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Identification of vibration for balancing in Fehn pollux ship with ECO Flettner rotor

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Abstract: Flettner rotors are wind propulsion systems using the Magnus effect to generate thrust, thereby reduce fuel consumption and carbon emissions in the ships. However, rotor unbalance can cause excessive vibrations and energy loss, affecting the performance and stability of the system. There is a need to have a system onboard, which can predict the vibrations. The paper proposes a deep learning approach to predict the vibrations and unbalanced forces of a Flettner rotor based on the data of ECO Flettner rotor onboard the vessel MV Fehn pollux. The paper develops two methods to estimate the direction and magnitude of the unbalanced forces using the reading values of the strain gauges. The work also compares two recurrent neural network models, namely Long-short term memory and Gated Recurrent Unit, for vibration prediction and evaluates their performance using Mean Absolute Error and Root Mean Squared Error metrics. The results show that Long-short term memory model outperforms Gated Recurrent Unit model in prediction accuracy and can be implemented on the system onboard to monitor and prevent rotor unbalance. The paper also suggests some possible solutions for automatic self-balancing of the rotor and identifies some areas for future work.

Keywords: *Anomaly detection, Deep neural networks, Flettner rotor, Gated recurrent unit, Long-short term memory, Moving median, Rotor balancing*

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Nomenclature	
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
RNN	Recurrent Neural Network
DBSCAN	Density Based Spatial Clustering of Applications with Noise
KDD	Knowledge Discovery Databases
AWS	Apparent Wind Speed
AWA	Apparent Wind Angle
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
FFT	Fast Fourier Transform

1. INTRODUCTION

Modern shipping poses major challenges, which are to reduce fuel consumption, ocean sustainability and reduce the overall cost of travel. Wind propulsion technology promises to reduce consumption of fuels in ships, reduction in freight rate and reduction of greenhouse gas emissions [1]. Flettner rotor is an active sail with hollow cylindrical body with an end plate mounted to the top and it is installed on ships. It rotates with an electrical motor around its axis. It is a wind propulsion technology that makes use of the Magnus effect [2]. As per Magnus effect, when air travels across the Flettner rotor, a pressure difference is created which produces a thrust force on the ship in the opposite direction of the ship and perpendicular to both airstream direction and the rotor axis [3,4]. As per Ref. [5], it was discovered that Flettner rotors are able to produce very high lift coefficients and aerodynamic efficiency. Unbalancing is a vital issue in a Flettner rotor system. Indeed, it is unequal distribution of mass along a rotational axis, which is known as rotating imbalance. When the center of mass (inertia axis) of a rotating mass, or rotor, is out of line with the center of rotation, it is said to be out of balance (geometric axis). When the rotor rotates, the mass imbalance causes vibration; as the rotor's speed increases, so does the vibration. The vibration can damage the rotor and, in certain situations, cause the system to fail completely; it also shortens the life of bearings. Unbalanced forces would be created as a result of the incorrect mass distribution, which should be corrected. The rotor should be balanced to achieve this goal [6].

Several methods have been proposed to analyze and predict the vibration characteristics of Flettner rotors by using different techniques. For example, Ref. [7] proposes a method for analyzing the vibration of electric motors that considers the rotating structure of the rotor using a coupled analysis of flexible multibody dynamics, electromagnetism and structural vibration. The method aims to predict motor vibration accurately by incorporating the electromagnetic force characteristics, the rotational motion of the flexible rotor, and their interactions at different operating speeds. The paper develops a three-dimensional finite element model of the motor and validates it with an impact hammer test. The paper also contrasts the proposed method with the conventional finite element analysis-based method and shows that the former can capture not only the electromagnetic force harmonics but also the sideband harmonics caused by rotor eccentricity-induced large vibrations. Ref. [8] uses computational fluid dynamics (CFD) to simulate the aerodynamic forces and moments acting on the rotors and the ship hull. Ref. [9] presents a method based on the calculation of the natural frequencies and mode shapes of the rotor with initial bending using finite element analysis. The authors also proposed a balancing algorithm that can adjust the rotor speed and angle to minimize the unbalance force. Ref. [10] proposed a method based on the frequency spectrum analysis of the strain gauge signals to detect the unbalanced mass and its angular position on the rotor. They also suggested a balancing method that can add or remove masses on the rotor to achieve balance. The proposed method is based on the adaptive filtering technique to extract the fundamental vibration component of the rotor in the process of start-up and shutdown. They also developed a fault diagnosis system that can identify the type and location of the fault based on the extracted vibration component. However, most of the existing methods have some limitations or challenges in terms of accuracy, robustness, applicability, or convenience. For example, Ref. [9] relied on empirical formulas or assumptions that may not be accurate or applicable for different types of Flettner rotors. Ref. [10] required manual intervention or additional equipment to perform balancing, which may not be feasible or convenient for practical applications. It used a fixed filter order and step size that may not be optimal for different operating conditions or noise levels. Therefore, there is a need for a more advanced and automated approach to predict and balance the vibrations and unbalanced forces of Flettner rotors.

