Computational meta-heuristics based on Machine Learning to optimize fuel consumption of vessels using diesel engines

Paulo Oliveira Siqueira Júnior (Corresponding author)
Student of the Graduate Program in Engineering, Process, Systems and Environmental Management (PPG-EGPSA), ITEGAM, Brazil.
ORCID: https://orcid.org/0000-0001-8071-3972
Email: paulojunior051996@gmail.com

Manoel Henrique Reis Nascimento
PhD in Electrical Engineering from the Graduate Program in Engineering, Process, Systems and Environmental Management (PPG-EGPSA), ITEGAM, Brazil.
ORCID: https://orcid.org/0000-0003-4688-6751
Email: hreys@bol.com.br

Ítalo Rodrigo Soares Silva
Student of the Graduate Program in Engineering, Process, Systems and Environmental Management (PPG-EGPSA), ITEGAM, Brazil.
ORCID: https://orcid.org/0000-0002-2827-1078
Email: italo.computation@gmail.com

Ricardo Silva Parente
Student of the Graduate Program in Engineering, Process, Systems and Environmental Management (PPG-EGPSA), ITEGAM, Brazil.
ORCID: https://orcid.org/0000-0003-3096-9069
Email: ricardosilvaparente@gmail.com

Milton Fonseca Júnior
PhD in Electrical Engineering from the Graduate Program in Engineering, Process, Systems and Environmental Management (PPG-EGPSA), ITEGAM, Brazil.
ORCID: https://orcid.org/0000-0001-6001-3098
Email: milton.fonseca.jr@gmail.com

Jandecy Cabral Leite
PhD in Electrical Engineering from the Graduate Program in Engineering, Process, Systems and Environmental Management (PPG-EGPSA), ITEGAM, Brazil.
ORCID: https://orcid.org/0000-0002-1337-3549
Email: jandecycabral@hotmail.com

Abstract

With the expansion of means of river transportation, especially in the case of small and medium-sized vessels that make routes of greater distances, the cost of fuel, if not taken as an analysis criterion for a larger profit margin, is considered to be a primary factor , considering that the value of fuel specifically diesel to power internal combustion machines is high. Therefore, the use of tools that assist in decision-

making becomes necessary, as is the case of the present research, which aims to contribute with a computational model of prediction and optimization of the best speed to decrease the fuel cost considering the characteristics of the SCANIA 315 machine. propulsion model, of a vessel from the river port of Manaus that carries out river transportation to several municipalities in Amazonas. According to the results of the simulations, the best training algorithm of the Artificial Neural Network (ANN) was the BFGS Quasi-Newton considering the characteristics of the engine for optimization with Genetic Algorithm (AG).

Keywords: Internal Combustion Engine (MCI), Optimization and Forecasting, Artificial Neural Networks (RNA), Genetic Algorithm, Meta-heuristics of computing.

1. Introduction

One of the river activities widely practiced is the transportation of cargo and passengers by vessels (DELGADO-HIDALGO, RAINWATER and NACHTMANN, 2020), where the travel flow develops actively according to the vessel's travel needs. However, one of the problems of this mode of transport is the cost of supply, considering that the lack of resources that allow a strategic view of the business is a reality (TAN, DURU and THEPSITHAR, 2020).

Considering the characteristics related to the vessel in terms of estimated travel time, specific fuel oil consumption, average speed and distance, it is possible to analyze intelligent measures to achieve the minimum effort for the engine and, consequently, the reduction of fuel costs, such as occurs in the SCANIA model of power 315hp where the production of emission gases harm the environment according to the relative fuel consumption (HATAMI, HASANPOUR and JING, 2020).

Thus, one of the great difficulties in measuring or analyzing methods that assist in decision making is the lack of intelligent models that optimize or make projections of the best scenario studied (MENZEL *et. al.*, 2020), thus, the idea of the present research arises to contribute with a combination of algorithms for optimization and prediction of fuel consumption that inform the best speed solution for the vessel.

Heuristic computation methods are commonly used in optimization problems where an efficient algorithm is not known, despite the computational effort to find the best solution, it is still a viable procedure when combined with other methods (HOSSEINIOUN *et. al.*, 2020), in the classification of meta-heuristics we have: Genetic Algorithms, Simulated Annealing, Greedy Randomized Adaptive Search Procedure (GRASP), Taboo Search, Ant Colony, Bee Colony and Lichtenberg Algorithm (CHEN *et. al.*, 2020; ABD ELAZIZ, EWEES, OLIVA, 2020). The objective function aims to provide mathematical means of solving the problem to be optimized, however, hybrid models have been used assiduously, showing satisfactory results with regard to approximation of results (GAO *et. al.*, 2020).

Among the existing combination methods is the computational model based on machine learning, Artificial Neural Networks that are inspired by the human nervous system, with this bio-inspired method it is possible to perform pattern recognition, prediction and classification procedures (HUANG *et. al.*, 2020; FAGUNDEZ *et. al.*, 2020). The application of the aforementioned methods allows the combination of algorithms for optimization and prediction where finding the best solution to the fuel consumption problem of vessels using internal combustion machines is the problem (FAGUNDEZ *et. al.*, 2020). Thus, the research aims to develop a computational model for optimizing and predicting the best speed for the characteristics of the SCANIA 315hp engine considering the reduction in fuel consumption.

2. Theoretical Reference

2.1 Internal Combustion Engines (MCI)

The engine that is one of the inventions that caused great impacts on society, the economy and the environment, are machines that transform energy from chemical reactions into mechanical energy (FAGUNDEZ *et. al.*, 2020; HATAMI, HASANPOUR and JING, 2020). These engines that are commonly used to propel mobile systems are also used in industrial applications such as oil, gas, compression, quarrying, recycling and power generation (SHEYKHI *et. al.*, 2020; BASKOV, IGNATOV and POLOTNYANSCHIKOV, 2020).

These diesel engines are characterized by compression ignition, machines that propel heavy vehicles such as trucks, trains and ships are based on diesel-electric propulsion (FAGUNDEZ *et. al.*, 2020; SILVA et. al., 2019). The reciprocating movement of the piston inside the cylinder is transformed into a rotary movement through the connecting rod and crankshaft (SILVA *et. al.*, 2019). In 4-stroke engines where gases are used, a thermodynamic cycle is completed every two turns on the shaft, at which time admission and compression occurs in one turn and heat transfer in the second (BERTONI JUNIOR, 2020; SINGH, KUMAR and AGARWAL, 2020). The largest marine propulsion engines, Diesel operate in 2 times with the use of only one window and a valve on the cylinder head. Figure 1 illustrates a schematic of a piston internal combustion engine.

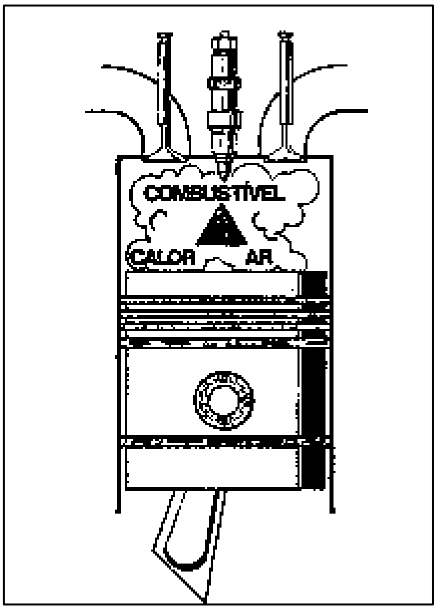

Figure 1: Piston MCI scheme.
Source: Adapted from (DALPRÁ, 2020).

