intelligence research

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could lead to significant environmental impacts (Strubell et al., 2019).

Raghnavendra et al. (2020) developed the carbon-tracker tool to track and predict the energy consumption and carbon footprint of machine learning algorithms during the training phase. Furthermore, in reference Stamoulis et al. (2018), the authors proposed a tool (neural power) based on a layer-based predictive framework to estimate the amount of gas emitted. Alfredo Canziani et al. (2017) evaluated the accuracy of the image classification model as a function of the model size and images.

Today, maritime transport is one of the sectors most affected by the energy transition. As the second largest producer of greenhouse gases (a quarter of global emissions, according to the International Energy Agency), transport is often singled out in international carbon assessments.

Wuisan et al. (2012) undertook the exercise of projecting carbon dioxide emissions from maritime transport to 2050. They developed scenarios combining assumptions on economic growth, fleet development and the diffusion of liquefied natural gas as a marine fuel. These projections take into account the effects of the reduction policies currently adopted. For the authors, carbon dioxide emissions will increase exponentially (Gouvenal et al., 2014). This explains why any effective climate change mitigation strategy requires a profound change in the economic and social models of energy supply and demand. They also require an improvement in the quality of infrastructure and the quality of operations (Temim, 2023). There are several areas of contribution, but in the case of this paper, we believe that it is important to find mechanisms that can contribute to greater commitment and responsibility in reducing greenhouse gas emissions, particularly in port areas. We used artificial neural network techniques in artificial intelligence to predict the carbon footprint during disembarkation and embarkation operations on ships moored in a seaport. After the introduction, we discuss the data acquisition steps, then the clarification of our neural network model followed by the analysis of the results and we end with a conclusion.

## Issues and Contributions

Port handling equipment emits significant quantities of greenhouse gases. Thus, port decarbonisation is played out at the structural and logistical levels (Marjorie Doudnikoff et al., 2014).

During the waiting period of ships in ports where they are moored at non-electrified quays, at least one of their engines remains running to ensure their electricity needs (Guillaume Bourgeois, 2023). Due to the quality of the fuel, they use, this contributes to significant atmospheric pollution, resulting in the emission of quantities of greenhouse gases.


**Figure 1: Ship operations at Quay.**

Considering the consequences that this entails, our contribution in this paper:

- On the one hand, obtaining certain data related to ships is complex because the ships are operated by the private sector. From the work encountered in the literature and the experiences of interviews and discussions during our practical training at the seaport of Abidjan, we developed a linear model. Its resolution allowed us to have satisfactory data that is consistent with reality and the results of several other researchers encountered in the literature.
- From the data obtained and in a MATLAB environment, we applied neural network techniques to predict the amount of greenhouse gases emitted. This approach aims to help organisations better understand the impacts of their activities on the ecosystem and adopt more environmentally friendly practices to minimize their impact on the climate.

## Data Acquisition

This data acquisition phase took place in two stages, which are an interview and the use of a mathematical model.

### Interviews

During our practical training at the maritime port of

Abidjan, we collected data mainly from interviews and focus groups. After collecting these data which were small in number, we developed a mathematical model whose resolution allowed us to confirm the data already collected, but also to increase their number in order to be able to use them in the continuation of our reflection.

We did this because the port authorities did not have control over the ships. By using the parameters, they have, we obtain an estimate of the quantities we are looking for. Hence the mathematical modeling.

**Mathematical Formulation**

To acquire a solid database, our modelling follows several steps:

**Model sets**

We designate by:

N: Set of ships indexed by n.

S: Set greenhouse gases indexed by s.

G: Set of quay cranes assigned to the ship n for handling containers indexed by g.

C: Set of containers that will be handled on the ship n indexed by i and j. Containers are understood to mean any object or baggage that is unloaded or loaded onto the ship by quay cranes. These containers are known.

R: Set of yard gantry cranes used for handling containers on the storage yard indexed by r. They handle containers in the storage yard. They do not intervene on the ship.

K: Set of transport trucks used in the transfer of containers to the ship and the storage park indexed by k. They ensure the transport of containers between the docks and their locations in the storage park.

**Model parameters**

$A_n$: Time of the end of the ship n mooring at the quays.

This is the end of the docking and mooring of the ship.