The main contributions of this paper are as follows: First, we propose a smoothing technique to reduce the anomalies in the data and make it suitable for machine learning. Second, we implement and explore two methods to identify and predict the rotor unbalance using the reading values of the strain gauges.

Third, we suggest different ways to achieve balancing of the Flettner rotor, such as adjusting the rotor speed and angle, adding or removing masses on the rotor, or using automatic self-balancing mechanisms. The rest of the paper is organized as follows: Section 2 provides a brief overview of Flettner rotors and their vibration characteristics. Section 3 describes the data collection and preprocessing steps along with the proposed methods for unbalance prediction and balancing. Section 4 reports the experimental results and discussions. Section 5 concludes the paper and suggests some directions for future work.

2. BACKGROUND AND THEORY

Vibrations and rotor unbalance are critical issues for Flettner Rotor. This chapter discusses further factors contributing to unbalance and approaches for balancing.

2.1. Flettner Rotor

Every rotor, regardless of size or proportions, has some mass imbalance. Several factors contribute to this issue, including blow holes in the casting, distortion, eccentricity, deposits built-up, and corrosion. The rotor mass unbalance is one of the causes for vibrations. Other sources of vibrations include propulsion shafts, main engine, electro drive, and shafts. Balancing may be accomplished in two ways: One is by removing mass from the direction of the mass unbalance, and the other is by adding counterweights in the opposite direction of the unbalanced mass. To decrease vibrations and maintenance costs, while also enhancing the Flettner rotor's operational frequency range, a high-tech rotor balancing mechanism is required. In reality, this approach would save money on wearing and expand the Flettner rotor's applicability in various wind situations at sea, resulting in increased energy savings and lower sailing costs. As a result, Flettner rotor balancing saves energy and money by using less fossil fuels [11,12,13].

2.2. Balancing

There are two types of rotors, ie. flexible and rigid. Flettner rotor falls in the latter category. When it is balanced, it operates at 70% of its critical speed and will stay balanced throughout its operating speed range. For balancing the rotor, it is required to first detect and measure the effect of unbalance along the length of the rotor. Once detected rotor mass distribution must be modified at the correction planes. The balancing steps should be repeated until the minimum unbalance effect which is up-to a certain threshold criterion is observed along the length of the rotor [14,15]. The aerodynamic coefficient of Flettner rotor is dependent on both functional and geometrical parameters. The main parameters include velocity ratio, angular speed, diameter of the rotor, free stream velocity, aspect ratio i.e., the ratio of rotor length to its diameter. The end plate also plays a significant role in the Flettner rotor. It has been observed that smaller plates offer significantly lower drag at low velocity ratios; bigger plates are preferable for applications at mid velocity ratios to prevent the increase in induced drag, while smaller plates are favored for high spin ratio applications [2].

3. APPROACH

The prediction of rotor vibrations can be affected by many factors like data quality, data preprocessing, and machine learning model etc. This section demonstrates the methodology adopted for data modeling and the data used in the modeling.