The engine is divided into fixed and moving parts, the fixed ones are: block, crankcase and head, the furniture are: crankshaft, piston, connecting rod and valve control (SINGH, KUMAR and AGARWAL, 2020). The following are some of the component parts of an internal combustion machine as a way of exemplifying the process of composition and operation of the same.

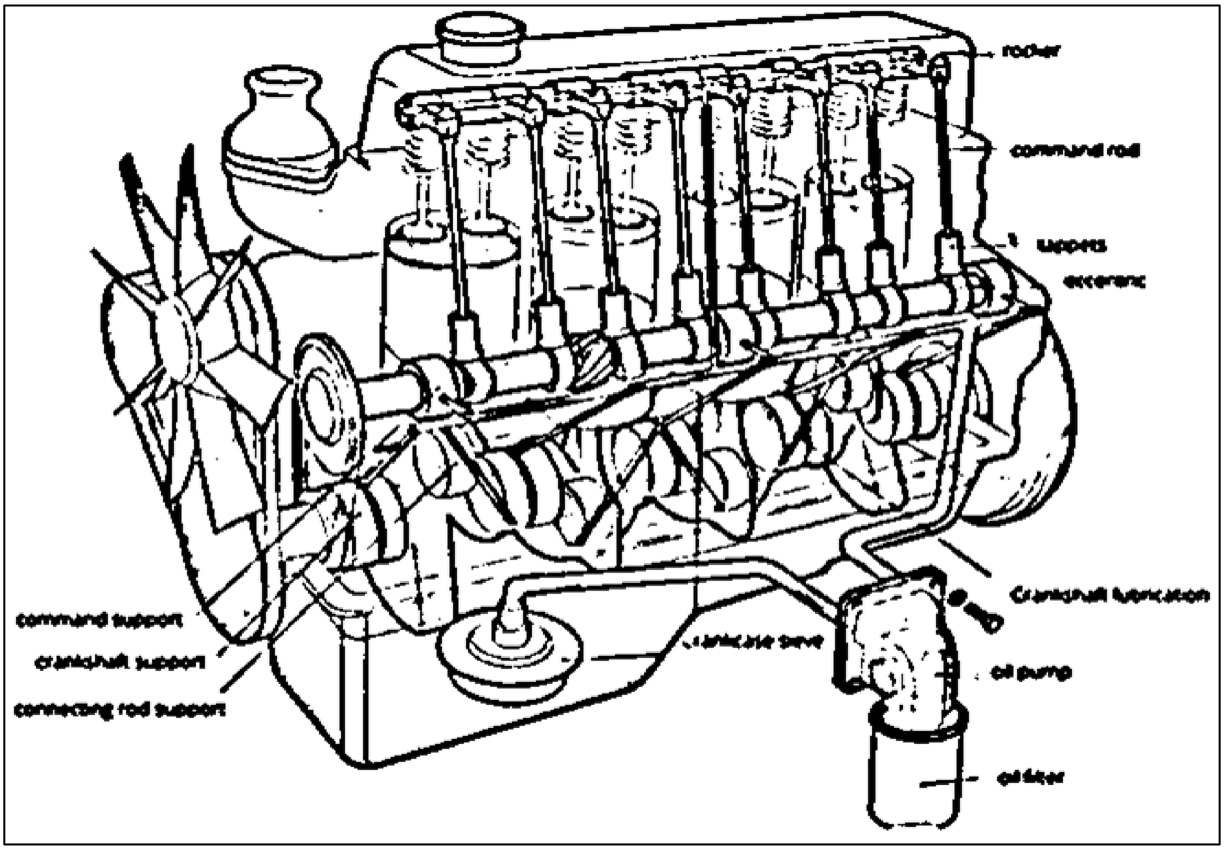

Figure 2: Schematic of a SCANIA MCI model.
Source: Adapted from (JUNIOR and CALLADO, 2020).

The cylinder is the part that receives the movement of gas expansion, normally made of aluminum or aluminum alloy with a cylindrical shape, the middle part is called a cup where there are two circular holes to accommodate the piston shaft that connects it to the connecting rod (SINGH, KUMAR and AGARWAL, 2020; SILVA *et. al.*, 2019). Figure 4 shows a piston or piston inside a cylinder.

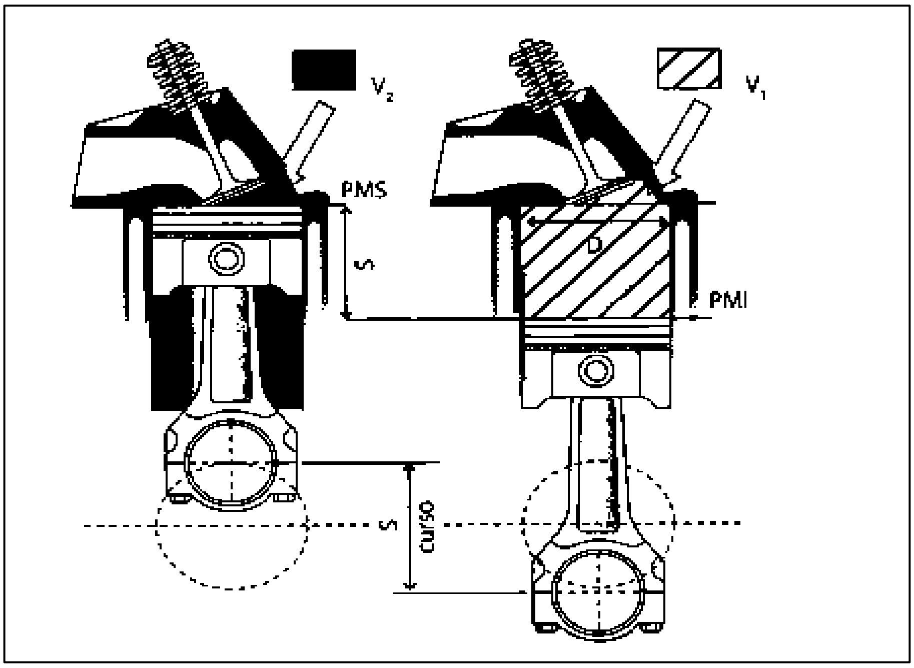

Figure 3: Piston inside a cylinder.
Source: (BRUNETTI, 2018).

