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Deep learning neural networks to decide whether to operate the 174K Liquefied Natural Gas Carrier's Gas Combustion Unit

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Abstract : *Gas Combustion Unit (GCU) onboard liquefied natural gas carriers handles boil-off to stabilize tank pressure. There are many factors for LNG cargo operators to take into consideration to determine whether to use GCU or not. Gas consumption of main engine and re-liquefied gas through the Partial Re-Liquefaction System (PRS) are good examples of these factors. Human gas operators have decided the operation so far. In this paper, some deep learning neural network models were developed to provide human gas operators with a decision support system. The models consider various factors specially into GCU operation. A deep learning model with Sigmoid activation functions in input layer and hidden layers made the best performance among eight different deep learning models.*

Key words : *neural networks, deep learning model, activation function, gas combustion unit, boil-off gas*

1. Introduction

The less natural gas gets combusted by Gas Combustion Unit (GCU) onboard liquefied natural gas carriers, the more optimized gas operation could be achieved either commercially or environmentally for gas shipping companies. So it is important to maintain cargo tank pressure below a certain level in order to minimize the utilization of GCU. Nevertheless, in some cases the tank pressure cannot be easily controlled. That is generally due to terminal's request or ship operation at low speeds. In such cases, GCU shall be utilized for safety purposes. However, there are so many factors that should be considered to decide whether to use GCU.

An actual LNG carrier's daily basis operation data was used to develop our own deep learning models. The models have various activation functions in hidden layers of artificial neural networks. Performance analysis of each model has been discussed in this paper.

2. Previous works

Previous maritime studies have mainly focused on the optimized sea speeds to minimize not gas but fuel oil consumption.[1] But recently membrane type LNG carriers are mainly consuming gas to propel to handle gas tank pressure and respond to the IMO environmental regulations. A research on gas re-liquefaction optimization and prediction of gas consumption using machine learning has been studied.[2,3] In this paper, deep learning models were developed to decide whether to operate GCU.

3. Deep learning models

As ship operates the main engines at low speeds, it is not able to consume natural gas as much as needed to control the tank pressure. When LNG terminals request to shortly decrease tank pressure to a certain level that ships cannot reach within main engines capacity, GCU is used to control the pressure. So, the operation of GCU is determined depending on the features of cargo tank pressure, main engines gas consumption, generator's gas consumption, boil-off gas, and re-liquefied gas. And these features are used to get a target to decide whether to utilize GCU or not. It leads to a binary classification problem. Some deep learning models were developed. They have different activation functions in neural networks.

1,137 data sets are used in these models. They are sourced from H shipping company. 174K LNG carrier's

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daily-basis gas flow meter record was put into the models. Data collection period is between Oct. 14th. 2020. and Aug. 28th. 2022., which was recorded for ten voyages.

A Python program running in the Colab was developed. 70% of the data was put in the training set, and the other 30% of the data was put in the test set for the deep learning models. The Tensorflow Processing Unit (TPU) with High RAM was used to build up the models on the Tensorflow and Keras libraries. The epoch and batch size were configured as 200 and 20, respectively.

Table 1 shows the models with several activation functions. Linear is an activation function which does not change the weighted sum of the input in any way and instead returns the value directly. ReLu is the rectified linear function. Leaky ReLu is a deformed type of ReLu, but it has a small slope for negative values instead of a flat slope. Selu is the scaled exponential Linear Unit. Silu is computed by Sigmoid function multiplied by its input. Swish is a smooth, non-monotonic activation function. Sigmoid is a logistic activation function which limits the output to a range between 0 and 1. Finally, Tanh is the hyperbolic tangent activation function.

Only Sigmoid was used as output layer activation function since the target is a type of binary class. Adam was applied to an optimization function with a learning rate of 0.001, and the binary cross-entropy was used as a loss function.

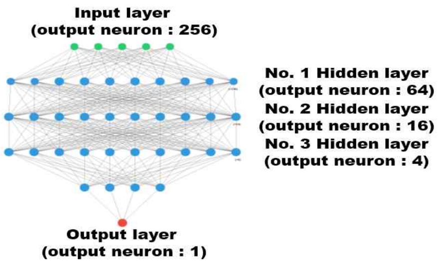

Fig 1. A developed neural network model

4. Performance comparison

Eight different activation functions are applied in input layer and hidden layers. Table 1 shows performances of the deep learning models. The accuracy, precision, recall, f1 score, and loss values were evaluated as performance results.

Sigmoid activation function in input layer and hidden layers achieved the best result. It shows that Sigmoid might not bring about the Vanishing Gradient Problem (VGP) to the acquired GCU data analysis since the total amount of boil-off gas and consumed gas is limited in a certain range in actual. the model might be able to avoid from the normalization problem as well.

Table 1. Performance of models

activation function	category	accuracy	precision	recall	f1_score	loss
linear	min	0.944591045	0.819397986	0.964566946	0.886075949	0.027001217
	mean	0.986719447	0.966702008	0.977559066	0.971379995	0.533105621
	max	0.997361481	1	0.988188982	0.994059406	3.295814037
relu	min	0.776605129	0	0	0	0.503313005
	mean	0.776605129	0	0	0	0.509049803
	max	0.776605129	0	0	0	0.531180739
leaky_relu	min	0.920844316	1	0.645669281	0.784688995	0.017968211
	mean	0.984872466	1	0.932283473	0.961842495	32.73653258
	max	0.996481955	1	0.984251976	0.992063492	251.3922119
selu	min	0.776605129	0	0	0	0.088507146
	mean	0.81829378	0.2	0.186614174	0.193053896	0.426950258
	max	0.989445925	1	0.952755928	0.975806452	0.503554106
silu	min	0.776605129	0	0	0	0.503262281
	mean	0.776605129	0	0	0	0.504620922
	max	0.776605129	0	0	0	0.509992778
swish	min	0.776605129	0	0	0	0.503269017
	mean	0.776605129	0	0	0	0.504700637
	max	0.776605129	0	0	0	0.516781092
sigmoid	min	0.974494278	0.959677398	0.885826766	0.939457203	0.058832731
	mean	0.981002641	0.993518758	0.921259832	0.955805418	0.082186021
	max	0.987686872	1	0.944881916	0.971659919	0.105322875
tanh	min	0.973614752	0.949806929	0.88188976	0.937238494	0.054356657
	mean	0.982585752	0.994140357	0.927952743	0.959616395	0.073595741
	max	0.986807406	1	0.968503952	0.969574037	0.100146495

5. Conclusion

Sigmoid activation function applied to all the layers resulted in the best performance. It seems like that the model was not affected by VGP.

On the basis of the result, further study will be more focused on reducing shipping's carbon emissions to satisfy the IMO emission regulations. That should be tackled by designing more sophisticated models to estimate accurate carbon emission amount.

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