3.1. Time Series Data from MV Fehn Pollux

The focus of this research paper is to predict the vibration of Flettner rotor using machine learning and deep learning approach. The vibration of the Flettner rotor (amplitude and frequency) can be derived from the force measured using strain gauges installed on the basepipe and body of the Flettner rotor. With the advancements in deep learning, it is possible to predict the amplitude and frequency of the rotor to determine the unbalance. For implementation, data of ECO- Flettner rotor which is installed on board the vessel MV Fehn Pollux is considered [16]. On average, the ECO-Flettner rotor saves 10 - 15% of the ship's energy consumption [17].

The vessel MV Fehn Pollux maintains a SQL database consisting of parameter readings from 57 sensors which are installed on the Flettner rotor. These data are real and the parameters include rotor speed, wind angle, wind speed, heeling angle of the ship and drag forces. There are 4 contact type sensors and 4 strain gauges installed on the ECO-Flettner rotor. Two of the sensors are on the basepipe at upper and lower bearing respectively. The rest of the sensors are installed radially to the bearing in a similar way. The principle behind the positioning of the sensors is that the base pipe will give the overall vibrations whereas the bearing will provide vibrations due to rotor imbalance, but both are interrelated. The unbalanced rotors impart force and displacement to the support. This force and displacement are calculated by the installed sensors. After that the sensor signals are fed through a filtering system to retain the required component of the signal. The imbalance effect at the sensor location is measured by the filtered signal [14]. The strain gauge records the propulsive force along horizontal and vertical direction at all 4 locations.

3.2. Methodology

Knowledge discovery database (KDD) has been utilized to implement the proposed implementation [18]. KDD is a systematic method for identifying valid, useful, and intelligible patterns in large and complicated datasets. The inference of algorithms that explore the data, construct the model, and identify previously unknown patterns is at the foundation of the KDD approach. The following flow diagram (Fig. 1) illustrates the KDD process.

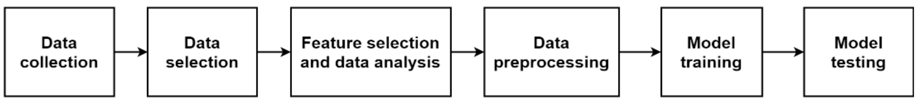

Figure 1. The implementation process using LSTM and GRU

Each of the blocks shown in Fig. 1 is implemented in detail in the following subsections.

3.2.1. Data collection

The Flettner rotor's control cabinet's function is to collect the rotor's signals and transmits them to the bridge's control panel. The installed system on the MV Fehn pollux receives the signals acquired from the installed strain gauges. Apart from these signals, the system also receives real time readings for apparent wind speed (AWS), apparent wind angle (AWA), rotor speed. The data is stored in the MySQL server running on the PC onboard the ship. The SQL file obtained from the system on board is used on a relational database management system i.e., SQL server in laboratory computer. It can be used to accomplish tasks like data selection, data retrieval, and data transformation. In this phase, data from 20 June 2018, 00:00:01 GMT to 31 August 2018, 11:39:54 GMT has been recorded.

3.2.2. Data selection

Machine learning is not always possible even if a massive amount of data is available. A certain level of data quality is also required. In order to solve this complex problem, it is made sure to choose data which is continuous and where wind speed, wind angle, and rotor speed have a broad range of values. 50000 timestamps are loaded. For the problem even dataset where rotor speed is nonzero is considered so that vibrations caused by the rotor only are considered for the model. For machine learning modeling the data is divided into 2 categories i.e., train and test data. 80 % as training data and the remaining 20% as test data. Since recurrent neural networks retain memory, order is important therefore the split does not perform random shuffle. In this case, the model contains memory and keeps track of previous events which means it is mapping a sequence of attributes to the following time steps x_{T-2}, x_{T-1}, x_T ... $\rightarrow$ y_{T-2}, y_{T-1}, y_T ..., and hence the order is important. For the same reason, a cross validation technique like *K* fold has not been used to split the dataset into train and test data.