$d_{ijg}$: Travel time of crane g between container i and container j regardless of their addresses on the ship.

$t_i$: Travel time of the truck carrying container i between the dock and the storage yard.

$H_1$: The exact time for the crane to move a container between its address on the ship and the transport truck. it is a constant.

$\tau_n{}^1$: Average fuel consumption per hour of the ship n.

$\sigma_n{}^3$: Emission coefficient of greenhouse gases by ship n

$\beta_n{}^1$: Atmospheric greenhouse gases pollution coefficient of the ship n.

$\gamma_n{}^3$: Global warming potential of greenhouse gases s of ship n.

It is defined by: $\beta_n^1 = (\Sigma_{s=1}^{S} \gamma_n^s . \times \sigma_n^s) \times \tau_n^1$

$\tau_n^2$: Average fuel consumption per hour and per liter of a truck assigned to the ship n.

$\rho_n^2$: Emission coefficient of greenhouse gases emitted by a truck assigned to ship n.

$\in_n$: Total number of trucks used in the ships n. operations

$\beta_n^2$: Atmospheric greenhouse gases pollution coefficient of trucks assigned to ship n.

It is defined by: $\beta_n^2 = (\Sigma_{s=1}^{S} \gamma_n^s . \times \rho_n^s) \times \tau_n^2 \times \varepsilon_n$

Trucks are identical in terms of consumption and pollution

On note $\Gamma_n$: The total atmospheric coefficient associated with the ship n operations.

So, $\Gamma_n = \beta_n^1 + \beta_n^2$

$T_{\max}$: The maximum waiting time for loaded trucks in the storage yard. This value is set by the port authorities in order to make handling operations efficient.

**Model variables**

$D_n$: Departure time of ship n from the quays.

$H_i$: Time required to handle container i on the ship. This positive value includes the transfer time and unproductive movements generated during the handling of container i by a quay crane.

$HD_i$: The start time of processing of container i on the storage yard by a yard gantry.

$h_i$: Time required to handle container i to its address where it is stored in the yard. This positive value includes the duration of the transfer and unproductive movements generated during the handling of container i by a yard gantry.

$DD_i$: The start time of unloading operations on the ship of container i. These containers are unloaded from the ship and placed on a truck which transports them to their addresses in the storage yard.

$DP_i$: The time of departure from the docks of the truck transporting the container i to store it at its address in the storage park.

$DF_i$: The end time of loading of container i onto the ship by a quay crane.

$DQ_i$: Time of arrival at the quays of the truck loaded with container i. These containers are then loaded onto the ship.

$$X_{ijg} = \begin{cases} 1\, if\ \ containers\ i\ and\ \ j\ are\ handled\ in\ this \\ order\ by\ quay\ crane\ g, \forall i, j \in C, \forall g \in G \\ 0\ otherwise \end{cases}$$

$$V_{gn} = \begin{cases} 1\, if\ \ the\ quay\ crane\ g\ is\ assigned\ to\ the\ ship\ n \\ \forall n \in N, \forall g \in G \\ 0\ Otherwise \end{cases}$$

$$Y_{ik} = \begin{cases} 1\, if\ \ truck\ k\ carries\ container \\ \forall n \in N, \forall g \in G \\ 0\ Otherwise \end{cases}$$

$$W_{kn} = \begin{cases} 1\, if\ \ truck\ k\ is\ assigned\ to\ ship\ n \\ \forall n \in N, \forall k \in K \\ 0\ Otherwise \end{cases}$$

$$P_{ijr} = \begin{cases} 1\, if\ \ the\ yard\ gantry\ r\ handles\ container\ \ j \\ just\ after\ container\ i, \forall\ i,\ j \in C, \forall\ r \in R \\ 0\ Otherwise \end{cases}$$

