1. INTRODUCTION

The rising volume of water and the falling volume of water at sea and ocean levels, known as tides, mainly happen because of the gravity effect from the moon that rotates on earth and earth that rotates the sun [1]. It caused the rising volume of water and also the falling volume of sea level water in some regions. The information on sea level height is necessary for scheduling ships with a deep draft to navigate through shallow water [2]. The data is essential for the ship navigator and port operation services to manage the scheduling in their port [3].

The historical data can also be used to predict the future sea level, which is important for planning on building structures, especially in the construction stage around offshore areas [4]. The reason for projecting the sea level is also used to gather knowledge on a changing climate and how big the chance of sea level rise is in the future. By predicting the sea level, we can limit the consequences, particularly in coastal areas, such as floods [5]. From [6], tidal components are the major factors shaping sea level since they are the most stable pattern in oceanography. It is because of the simplicity and predictability of drives and the near-linearity of the oceanic dynamic response. Non-tidal forces, such as wind, can also affect the sea level [7]. Nevertheless, predicting sea levels using tidal harmonic analysis requires long-term historical data for accurate prediction. Non-tidal forces, such as wind, can also affect the sea level [7], which cannot be accommodated by using tidal harmonic analysis.

This paper aims to develop a reliable method for predicting sea levels using only relatively short historical data. We use the recently developed deep learning model Transformer to forecast sea levels. The model was initially developed for Natural Language Processing (NLP) but can process sequential data such as time series of sea levels as in this paper. For forecasting cases, the Transformer can be trained to take a sequence of past values as input and predict the next value in the sequence. In the forecasting problem, the goal is to predict the object based on past patterns. The transformer model can effectively capture complex patterns in the data and make more accurate predictions than RNNs and LSTMs, which may struggle with long-range dependencies. One of the main reasons the Transformer model has been successful in these tasks is that it can process sequential data in parallel, using attention mechanisms to weigh the input data at each step. This step will permit the model to handle the long-range types of dependencies in the data more effectively and make more accurate predictions.

In this paper, we use the sea level data on the coastline of Pangandaran Beach, Indonesia, collected using an Inexpensive Device for Sea Level measurement or IDSL. Here, we only use four months of data; January 3rd to Sunday 2nd May, 2021. Moreover, we also compare the transformer model with two other popular deep learning models for sequential data, i.e., Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM). The prediction result will be tested for accuracy using Coefficient Correlation (CC) and Root Mean Squared Error (RMSE). The computing time will also be used for comparing the computing time of the Transformer, RNN, and LSTM methods.

The content of the paper is as follows. Section 2 discusses the literature review of sea level forecasting and briefly describes the Transformer model. Section 3 describes the methodology performed in this paper, and the results and discussion will follow in section 4. Then the paper will be closed with the conclusion in the last section.