3.2.3. Data preprocessing

For the anomaly detection process, the sensors installed on the vessel often records anomalies and missing data due to noise, vibrations, and sensor errors because of which there is a need to treat such records. The missing data is treated with the help of the moving median method. High quality data is critical for machine learning models. Machine learning models are designed to comprehend the relationship between data points; therefore, anomalies or outliers might affect the quality of this training data. With the presence of outliers in the data the model's accuracy is skewed resulting in changing the patterns it learns. While analyzing the data, it was observed that there were some data points which were very different from the actual measured data physically in the system on board. Fig. 2 illustrates the sudden extreme deviations in data points for each sensor.

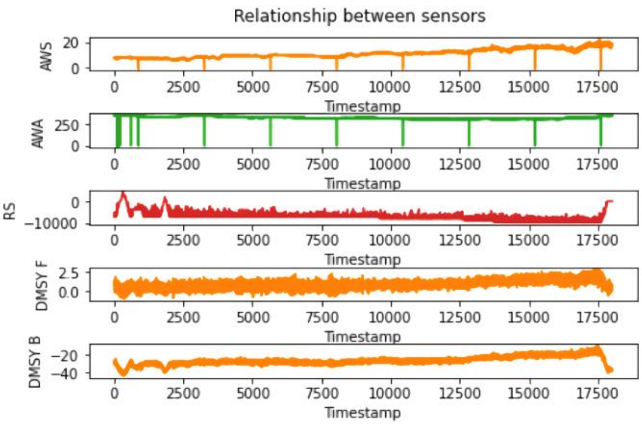

Figure 2. Relationship between sensors.

There are three categories for anomaly detection, statistical method, neural network method, and nearest neighbour method. Statistical methods assumes that the set of data points follow some category of known probability distribution, it includes methods like *z*-score, Interquartile region, box plot and histogram. Deep learning process uses neural networks to learn feature representations or anomaly scores in order to detect anomalies. Ref. [19] illustrates a number of deep learning approaches all of which have demonstrated much superior performance than traditional anomaly detection in a range of real-world situations. Ref. [20] demonstrates three different approaches for anomaly detection for the Flettner rotor on MV Fehn pollux. The nearest neighbour method assumes that similar data points occur in dense clusters, whereas the anomalies are far away from these clusters [21]. DBSCAN (Density based spatial clustering of applications with noise) and Gaussian mixture models are well known and used approaches for nearest neighbour method for anomaly detection. Fig. 3 shows the anomalies detected in sensors.

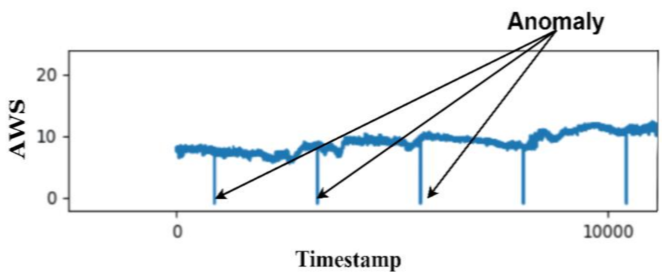

Figure 3. The anomaly data

3.2.4. Data transformation

For the anomaly treatment, one should choose the suitable data for machine learning, and the anomalies must be removed. Since the dataset is a time series data, removing anomalies is not the best idea because once the anomaly is removed, the timestamp for that record is also removed thus giving discontinuity in the dataset. The better approach is to treat the anomalies by smoothing. It can be a beneficial step for the time series data as it reduces random variations and volatility in data. It utilizes data from past time period. Moving average method has been utilized in this analysis to smoothen the anomalies. It minimizes the random noise while maintaining a clear step response, as a result it is well suited for time series data. This method requires selecting the window size and for this model window size 3 was chosen. Fig. 4 illustrates the data after smoothing. To have a normal distribution the data was then standardized after treating the anomalies. By standardizing the data the features are transformed by scaling in the range -1 to 1.