**Objective Function**

Ships leave the port as soon as the loading operations are completed. We then translate according to (Damien Rafanel et al., 2013) the product between the duration of the operations and the parameters allowing to estimate the quantity of greenhouse gases emitted by ship n during the duration of the operations:

$$\text{Min } \Gamma_n = (D_n - A_n)$$

**Under constraints**

$$\sum_{k=1}^{|K|} Y_{ik} = 1,\ \forall\ i \in C \tag{1}$$

$$\sum_{i=1}^{|C|} \sum_{g=1}^{|G|} X_{ijg} = 1,\ \forall\ i \in C,\ I \neq j \tag{2}$$

$$\sum_{i=1}^{|C|} \sum_{r=1}^{|R|} P_{ijr} = 1,\ \forall\ j \in C,\ I \neq j \tag{3}$$

$$\sum_{k=1}^{|K|} W_{kn} \leq 1,\ \forall\ n \in N \tag{4}$$

$$\sum_{g=1}^{|G|} V_{gn} \leq 1,\ \forall\ n \in N \tag{5}$$

$$\sum_{i=1}^{|C|} X_{ijg} = \sum_{i=1}^{|C|} X_{ijg} \quad \forall\ j \in C,\ I \neq j,\ \forall\ g \in G \tag{6}$$

$$\sum_{i=1}^{|C|} Y_{ki} = \sum_{i=1}^{|C|} Y_{ki} \quad \forall\ k \in K \tag{7}$$

$$\sum_{i=1}^{|C|} P_{ijr} = \sum_{i=1}^{|C|} P_{jir} \quad \forall\ j \in C,\ I \neq j,\ \forall\ r \in R \tag{8}$$

$$\left.\begin{array}{c} DD_j - DD_i - d_{ijg} \leq MX_{ijg} \\ DD_j - DD_i - d_{ijg} \leq H_i - \left(1 - X_{ijg}\right) H_1 \\ H_i - DD_j + DD_i + d_{ijg} \geq M\left(1 - X_{ijg}\right) \\ DQ_j - DQ_i - d_{ijg} \geq H_1 X_{ijg} \end{array}\right\} \forall\ i,\ j\ C, I \neq j \forall g G \tag{9}$$

$$\left.\begin{array}{c} DF_j - DF_i \leq MX_{ijg} \\ DF_j - DF_i \leq H_i - \left(1 - X_{ijg}\right) H_1 \\ H_i - M\left(1 - X_{ijg}\right) \geq DF_j - DF_i \\ DF_j - DF_i \geq H_1 X_{ijg} \end{array}\right\} \forall\ i,\ j \in C, I \neq j \forall g \in G \tag{10}$$

$$\left.\begin{array}{c} DD_j - DD_i - d_{ijg} \leq MX_{ijg} \\ DD_j - DD_i - d_{ijg} \leq H_i - \left(1 - X_{ijg}\right) H_1 \\ H_i - DD_j + DD_i + d_{ijg} \geq M\left(1 - X_{ijg}\right) \\ DQ_j - DQ_i - d_{ijg} \geq H_1 X_{ijg} \end{array}\right\} \forall\ i,\ j \in C,\ i \neq j,\ \forall\ g \in G \tag{11}$$

$$DF_i \geq DQ_i + H_1,\ \forall\ i \in C \tag{12}$$

$$D_n \geq DF_i + H_1,\ \forall\ i \in C \tag{13}$$

$$A_n \leq DD_i + h_i,\ \forall\ i \in C \tag{14}$$

$$DQ_j \geq DP_i + (1 - X_{ijg})M,\ \forall\ i,\ j \in C \tag{15}$$

$$DP_i + t_i + \leq HD_i,\ \forall\ i \in C \tag{16}$$

$$HD_i + h_1 \leq DQ_i,\ \forall\ i \in C \tag{17}$$

$$HD_i + t_i + h_i + H_1 \leq DF_i\ \forall\ i \in C \tag{18}$$

$$HD_\text{i} - t_i - DP_i \leq T_{\max},\ \forall\ i \in C \tag{19}$$

- The constraints (1), (2) and (3), respectively, guarantee that each container is assigned to a single transport truck, handled by a single quay crane and a single yard gantry.
- The constraint (5) guarantees that each quay crane is assigned to at most one ship.
- The constraint (4) ensures that each truck is assigned to at most one ship.
- The constraints (6) (8) and (7) respectively ensure the conservation of the flows of trucks, cranes and yard gantries.
- The linearised constraints (9), (10), (11) and (12)

ensure order in the handling of containers at the quay cranes.

- The constraints (13) and (14) ensure that the unloading operations begin after the mooring of the ship which definitively leaves the quays after the end of the loading operations on the ship.
- The constraint (15) guarantees that the loading operations on the ship begin after the unloading operations have been completely done.
- The linearized constraints (16), (17) and (18) ensure order in the processing of containers at the storage yard level.
- The constraint (19) ensures that no loaded truck must wait in the storage yard beyond a certain duration set by the port authorities.