To understand the engine displacement, it is necessary to understand the unit displacement also known as useful displaced volume (RUFINO *et.al.*, 2020; BRUNETTI, 2018), the displacement of the volume is obtained by equation 1:

$$V_u = \frac{\pi \, . D^2}{4} S = V_1 - V_2 \qquad (1)$$

Where:
S = piston stroke;
V_1 = Volume of the entire cylinder;
V_2 = Volume of the combustion chamber;
D = Diameter of the cylinder
The total engine capacity is obtained by equation 2:

$$V = V_u . Z \qquad (2)$$

Where:
V_u = Unit volume;
Z = cylinders that the engine has

The compression ratio of the engine is the volumetric relationship between the volume of the entire cylinder and the volume of the combustion chamber (RUFINO *et.al.*, 2020; BRUNETTI, 2018), obtained by equation 3:

$$T_c = \frac{V_1}{V_2} \qquad (3)$$

Where:
V_1 = Volume of the entire cylinder;
V_2 = Volume of the combustion chamber;

The power of an engine is defined as the work performed in a unit of time (RUFINO *et.al.*, 2020; BRUNETTI, 2018), obtained through equation 4:

$$\bar{W} = \frac{F . d}{t} \qquad (4)$$

Where:
$\bar{W}$ = power expressed in cv, ps, hp or watts;
F = intensity of the force;
d = distance between the axis and the force;
t = time

2.2 Computation meta-heuristics

A meta-heuristic can be understood as an unspecified search strategy for a given problem, which tries to efficiently explore the search space, that is, it takes into account the neighborhood. Some authors classify the meta-heuristics in: Search for surroundings, Relaxation, Constructive, Evolutionary (WANG *et. al.*, 2020). Some of the optimization algorithms known to be classified as metaheuristics are: Genetic Algorithms, Simulated Annealing, Greedy Randomized Adaptive Search Procedure (GRASP), Taboo Search, Ant Colony, Bee Colony and Lichtenberg Algorithm (CHEN *et. al.*, 2020; ABD ELAZIZ, EWEES, OLIVA, 2020).

2.3 Systems Optimization

The search strategy for a meta-heuristic depends on the methodology of escaping local and global minimums in order to efficiently explore the search space for better solutions (WANG *et. al.*, 2020; NASCIMENTO *et. al.*, 2017).

Whether f is a function with domain $S,$ characterized as a cost function or objective function, there is a minimization problem when given f one wants to find $s \epsilon S$ such that $f(s) \leq f(S), \forall\, s \epsilon S$, if the goal is to find an $s \epsilon S$ such that $f(s) \geq f(S), \forall\, s \epsilon S$, then you have a maximization problem (OSABA *et. al.*, 2020).

Thus, a global optimum point represents the maximum or minimum point corresponding to the best solution of the search space while a local optimum point represents the maximum or minimum point among a set of limited points. (WANG *et. al.*, 2020; OSABA *et. al.*, 2020). Figure 6 illustrates an example of a search space with local and global minimums.

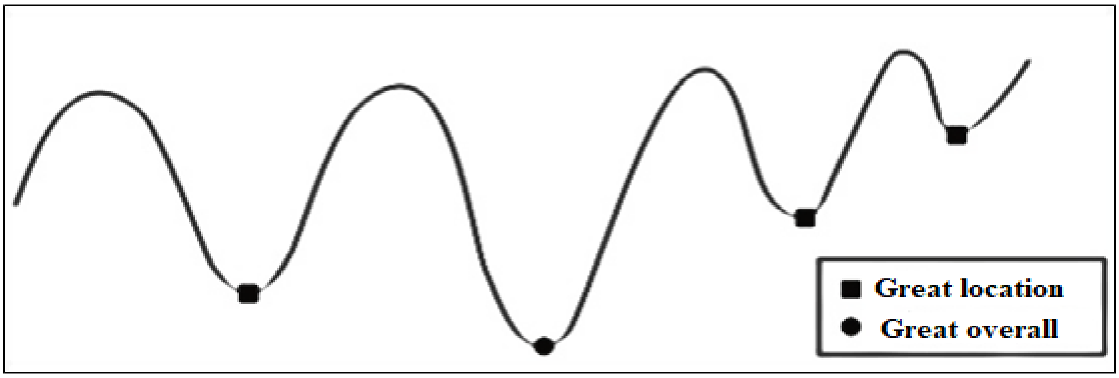

Figure 4: Local and global minima.
Source: Adapted from (SCHELLENBERG, LOHAN and DIMACHE, 2020).

Optimization problems with constraints consider limits for AG variables defined by a number n_{restr} functions $g_{nrestr} : \Re^n \longrightarrow \Re$, which originate a subset $F = \{\vec{x} \in M | g_j(\vec{x}) \geq 0 \forall j\} \subseteq M$, known as a set of viable solutions for f (SCHELLENBERG, LOHAN and DIMACHE, 2020).

2.4 Genetic Algorithm

It is a class of algorithm that performs search procedures based on the concept of natural selection and survival of the fittest individual, composed of a sequence of computational routines in order to simulate evolutionary behavior (WANG *et. al.*, 2020; NASCIMENTO *et. al.*, 2017).

```
function Genetic Algorithm(pop, objective) out: bestIndividual
  inputs: definition pop;
          definition objective
do
    parentSelection(pop)
    recombination(pop)
    mutation(pop)
    evaluation(pop)
    apt(pop)
while don`t hit stop
return bestIndividual
```

Figure 5: AG Model.

Initial population: The AG initializes a population at random, that is, through computational draw, this procedure becomes essential for the coding of strings according to the formation blocks (HUI, ZENG and YU, 2020). Table 1 shows an example of populations in GA.

Table 1: Types of individuals.

		Population 1	**Population 2**	
Individual	**1**	0101100001101	17.1	7.9
	2	0101111001101	21.3	8.1
		...	...	
	3	0101100001010	15.7	6.8

Source: Adapted from (HUI, ZENG and YU, 2020).

Selection: For the selection of individuals some algorithms can be used, which are (HUI, ZENG and YU, 2020):

- ***Proportional Selection:*** *known as the Roulette Rule, it draws individuals for crossing, where the probability of drawing an individual* i *is given by* $p_i = \Phi(a_i)/\sum_{j=1}^{u}\Phi(a_j)$, *where u represents the population size and* $\Phi: B^l \longrightarrow \mathcal{R}^+$, *the evaluation function.*
- ***Scheduling:*** *each individual is evaluated to recalculate in* $f' = a.f + b$, *where f is the original evaluation function and the coefficients a and b can be chosen in other ways.*
- ***Selective Pressure:*** *method used to assess the assessment value of individuals that varies according to pressure, which increases or improves the exploration of the search space, tending to converge faster.*
- ***Tournament:*** *draws two individuals for crossing and selects the one with the best rating to participate in a crossing.*
- ***Linear Ranking:*** *In this method the population is ordered according to the evaluation values of each individual, where the probability of the individual's drawing is given by the equation:*$p_i(a_i^g) = 1/\lambda(n_{max} - (n_{max} - n_{min}).\frac{i-1}{\lambda-1})$, *where* n_{min} *= 2 -* n_{max} *e 1* $\leq n_{max} \leq 2$, a_i^g *corresponds to individual i and* λ *is the number of individuals in the population g.*

2.5 Elitism

Elitism consists of reintroducing a fit individual from one generation to the next avoiding the loss of important information, there are techniques that determine or control the amount of reintroductions from an individual to the next generation in order to escape local maximums (HUI, ZENG and YU, 2020; SCHELLENBERG, LOHAN and DIMACHE, 2020).

2.6 Crossing

The crossing is summarized in an exchange of substrings between two individuals, this operator recombines solutions and favors a better exploration of the search space. There are some methods for recombination: they are single, multiple and uniform (HUI, ZENG and YU, 2020).

2.7 Mutation

An evolutionary algorithm is able to encode a mutation probability in the individual, as long as there is a different value for crossing between individuals, throughout the execution it is expected that the mutation value will tend to smaller values contributing to the convergence of the same when finding the optimum point in a search space (HUI, ZENG and YU, 2020).