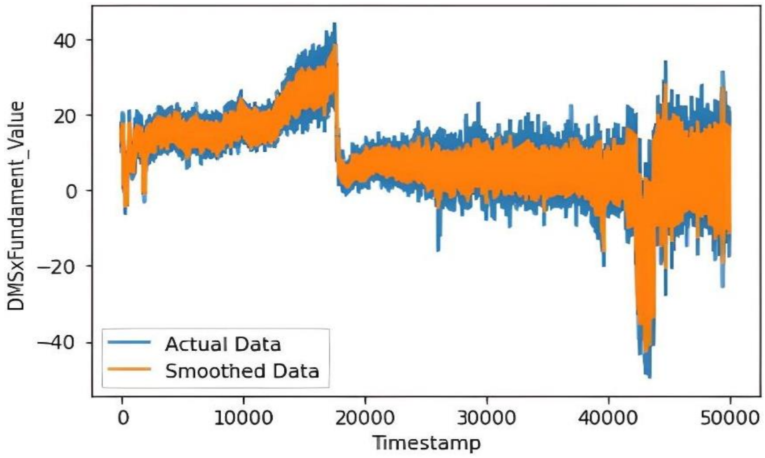

Figure 4. Actual data and smoothed data as time series.

3.2.5. Model selection and training

LSTM is a type of Recurrent Neural Network (RNN). To forecast, it is capable of remembering the historical values. LSTM is an extension of RNN model since RNN had difficulty to understand long-term dependencies. The memorizing process in LSTM is governed by a gating mechanism. The data is stored in an analog format. Sigmoid function is used for element wise multiplication resulting in values between 0-1. The resulting values help the model to update or forget the data.

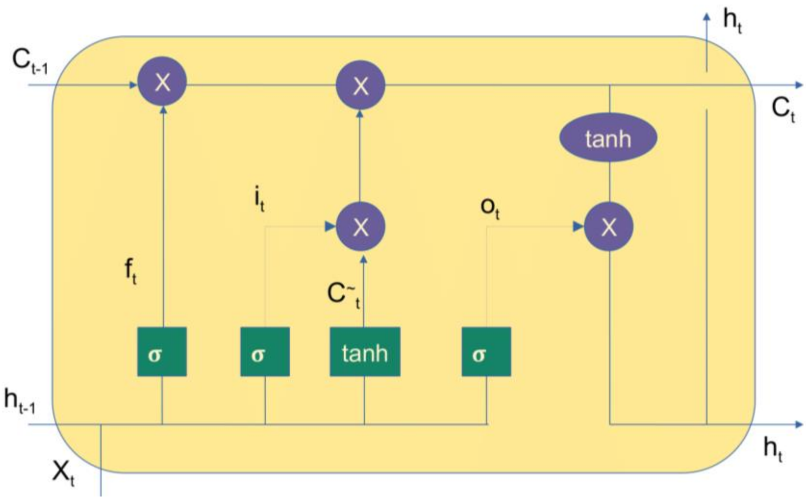

Figure 5. Structure of LSTM.

In LSTM architecture, there are 3 types of gates- forget gate, input gate, and output gate. It also have hidden layers also known as short term memory which holds current and previous timestamps. Forget gate decides whether to keep the data from the previous timestamp or forget it. The input gate is used to measure the significance of new data and how much to store in the memory. The value of the next hidden state is determined by the output gate. This state stores data from earlier inputs. The final hidden state is utilized for predictions [22]. The elements of the internal state vector C_{t-1} in Fig. 5 depend on how it interacts with the previous output h_{t-1} and the current input x_t. Here, σ represents the sigmoid activation function; *i*, *f*, and *o* denote the input, forget and output gates, respectively. These interactions decide which elements should be changed, kept or removed based on the outputs from the past time steps and the input from the current time step [23]. The problem is converted into a supervised time series problem by providing future output for the input of the current timestamp. Current timestamp and past two timestamps are considered for modeling i.e., t, t_1, and t_2. The deep learning open-source library, Keras is used here for model implementation [24]. GRU (Gated Recurrent Unit) is similar to LSTM in the sense that both try to extract information to prevent vanishing gradient problem, however, GRU is faster and easier to implement. GRU consists of two gates, update gate and reset gate. The update gate is responsible for long term memory and determines the amount of data which can be utilized for the future. The Reset gate is responsible for short term memory [24]. It is similar to the forget gate of LSTM as it determines how much of the past data to be left out and not consider in future. The detailed working of GRU can be found here [25]. GRU implementation is also accomplished by Keras library.