**Numerical Resolutions**

Representing about 99% of all atmospheric greenhouse gases, our simulation is carried out on the following greenhouse gases (MELCCP, 2022).

Carbon dioxide ($CO_2$), methane ($CH_4$) and nitrous oxide ($N_2O$). To perform the calculations, all data are converted into $CO_2$ (eq $CO_2$) according to the following Table 1.

**Table 1: Gas related parameters**

| *Gas type* | *Global warming potential* | *Emission coefficient* |
|---|---|---|
| $CO_2$ | 1 | 2,663 |
| $CH_4$ | 25 | 0,00015 |
| $N_2O$ | 298 | 0,000075 |

A large part of the parameters were collected during the maintenance phase. Our simulation is carried out on about thirty ships (Ademe, 2022).

The linear nature of the model justifies the choice of the small data size and the resolution method. We used the AMPL-CPLEX solver for the resolution. In the column 'ship type', we abbreviated the names of the ships used for the simulation of our model.

In the table, we have from left to right, the list of ships that were the subject of our study, the number of containers to be handled on the ship, the number of trucks, the duration of operations and the quantity of greenhouse gases emitted. These results are identical to those collected during the interview and discussion phase.

## Application of Neural Networks

The construction of an artificial neural network involves determining its architecture and choosing the activation functions associated with the neurons.

**Modelling by Neural Networks**

The neural network used in this work for greenhouse gas quantity prediction is a multilayer perceptron with a supervised learning algorithm which is an ensemble of interconnected neurons (Wuisan Lindse, 2012).

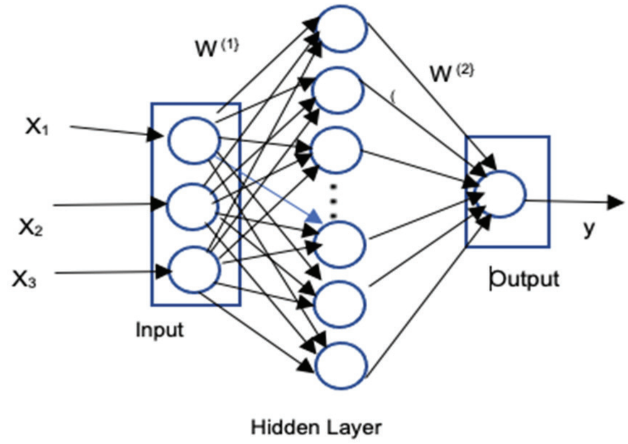


**Figure 2: Architecture of a multilayer perceptron.**

It consists of a set of artificial neurons interconnected by weights $w^1$ and $w^2$ which are respectively the weight column between the input layer - neuron layer 1 and the neuron layer 1 – the output layer. Their values influence the behaviour of the entire structure. The rules, according to which the connection adjustment operation is performed, characterize the network learning algorithm. The usual procedure in the context of forecasting consists of searching for a parameterized function $y(x_i, w)$ realized using a neural network, for which the cost function $C(w)$ is minimum.

$$C(w) = \frac{1}{2} \sum_{i=1}^{2} [\, y_n(x_i) - y(x_i, w^k)]^2$$

**Table 2: Ship related parameters**

| *Ship type* | *Dry bulk* | *Liquid bulk* | *Cargo* | *Container ship* | *Roro* | *Ferry* |
|---|---|---|---|---|---|---|
| Average consumption (t/h) | 0,4694 | 0,5715 | 0,2954 | 0,915 | 0,4483 | 1,1169 |