2.8 Artificial Neural Networks

They are computational techniques that present a mathematical model inspired by the human neural structure, through mathematical procedures it is possible to store information and generate knowledge (DADA *et. al*., 2021). The behavior of an ANN comes from the interactions between the processing units of the network.

However, in order to obtain the best performance in the classification, pattern recognition and prediction processes, it is necessary to have the necessary configurations of the ANN architecture, such as the definition of the activation function, number of layers, number of neurons, learning rate, number of iterations and choice of training algorithm (DADA *et. al.*, 2021). Table 2 presents some activation functions used in the configuration of neuron layers.

Table 2: Activation functions.

Acronyms	Function	Expression
Sigmoid	Sigmoid	$\sigma = \frac{1}{1+e^{x}}$
TanH	Hyperbolic Tangent	$tanh(x) = 2\sigma(2x) - 1$ $tanh'(x) = 1 - tanh^2(x)$
ReLU	Rectified Linear Unit	$ReLU(x) = \max\{0, x\}, sendo \begin{cases} 1, se\ x \geq 0 \\ 0, c.c \end{cases}$
ELU	Exponential Linear Unit	$ELU(x,\alpha) = \begin{cases} x, se\ x \geq 0 \\ \alpha(e^{x}-1), se\ c.c \end{cases}$ $ELU'(x,\alpha) = \begin{cases} 1, se\ x \geq 0 \\ ELU(x,\alpha)+\alpha, se\ c.c \end{cases}$
Leaky ReLU	Leaked Rectified Linear Unit	$LeakyReLU(x,\alpha) = \max\{\alpha x, x\}$ $LeakyReLU'(x,\alpha) = \begin{cases} 1, se\ x \geq 0 \\ \alpha, se\ c.c \end{cases}$

Source: Adapted from (Koçak and Üstündağ Şiray, 2021).

In addition, it is necessary to define the network architecture by configuring the number of hidden layers to be used and the number of neurons, thus the need for variation goes according to the convergence state of the simulation that can be analyzed by the Mean Square Error (KOÇAK and ÜSTÜNDAĞ ŞIRAY, 2021).

Finally, the definition of the training algorithm that depends on the formality of the problem to be solved, definition of the data set for training the network, as well as the target data of the simulation (BOOB, DEY and LAN, 2020). In short, the choice of the algorithm allows to obtain a precision in the approximation of functions in the training state and a shorter convergence time, guaranteeing an optimized accuracy in learning.

For Mohammadi *et. al*. (2020) Among the existing training algorithms are: Levenberg-Marquardt, Bayesian Regularization, Broyden – Fletcher – Goldfarb – Shanno Quasi-Newton, Resilient Backpropagation, Scaled Conjugate Gradient, Conjugate Gradient with Powell/Beale Restarts, Fletcher-Powell Conjugate Gradient, Polak-Ribiére Conjugate Gradient, One Step Secant and Gradient Descent.

3. Materials and Methods

For this study, an on-site visit and interviews with specialists were carried out to ascertain the feasibility of the study through the granting of travel records related to the Manaus River Port, where the flow of vessels that carry out the river transportation is frequent, according to the interviews the vessels transport cargo and passengers to several locations in the northern region of the state of Amazonas - Brazil. The data collected from documentary records and experiences of owners and seafarers are from 2018 to 2019.

3.1 Collection and analysis of vessel data and the engine under study

Among the 14 vessels registered to carry out river transport legally, 1 was chosen for the study and which has the following characteristics, figure 6 illustrates an example of the machine under study, on the left side the SCANIA model and on the right a ZF reverser 3x1:

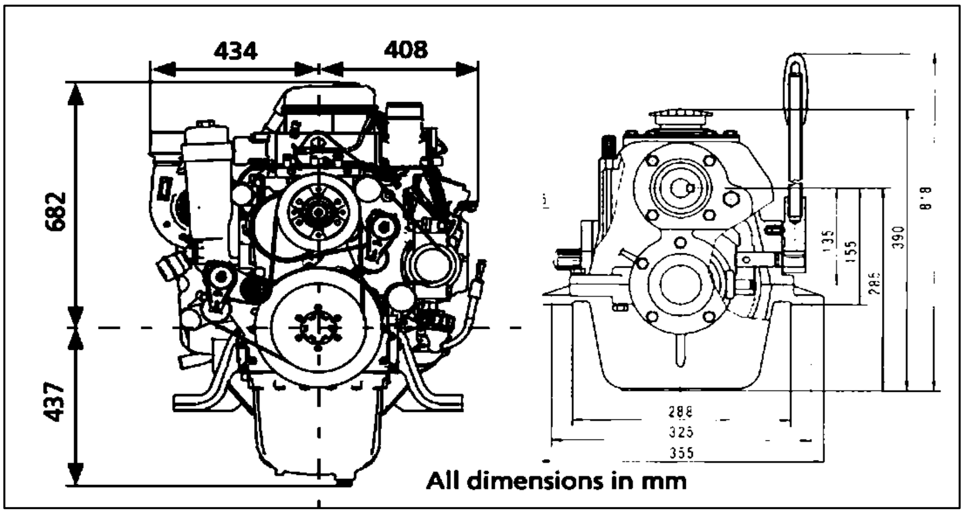

Figure 6: SCANIA machine models and ZF 3X1 reverser.
Source: Adapted from (SCANIA, 2020; ZF, 2020).

- **Vessel name:** Fábio Júnior VI;
- **Length:** 16m;
- **Capacity:** 50 passengers;
- **Type of vessel:** Iron;
- **Allocation:** GRAFA Navigation.

The aforementioned vessel has an internal combustion engine in which it has the following characteristics:

Brand: SCANIA;
Model: Propulsion;
Power: 315 hp;
Number of cylinders: 5;
Weight: 950kg;
Piston speed at 1500 rpm: 7,0 m/s;
Piston speed at 1800 rpm: 8,4 m/s;
Piston type: aluminum;
Oil capacity: from 31 to 36 dm^3
Reverser: zf 3x1 W220;
Reed: aluminum with 3 blades;
Reduction ratio: between 1800 rpm to 2800 rpm;
Approximate oil capacity: 8L;
Approximate dry weight: 105 kg;

3.2 Choice of variables for the optimization model

Thinking about the necessary requirements to implement a computational model that allows the optimization of fuel consumption, the following variables were analyzed and chosen:

- Nautical miles;
- Distance in KM;
- Consumption in Liters.

For this, a temporal analysis from 2018 to 2019 was carried out with travel records and experts' experiences, which allowed a standardized database for the study to be popular, which will be used to train the best ANN model.

3.3 Computational Model for Forecasting and Optimization

In this stage, a bibliographic study of the existing forecasting techniques and models was carried out, in addition, the other Neural Network architectures, training approach and computation meta-heuristics were considered to carry out the forecasting and optimization procedures.

To choose the best RNA architecture, the algorithm classifies among 12 models, namely: Levenberg-Marquardt, Bayesian Regularization, Broyden – Fletcher – Goldfarb – Shanno Quasi- Newton, Resilient Backpropagation, Scaled Conjugate Gradient, Conjugate Gradient with Powell/Beale Restarts , Fletcher-Powell Conjugate Gradient, Polak-Ribiére Conjugate Gradient, One Step Secant and Gradient Descent the best for predicting the parameters that are used in the Simple Genetic Algorithm. Figure 7 illustrates the steps that were taken to consolidate the algorithm.