4. RESULTS AND EVALUATION

To make the dataset suitable for machine learning, the dataset was optimized by treating the anomalies by smoothing the data using moving average method. Different window sizes were experimented and window size 3 was found to give the best results. Each record in the dataset was provided previous two timestamps. With experiments, it was found out that adding the extra timestamp in training data helped model learn and forecast better.

The LSTM and GRU models were implemented for the time series forecasting to forecast values of the 4 sensors. GridsearchCV method helped to choose the best parameters for hypertuning for both the models. Table 1 describes the architecture of both the models. The LSTM model has been configured with 12 hidden layers and 1 output layer with Adam optimizer and mean absolute error as loss function. Loss functions are used to determine how close a predicted value is to the true value. Mean absolute error is a robust loss function and is an ideal option if the dataset contains outliers. The model was trained for 50 epochs and with batch size 50. Here GRU is implemented with 10 hidden layers and 1 output layer. Similar to LSTM model mean absolute error and adam were used for loss function and optimizer respectively.

Table 1. The Selected LSTM and GRU Models.

	LSTM	**GRU**
Input Layer	10 Inputs No Bias	10 Inputs no bias
Hidden Layer	12 Hidden layers	10 Hidden layers
Output Layer	1 Output layer	1 Output layer
Optimizer	Adam	Adam
Loss Function	Mean Absolute Error	Mean Absolute Error
Data Separation	80% for training and 20% for testing	80% for training and 20% for testing
MAE	0.056	0.155
RMSE	0.098	0.228

The predicted values were evaluated against the test dataset. The model results were evaluated by the metrics Mean absolute error (MAE) and Root mean square error (RMSE). Both RMSE and MAE are good metrics for model evaluation [26]. In all the cases LSTM has outperformed GRU and has given better results. GRU has shown much higher RMSE and MAE, which is not a desirable trait for predictions whereas the LSTM model has shown much less RMSE and MAE and its results are very close to the actual values from the test data. The values for LSTM predicted values and actual values are plotted in Fig. 6.

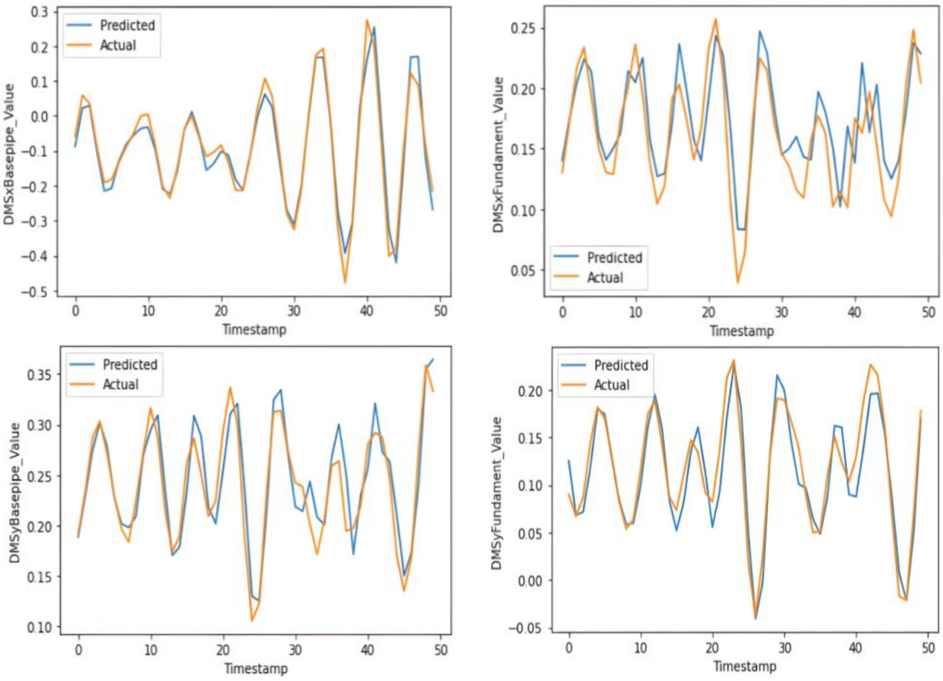

Figure 6. Prediction results.