**Table 3: Simulation results**

| *Settings* | | | | *Ampl-Cplex Results* | |
|---|---|---|---|---|---|
| *Ship name* | *Num. cont* | *Num.trucks* | *Quay crane* | *Time (/min)* | *Gas emission (kg. eq$CO_2$)* |
| OBS | 47 | 8 | 1 | 175 | 1 ,360 |
| GAZW | 45 | 7 | 1 | 117 | 1,561 |
| CARG | 46 | 7 | 1 | 162 | 2,231 |
| ANA | 52 | 8 | 1 | 152 | 2,188 |
| INF | 50 | 9 | 1 | 248 | 2,78 |
| BELA | 54 | 10 | 2 | 288 | 4,096 |
| SOL | 50 | 8 | 1 | 225 | 2,335 |
| AYT | 56 | 10 | 2 | 188 | 2,207 |
| MAB | 42 | 10 | 2 | 101 | 1,352 |
| EDM | 33 | 7 | 1 | 90 | 1,322 |
| MEA | 27 | 7 | 1 | 80 | 1,195 |
| FED | 62 | 9 | 1 | 256 | 3,792 |
| JUN | 42 | 7 | 1 | 60 | 1,103 |
| ICM | 67 | 13 | 2 | 294 | 4,672 |
| SHY | 60 | 10 | 2 | 293 | 4,088 |
| Top.B | 54 | 9 | 2 | 281 | 4,130 |
| Rep.C | 64 | 12 | 2 | 293 | 4,223 |
| ETOILE | 47 | 7 | 1 | 192 | 2,234 |
| COLB | 55 | 8 | 1 | 253 | 3,565 |
| MSC | 60 | 11 | 2 | 299 | 3,787 |
| VIET | 40 | 6 | 1 | 105 | 1,441 |
| CHN | 53 | 8 | 1 | 193 | 2,030 |
| DERA | 50 | 9 | 1 | 176 | 2,222 |
| WID | 67 | 12 | 2 | 299 | 4,225 |
| ELIA | 37 | 8 | 1 | 185 | 2,218 |
| Mam.B | 110 | 13 | 2 | 107 | 1,470 |
| ORI | 43 | 11 | 2 | 104 | 1,841 |
| YUA | 57 | 10 | 1 | 270 | 3,562 |
| HAT.A | 33 | 9 | 1 | 72 | 1,112 |
| Rep.B | 40 | 8 | 1 | 161 | 3,356 |

$x_1$:The number of transfer trucks assigned to the ship.
$x_2$: The number of cranes assigned to the ship.
$x_3$: The number of containers assigned to the ship.

*Y*: The output layer that contains only one neuron represents the amount of greenhouse gas emitted by the ship.

To estimate the performance of a neural model, the most frequently used performance index is the Mean Square Validation Error (MSVE) whose expression is:

$$\text{MSVE} = \sqrt{\frac{1}{VV}\sum_{i=1}^{VV}\left[y_{\text{n}}\left(x_i\right)-\text{y}(x_i,w^k)\right]^2}$$

The resulting error (MSVE) is compared to the Learning Mean Square Error (MSE) with:

$$\text{MSE} = \sqrt{\frac{1}{VA}\sum_{i=1}^{VA}\left[y_{\text{n}}\left(x_i\right)-\text{y}(x_i,w^k)\right]^2}$$

The values VV and VA are respectively the number of elements in the validation and training sets.

### Model Used

We used the hyperbolic tangent function as the activation function for all neurons in the hidden layer, and the identity function as the activation function for the output neuron. Our strategy is to vary the number of neurons in the hidden layer and then choose the optimal network that gives the smallest possible test mean square error.

In order to adapt our data to the realisation of the neural model, we proceeded to the normalisation of their values in an interval [0, 1] by the relation.

$$x_n' = \frac{x_{max} - x_n}{x_{max} - x_n}$$

$x_{max}$ and $x_{min}$ represent respectively the maximum and minimum values of the data represented as a vector $x$.

We have subdivided our database into three groups of which 80% are used for training, 10% for validating the network, and 10% for testing the model.