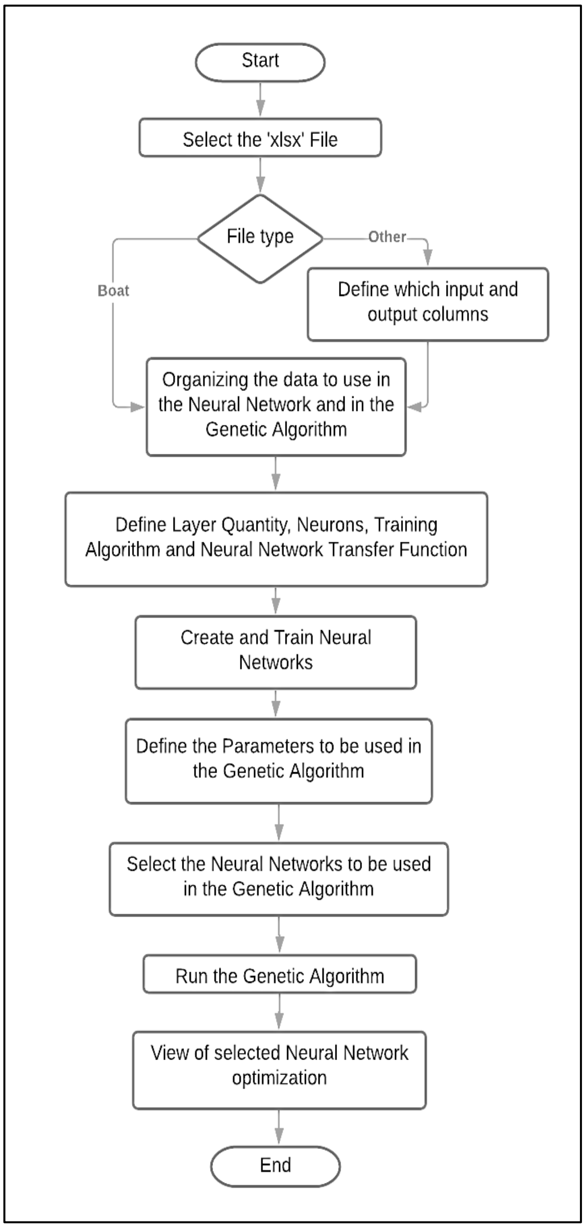

Figure 7: Flowchart of the Algorithm.

The algorithm was dynamically designed to meet the needs of other vessels with other specifications, the algorithm reads the important variables and performs the proper procedures for standardization and data organization, this is done through the MatLab 2016a software.

In this way, the algorithm defines the RNA configurations, later it creates and trains the network and with the defined parameters it is passed to the genetic algorithm where it identifies the optimum speed point considering the model input variables, in the end the algorithm displays the information of the winning RNA models, the optimization model prepared for the simulation and the results.

3.4 Analysis and comparison of the results obtained

To carry out the analysis and comparison of the results, the forecasting model compares the 12 training algorithms of the ANN and through the mean square error it chooses the best forecasting architecture for the optimization model.

- For the stage of training and validation of RNA models, the following configurations were used:
- 70% of the data for training;
- 15% of the data for validation;
- 15% of the test data.

The configurations of the machine that was used to perform the training and simulation of the data were: 16GB of RAM, 10th generation core i5 processor with 2.50 GHZ frequency, 8 processing cores and 500 GB of SSD.

The data used for the network simulation were the same as the input data to validate the accuracy of the model and design forecast scenarios. In addition, to achieve the results presented in the next section, the following RNA architecture configuration was used, which is illustrated in figure 8.

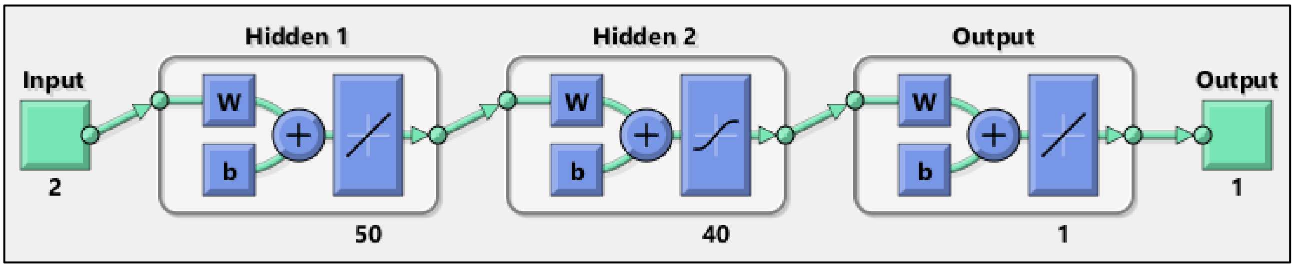

Figure 8: RNA architecture.

Finally, with the data adjusted by the network, the simulation parameters are defined using the genetic algorithm to optimize fuel consumption based on the characteristics already surveyed of the vessel and the engine. In the end the user has a survey of the best neural networks and the results of the optimization.

3.5 Simulation scenarios

Having in hand the results of the best architectures and configurations of neural networks, the necessary configurations and parameterizations for the genetic algorithm were carried out in order to collect the results of optimization of fuel consumption and the prediction of the best speed based on 3 scenarios with a path designed for vessels where distance data was collected from the Rom2Rio platform, which aims to plan trips in advance to any location in the world in a safe and easy way, with transport options: flight, train, bus, boat or car.

Figure 9 illustrates the path that should be taken by a vessel leaving Manaus to Itacoatiara, where the distance is 195.30 km.

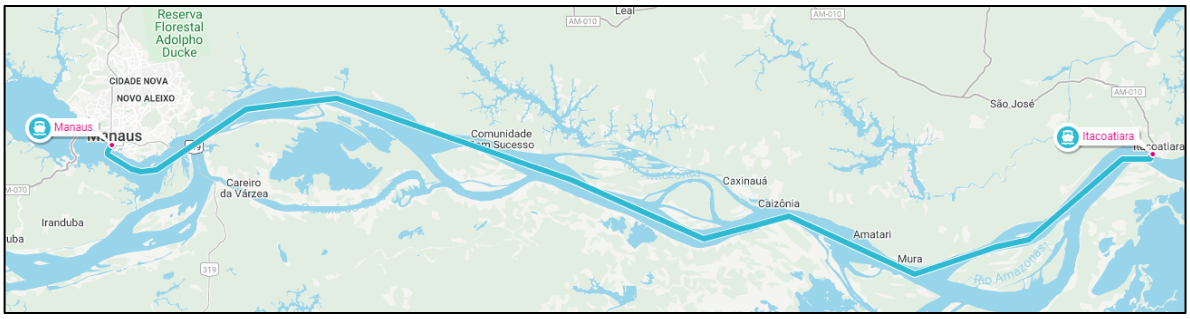

Figure 9: Route Manaus to Itacoatiara.

Source: (ROM2RIO, 2021).

Figure 10 illustrates the route that should be taken in the second scenario by a vessel from Manaus to Parintins, where the distance is given by 433.75 km.

Figure 10: Route Manaus to Parintins.

Source: (ROM2RIO, 2021).

Finally, the last scenario is intended for the route from Manaus to Barcelos, totaling a distance of 440.98 km, both scenarios are designed for vessels.

Figure 11: Route Manaus to Barcelos.

Source: (ROM2RIO, 2021).