5. ABOUT MECHANICAL BALANCING

As we already discussed, balancing can be achieved by compensating for the missing mass in a rotating body by adding counterweights in the opposite direction of surplus unbalanced mass, we call it the mechanical process of balancing. The main challenge in this approach is to find the correct position and amount of the counterweight. The analysis of the data gathered by the strain gauges using machine learning approaches can help to localize the position and the amount of the missing mass. To achieve this information, the position of the strain gauges should be known. Also, it is better that the strain gauge's data are calibrated, then we can relate the measurements with the physical parameters more easily. The mechanical process of balancing can be performed automatically or manually. Fig. 7 depicts a concept for manual balancing.

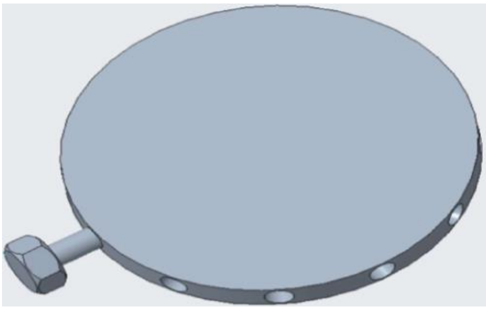

Figure 7. Manual balancing concept: Bolts around a disc.

This disc can be placed inside the Flettner rotor, or it can also be an inbuilt part of the Flettner rotor. There are 12 threaded holes round this disc where they are separated by 30 degrees. Two discs can be used and be placed at the two respective sensor positions as shown in Fig. 8.

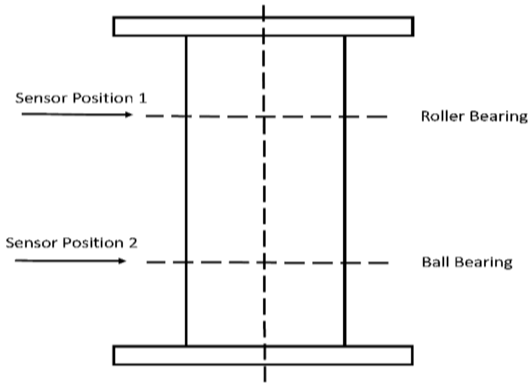

Figure 8. Disk and bearing positions.

In this concept, the weights (bolts) can be placed in each hole to balance the Flettner body. These moving weights can move along the diameter of Flettner rotor by tightening and untightening the bolts. If the offset angle between any two holes is 0-30 degrees, you can achieve balance by installing screws in the two holes and adjusting their length in the holes. The angular position may still not work; for this, screws with different material densities should be used. A practical solution to this problem is to drill multiple holes in the disc, as this reduces the space to a 30-degree angle and provides greater flexibility for the operator. Currently, a computer program called Innoanalyzer is used for identifying the position and value of the unbalanced weight for rotor balancing. It analyzes the frequency of vibrations and then use Fast Fourier Transform (FFT) to breakdown into further frequency components to identify the direction and the magnitude of unbalance in the rotor.

6. CONCLUSION

Flettner rotor is used to save energy and improve the efficiency of the vessel. Balancing is a critical concern in a Flettner rotor. The work utilizes a deep learning approach and proposes two methods of predicting rotor vibrations. For prediction, LSTM model has shown better prediction accuracy than GRU model as validated by RMSE and MAE. Due to the model's lower size and efficient framework, the implemented model can be saved and be easily deployed on the system onboard and can be utilized to predict the vibration, unbalanced forces, and direction of unbalance in the rotor. Automated self-balancing approach can be an alternative for manual balancing and can be an interesting topic for future work. In this approach the balancing process can be performed dynamically during the operation of the Flettner rotor. The automatic balancing can be enabled when the vibration exceeds the pre-determined limitations. The model can be best utilized to prevent rotor unbalance.

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