**Table 4: Normalised data**

| *A* | *B* | *C* | *D* | *E* |
|---|---|---|---|---|
| 0,75793 | 0,71428 | 1 | 0,51882 | 0,92808 |
| 0,78174 | 0,85714 | 1 | 0,76569 | 0,81173 |
| 0,76984 | 0,85714 | 1 | 0,57513 | 0,68399 |
| 0,69841 | 0,71428 | 1 | 0,61715 | 0,69582 |
| 0,72222 | 0,57142 | 1 | 0,21548 | 0,53019 |
| 0,67857 | 0,42857 | 0 | 0,04811 | 0,16127 |
| 0,72222 | 0,71428 | 1 | 0,31171 | 0,65473 |
| 0,65476 | 0,42857 | 0 | 0,46652 | 0,69053 |
| 0,82142 | 0,42857 | 0 | 0,82845 | 0,93026 |
| 0,9246 | 0,85714 | 1 | 0,87656 | 0,93866 |
| 1 | 0,85714 | 1 | 0,91631 | 0,97415 |
| 0,58333 | 0,57142 | 1 | 0,17991 | 0,24657 |
| 0,82142 | 0,85714 | 1 | 1 | 1 |
| 0,41984 | 0 | 0 | 0 | 0 |
| 0,51111 | 0,42857 | 0 | 0,02928 | 0,06344 |
| 0,6746 | 0,57142 | 0 | 0,0774 | 0,15193 |
| 0,56349 | 0,14285 | 0 | 0,0251 | 0,02577 |
| 0,7619 | 0,85714 | 1 | 0,44769 | 0,68306 |
| 0,67063 | 0,71428 | 1 | 0,11246 | 0,31008 |
| 0,60307 | 0,18571 | 0 | 0,00209 | 0,24782 |
| 0,84126 | 1 | 1 | 0,81171 | 0,90535 |
| 0,6865 | 0,71428 | 1 | 0,44351 | 0,74034 |
| 0,72222 | 0,57142 | 1 | 0,51673 | 0,68648 |
| 0,3238 | 0,04285 | 0 | 0,12515 | 0,12515 |
| 0,88095 | 0,71428 | 1 | 0,68742 | 0,68742 |
| 0 | 0 | 0 | 0,89726 | 0,89726 |
| 0,81349 | 0,28571 | 1 | 0,79327 | 0,79327 |
| 0,64285 | 0,42857 | 1 | 0,31102 | 0,31102 |
| 0,93253 | 0,57142 | 1 | 0,9975 | 0,9975 |
| 0,8492 | 0,71428 | 1 | 0,36861 | 0,36861 |

We simulated under MATLAB. We applied the linear regression algorithm using artificial neural networks. In 17 iterations, we obtained the results which are the relevant indicators of the model.

## Results and Analysis

After several trials, we obtain the performance indicators of our model. The weights and biases retained by the network are those that correspond to the minimum of the validation error. This minimum is reached after 7 iterations.

The coefficient of determination: describes the approximation of the predicted value and the observed value according to the artificial neural network model. A good correlation between the predicted value and the measured value is observed on the graph which results in a coefficient of determination of 0.97.

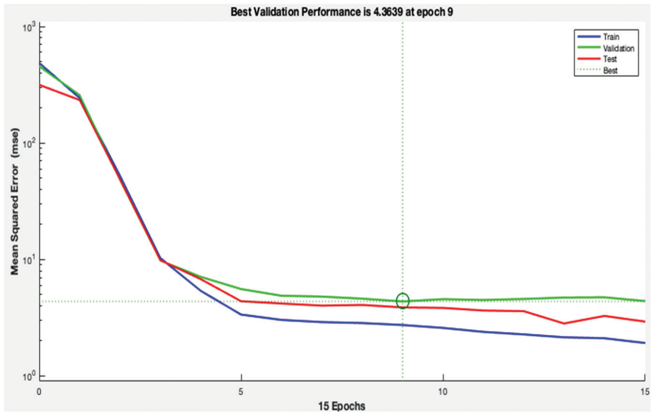


**Figure 3: Model performance graph.**

From the graphs obtained, we distinguish the error made on the training set in blue. In green, we have the validation set and finally, we have the test in red. We note that the mean squared error is low and it drops sharply as the learning progresses. We note that the amount of greenhouse gases measured and predicted using the data reserved for network training are very close.

The training was performed with an acceptable mean square error. The predicted amount of greenhouse gases is relatively close to the obtained values. The artificial neural network model is therefore able to predict.

We present the regression graph in order to visualise the distribution of the responses (quantities of greenhouse gases) around the regression line. We note a very good distribution around the regression line. This expresses a very strong indicator of the performance of the model with fairly high determination coefficients.