4. Results

Results of the best rna arquitectures

Table 3 presents the results achieved with the training of the parameters that serve as the basis for the Genetic Algorithm, according to Table 3 the network model that presented the highest success rate and the minimum error was the number 1 the Bayesian Regularization algorithm using the Sigmoide transfer function in the input and intermediate layers, this model showed 99% accuracy and a mean square error rate of 2.105840896.

Table 1: Results of best RNA.

#	Algorithm	Transfer Function	MSE	RMSE	NRMSE	MAPE	R
1	Regularização Bayesiana	Sigmoide	4,737465996	2,105840896	0,006289984	0,916017157	0,99997

As shown in figure 12, the best error performance is achieved at the 1000th time of the Bayesian Regularization training algorithm, where the training stood out with a rate of 4.80 average square error, the figure allows us to understand that the state of convergence is stabilized characterizing the optimal point of the function, in this way the trend curve decreases over time, reducing the error rate to a point. where it is stable.

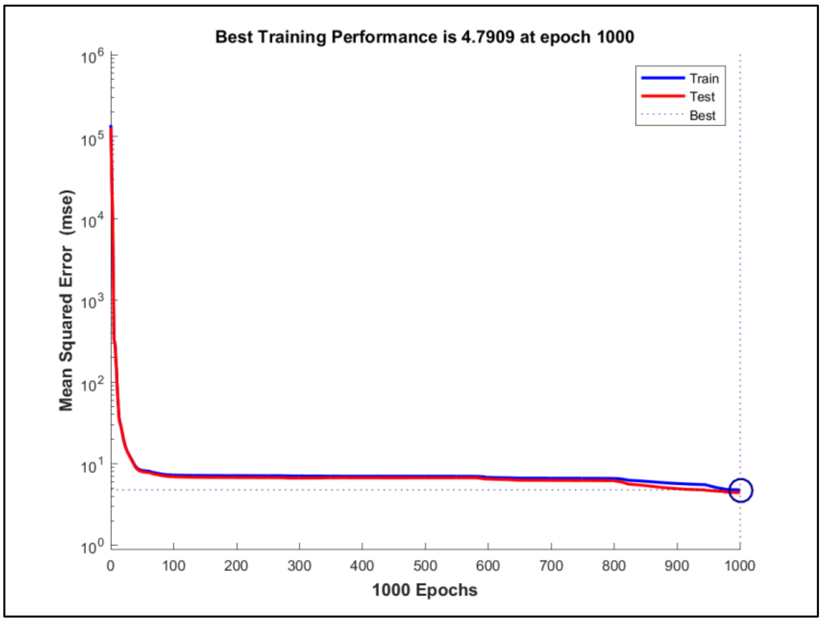

Figure 12: Error performance.

According to figure 13, it is possible to identify the regression results related to training, validation, test and the average of both, where the values coincide with the model's accuracy rate, characterizing 99% accuracy, with this, the line of trend of each result is close to the target line and the points found in accordance with the simulated values are close to the trend line showing the correlation between the resulting target and simulated vectors.

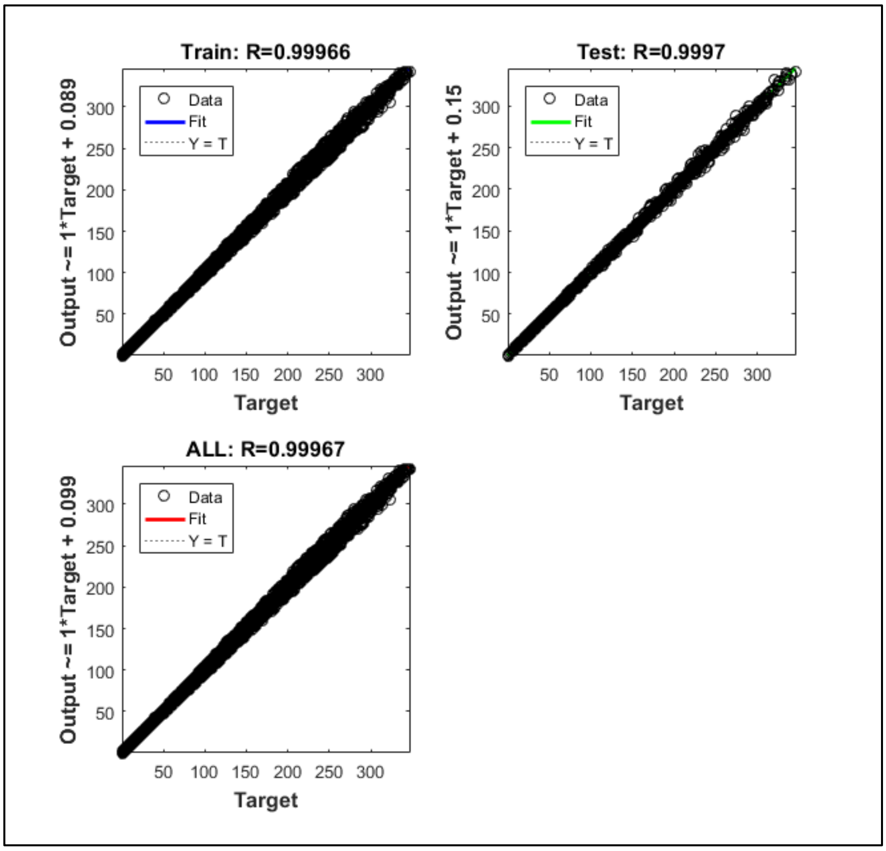

Figure 13: Result of regression of correct answers

Resultados of optimization

For the simulation of a trip from Manaus to Itacoatiara, the AG configuration parameters were:

- Population: 50;
- Máximum generations: 100;
- Fitness: 20;

Simulation at Manaus à Itacoatiara

Table 4 presents the results achieved from the optimization with genetic algorithm, taking as a scenario the trip from Manaus to Itacoatiara, the winning model is the BFGS Quasi- Newton, where the values related to the optimization are presented in Table 4, with the lowest consumption in liters 77.346281 at a speed of 81.030869 km.

Table 2: Optimization at Manaus à Itacoatiara.

#	Training algorithm	Distance in Nautical miles	Distance in KM	Speed in KM	Consumption in liters
1	Bayesian Regularization	105.453564	195.300000	81.030869	77.346281

Figure 14 illustrates two graphs indicating the best individual among 1000 generations and the average achieved for each generation, according to the graph, the best optimization result is given by 78.0781 for fuel consumption.