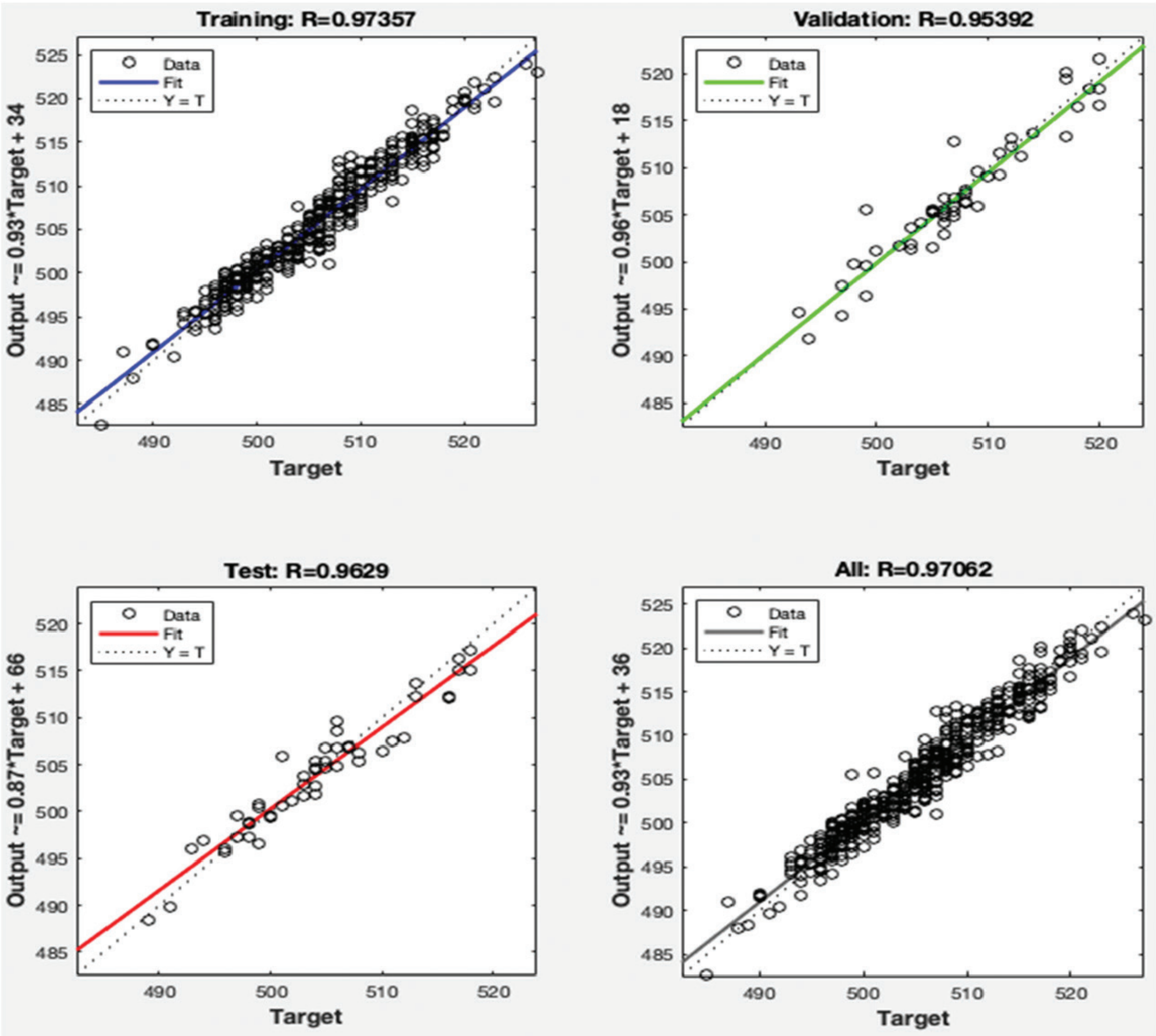


**Figure 4: Regression graph.**

## Conclusion

In this work, we have globally addressed the problem of greenhouse gas emissions in a port area. Based on the models known in our literature and several interviews and discussions with ship operations managers, we have developed a model whose resolution has allowed us to complete our database with several ships.

The Neural Networks toolbox of MATLAB software was used to train, validate and test the artificial neural network prediction model based on the Levenberg-Marquardt algorithm which is fast and allows better convergence towards a minimum of the squared error.

In 107 iterations, we obtained the relevant indicators. These results constitute a significant contribution to raising awareness among stakeholders to adopt more concrete policies in the fight against the effects of climate change.

Neural networks have demonstrated significant learning and prediction capacity.

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