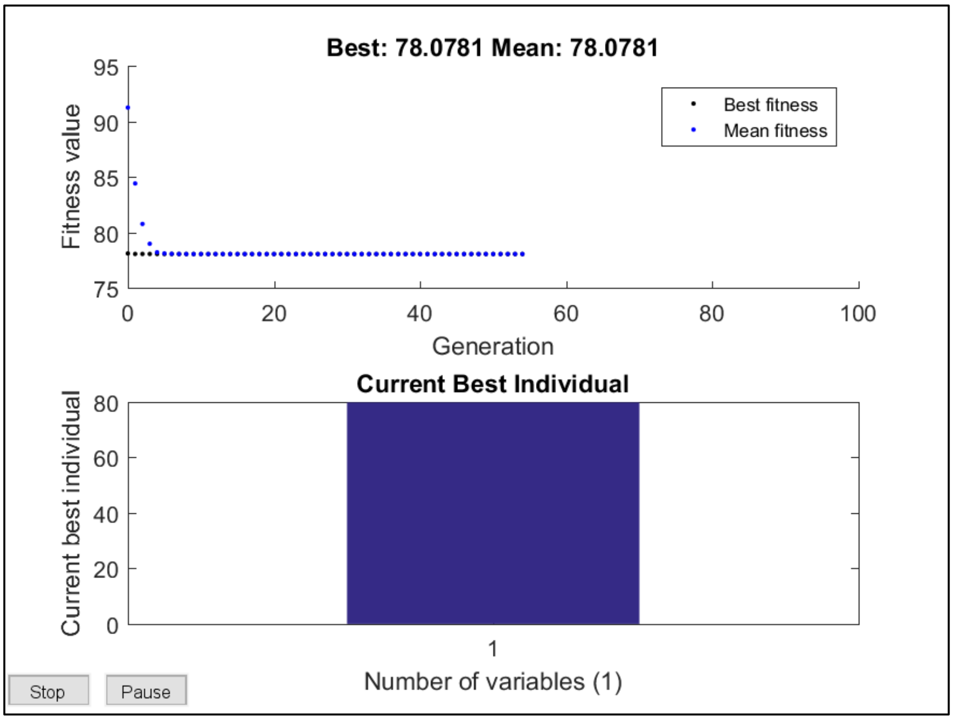

Figure 14: Generation of the best individuals from Manaus to Itacoatiara

Simulation at Manaus à Parintins

Table 5 presents the results obtained from the optimization with genetic algorithm, taking as a scenario the trip from Manaus to Parintins, the winning model is the Bayesian Regularization where the values related to the optimization are presented in the table, with the lowest consumption in liters 171.926091 at a speed 79.101562 km.

Table 3: Optimization at Manaus à Parintins.

#	Training algorithm	Distance in Nautical miles	Distance in KM	Speed in KM	Consumption in liters
1	Bayesian Regularization	234.206263	433.750000	79.101562	171.926091

Figure 15 illustrates two graphs indicating the best individual among 1000 generations and the average achieved for each generation, according to the graph, the best optimization result is given by 173.519 for fuel consumption.

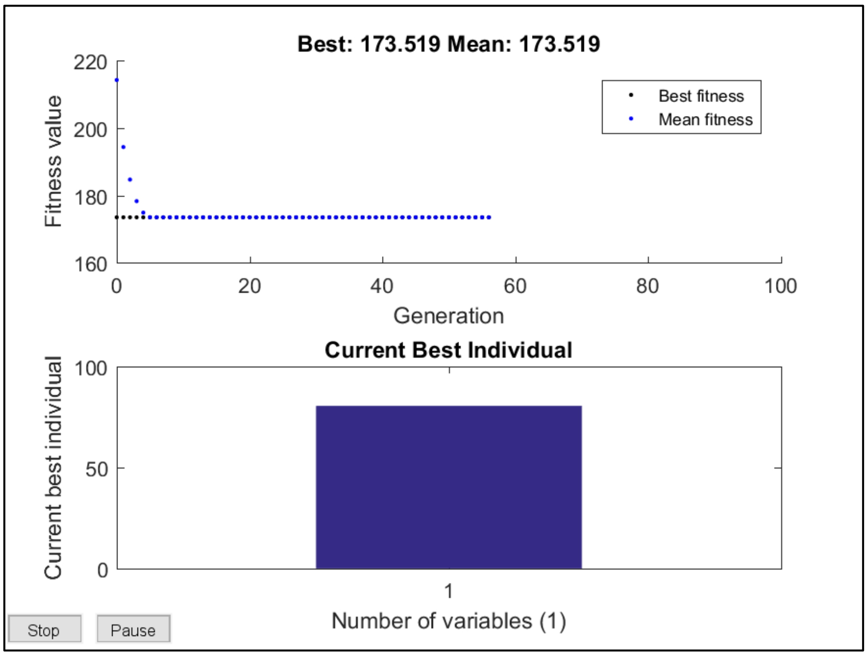

Figure 15: Generation of the best individuals at Manaus to Parintins.

Simulation at Manaus à Barcelos

Table 6 shows the results achieved from the optimization with genetic algorithm, taking as a scenario the trip from Manaus to Barcelos, the winning model is the Bayesian Regularization where the values related to the optimization are presented in the table, with the lowest consumption in liters 174.791856 at a speed 79.101562 km.

Table 6: Optimization at Manaus à Barcelos.

#	Training algorithm	Distance in Nautical miles	Distance in KM	Speed in KM	Consumption in liters
1	Bayesian Regularization	238.110151	440.980000	79.101562	174.791856

Figure 16 illustrates two graphs indicating the best individual among 1000 generations and the average achieved for each generation, according to the graph the best optimization result is given by 176.405 for fuel consumption.

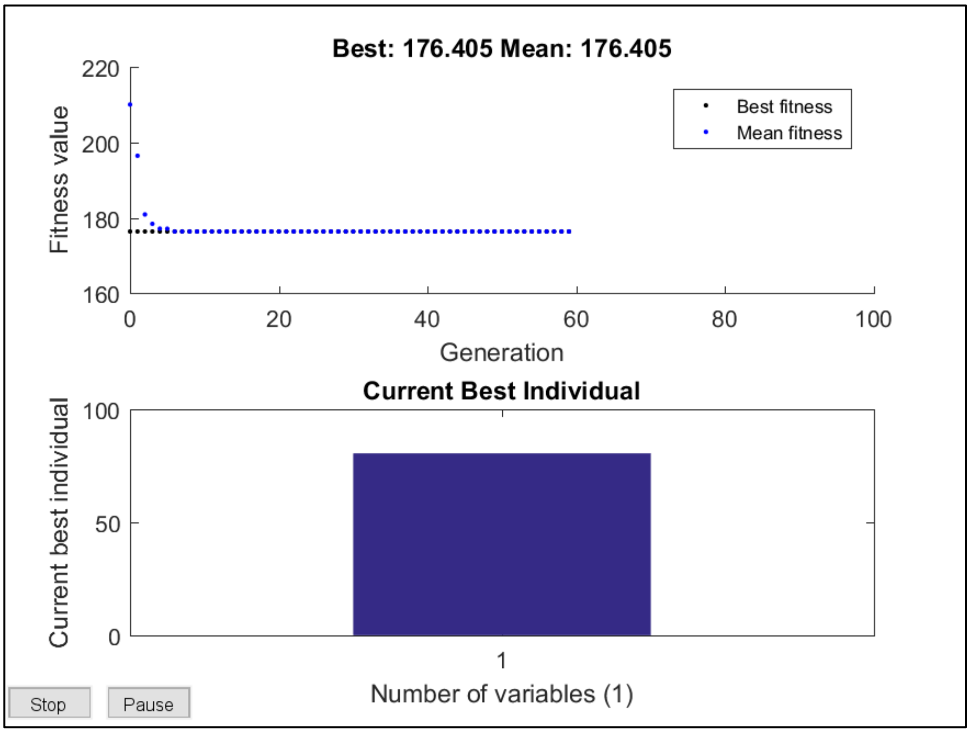

Figure 16: Generation of the best individuals from Manaus to Barcelos.

5. Conclusion

During the development of this work it was possible to identify opportunities for new research, considering that other resources can be explored with regard to the optimization of internal combustion engines, in addition to the continuous improvement of transport logistics with tools that learn routes and consult other databases to design scenarios of possible failures and act in decision making with better routes.

Among the training algorithms used in machine learning, it was possible to highlight and highlight the Bayesian Regularization to minimize fuel consumption considering the 3 simulated scenarios from Manaus to Itacoatiara, Manaus to Parintins and Manaus to Barcelos, with which it is possible to identify the values minimums for time spent and consumption in liters.

6. Acknowledgment

Acknowledgments to the Graduate Program in Engineering, Process, Systems and Environmental Management (PPG-EGPSA) and to the Galileo da Amazônia Institute of Technology and Education (ITEGAM).

7. References

ABD ELAZIZ, Mohamed; EWEES, Ahmed A.; OLIVA, Diego. Hyper-heuristic method for multilevel thresholding image segmentation. **Expert Systems with Applications**, v. 146, p. 113201, 2020.

BASKOV, Vladimir; IGNATOV, Anton; POLOTNYANSCHIKOV, Vladislav. Assessing the influence of operating factors on the properties of engine oil and the environmental safety of internal combustion engine. **Transportation Research Procedia**, v. 50, p. 37-43, 2020.

BERTONI JUNIOR, Ivan Luiz. Análise de desempenho e emissões de um motor ciclo diesel operando com fumigação de água e etanol super-hidratado. 2020.

BOOB, Digvijay; DEY, Santanu S.; LAN, Guanghui. Complexity of training relu neural network. **Discrete Optimization**, p. 100620, 2020.

BRUNETTI, Franco. Introdução ao estudo dos motores de combustão interna. In: MOTORES DE COMBUSTÃO INTERNA VOLUME 1, São Paulo, Edgard Blücher Ltda. 2018.

CHEN, Ming et al. Heuristic algorithms based on deep reinforcement learning for quadratic unconstrained binary optimization. **Knowledge-Based Systems**, v. 207, p. 106366, 2020.

DADA, Emmanuel Gbenga et al. Predicting protein secondary structure based on ensemble Neural Network. **ITEGAM-JETIA**, v. 7, n. 27, p. 49-56, 2021.

DALPRÁ, Agustinho J. et al. Experimentação planejada para análise dos fatores que influenciam os pontos ótimos de funcionamento de um motor de combustão interna. 2020.

DELGADO-HIDALGO, Liliana; RAINWATER, Chase; NACHTMANN, Heather. A computational comparison of cargo prioritization and terminal allocation problem models. **Computers & Industrial Engineering**, v. 144, p. 106450, 2020.

FAGUNDEZ, J. L. S. et al. Joint use of artificial neural networks and particle swarm optimization to determine optimal performance of an ethanol SI engine operating with negative valve overlap strategy. **Energy**, v. 204, p. 117892, 2020.

GAO, K. Z. et al. A survey on meta-heuristics for solving disassembly line balancing, planning and scheduling problems in remanufacturing. **Swarm and Evolutionary Computation**, v. 57, p. 100719, 2020.

HATAMI, Mohammad; HASANPOUR, Maryam; JING, Dengwei. Recent developments of nanoparticles additives to the consumables liquids in internal combustion engines: Part I: Nano-fuels. **Journal of Molecular Liquids**, p. 114250, 2020.

HOSSEINIOUN, Pejman et al. A new energy-aware tasks scheduling approach in fog computing using hybrid meta-heuristic algorithm. **Journal of Parallel and Distributed Computing**, v. 143, p. 88-96, 2020.

HUANG, Renfang et al. Energy performance prediction of the centrifugal pumps by using a hybrid neural network. **Energy**, v. 213, p. 119005, 2020.

HUI, Tianyu; ZENG, Wenjie; YU, Tao. Core power control of the ADS based on genetic algorithm tuning PID controller. **Nuclear Engineering and Design**, v. 370, p. 110835, 2020.

JUNIOR, José Tomadon; CALLADO, Raphael Tavares. Avaliação comparativa do ciclo de vida de materiais usados em blocos de motor. **Tópicos em Administração Volume 34**, p. 43. 2020.

Koçak, Y., & Üstündağ Şiray, G. New activation functions for single layer feedforward neural network. **Expert Systems with Applications**, 164, 113977. doi:10.1016/j.eswa.2020.113977. 2021.

MENZEL, Germano et al. Multi-objective optimization of the volumetric and thermal efficiencies applied to a multi-cylinder internal combustion engine. **Energy Conversion and Management**, v. 216, p. 112930, 2020.

MOHAMMADI, Farzaneh et al. Modeling and sensitivity analysis of the alkylphenols removal via moving bed biofilm reactor using artificial neural networks: Comparison of levenberg marquardt and particle swarm optimization training algorithms. **Biochemical Engineering Journal**, v. 161, p. 107685, 2020.

NASCIMENTO, Manoel Henrique Reis et al. New solution for resolution of the economic load dispatch by different mathematical optimization methods, turning off the less efficient generators. **Journal of Engineering and Tecnology for Industrial Aplications**, v. 3, p. 10, 2017.

OSABA, Eneko et al. Community detection in networks using bio-inspired optimization: Latest developments, new results and perspectives with a selection of recent meta-heuristics. **Applied Soft Computing**, v. 87, p. 106010, 2020.

ROME2RIO. https://www.rome2rio.com/pt/. Consultado em: 08/04/2021.

RUFINO, Caio Henrique et al. Conceptual study of an internal combustion engine with adjustable cubic capacity and compression ratio: Estudo conceitual de um motor com cilindrada e taxa de compressão ajustáveis. 2020.

SCANIA. DC09 074A. 232 kW (315 hp) EU Stage II, China Phase II and Russia Stage I. 2020.

SCHELLENBERG, Christoph; LOHAN, John; DIMACHE, Laurentiu. Comparison of metaheuristic optimisation methods for grid-edge technology that leverages heat pumps and thermal energy storage. **Renewable and Sustainable Energy Reviews**, v. 131, p. 109966, 2020.

SHEYKHI, Mohammad et al. Investigation of the effects of operating parameters of an internal combustion engine on the performance and fuel consumption of a CCHP system. **Energy**, v. 211, p. 119041, 2020.

SILVA, Jean da Silva de Abreu et al. PROPOSTA DE IMPLANTAÇÃO DE SISTEMA DE PROTEÇÃO CONTRA POTENCIAL DE FALHA DO MOTOR À DIESEL (DISPARO DO MOTOR). **ITEGAM-JETIA**, v. 5, n. 19, p. 06-11, 2019.

SINGH, Akhilendra Pratap; KUMAR, Vikram; AGARWAL, Avinash Kumar. Evaluation of comparative engine combustion, performance and emission characteristics of low temperature combustion (PCCI and RCCI) modes. **Applied Energy**, v. 278, p. 115644, 2020.

TAN, Roy; DURU, Okan; THEPSITHAR, Prapisala. Assessment of relative fuel cost for dual fuel marine engines along major Asian container shipping routes. **Transportation Research Part E: Logistics and Transportation Review**, v. 140, p. 102004, 2020.

WANG, Xiaoming et al. Meta-heuristics for unrelated parallel machines scheduling with random rework to minimize expected total weighted tardiness. **Computers & Industrial Engineering**, v. 145, p. 106505, 2020.

ZF. Reversor Marítimo Marine Gearbox ZF W220. 2020.