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THRESHOLD-BASED ANOMALY DETECTION IN DRY BULK CARGO VOLUME USING SIMULATED LSTM AUTOENCODER RECONSTRUCTION ERROR

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ABSTRACT

This study addresses the challenge of detecting anomalies in annual dry bulk cargo volumes at a major Indonesian port by simulating the reconstruction error typically produced by an LSTM Autoencoder model. Instead of applying deep learning directly, the research utilizes a statistical approximation involving a three-year centered moving average to emulate the expected cargo pattern. The absolute deviation between actual and smoothed values is treated as simulated reconstruction error. A statistical threshold is then calculated based on the mean and standard deviation of these errors to distinguish normal years from anomalous ones. Results indicate that only the year 2023 exceeded the anomaly threshold, suggesting significant irregularity in cargo flow during that period. The proposed method offers a practical and interpretable framework for anomaly detection, particularly in data environments lacking access to machine learning infrastructure. This approach enables port operators and planners to monitor unusual volume fluctuations efficiently and provides a foundation for further integration of data-driven risk management systems.

Keywords: *Dry Bulk Cargo, Anomaly Detection, Reconstruction Error, LSTM Autoencoder, Moving Average, Threshold Classification, Port Operations.*

1. PRELIMINARY

As an archipelagic nation, Indonesia inherently positions ports and sea transportation as profoundly strategic. Both function as irreplaceable primary nodes within the entire national transportation and logistics system. The role of ports extends beyond mere transit points; they are vital gateways serving as crucial entry and exit points for a nation's or region's economic activities, effectively facilitating the flow of both domestic and international trade.

Furthermore, ports act as essential links in every chain of the transportation system and global supply chain. They ensure seamless connectivity from the origin port of goods to their destination, integrating various elements of logistics movement. Ports also function as a dynamic Interface, where efficient meeting and transfer occur between sea transportation modes and land-based modes, such as railways or trucks, ensuring smooth distribution. Not only that, in their evolution, modern ports have transformed into comprehensive Industrial Entities. This means they can become integrated industrial units or zones that support various manufacturing, warehousing, and distribution activities in the port's vicinity. [1]

PT Pelabuhan Tanjung Priok (PTP) is a subsidiary of PT Pelabuhan Indonesia (Persero) or Pelindo Group, primarily focused on container and cargo terminal operational services at Tanjung Priok Port. As a vital part of Indonesia's main economic gateway, PTP plays a central role in the smooth flow of national and international logistics. The company is responsible for various activities, ranging from vessel services and container handling to terminal facility management. PTP's operational efficiency and infrastructure capabilities significantly influence Indonesia's export-import competitiveness, making it a key driver of the maritime economy.

Beyond container handling, Tanjung Priok Port also possesses facilities and capabilities to service bulk cargo. Bulk cargo refers to goods transported in large quantities without individual packaging, such as grains, sand, cement, fertilizers, coal, or liquid chemicals. Handling bulk cargo necessitates specialized equipment like grabs, conveyor belts, or pipelines for efficient loading and unloading. The heterogeneous nature of bulk cargo demands different safety and handling standards to prevent contamination, spillage, or damage. The presence of bulk cargo handling facilities at Tanjung Priok is crucial for supporting vital industries in Indonesia, ensuring the efficient supply of raw materials and distribution of basic products.

Bulk cargo volume is one of the key indicators in port logistics operations, as it is directly related to operational planning, resource allocation, and the efficiency of loading and unloading services. Unusual fluctuations or anomalies in cargo volume can significantly disrupt port activities, leading to mismatches between demand and capacity, delays in service delivery, or errors in vessel scheduling. Therefore, the ability to detect anomalies accurately and in a timely manner has become essential to support decision-making systems within port operations.

Based on the dry bulk cargo volume data at PTP from 2010 to 2023, there were significant fluctuations throughout the period. In the early part of the decade, the volume ranged between 10 to 12 million tons per year, showing a steady upward trend that peaked around 2019 with a sharp increase reaching nearly 24 million tons. [2]

However, after that peak, the volume began to decline gradually, although it remained relatively high compared to earlier years. This decline may have been influenced by global market dynamics, shifts in commodity demand, and external factors such as the pandemic or operational adjustments at the port. Overall, the long-term trend indicates substantial growth with several anomalous years, highlighting the importance of monitoring and early detection of unusual fluctuations in dry bulk cargo volumes.

In recent years, artificial intelligence-based approaches—particularly Long Short-Term Memory (LSTM) Autoencoders—have been widely employed to learn normal patterns in sequential data and identify deviations that may indicate potential anomalies. While these models have proven effective in generating reconstruction error values from input data, a critical challenge remains in determining the optimal threshold that distinguishes normal from anomalous instances. An inaccurate threshold may result in misclassification, including both false positives and false negatives, ultimately reducing the reliability of the anomaly detection system.

This study focuses on the determination of anomaly classification thresholds based on simulated reconstruction error, using annual bulk cargo volume data from one of Indonesia's ports, namely PTP. Unlike studies that directly build and train LSTM models, this research adopts a statistical approach to approximate the output of an LSTM Autoencoder in the form of reconstruction error. The simulation involves calculating the deviation between actual values and their corresponding moving averages to represent normal behavior. The resulting error values are then analyzed statistically to establish a threshold for anomaly classification, using the mean plus two times the standard deviation as a reference.

Through this approach, the study aims to offer a simple yet effective framework for determining anomaly thresholds, especially for institutions or data managers who do not have direct access to deep learning modeling capabilities. The outcomes of this research are expected to support efforts to improve operational efficiency in ports and serve as a foundation for developing more adaptive anomaly detection systems in the future.

2. LITERATUR REVIEW

Port

According to Law of the Republic of Indonesia No. 17 of 2008 on Shipping, a port is defined as an area consisting of land and/or water with specific boundaries, serving as a location for government and commercial activities used for berthing ships, embarking and disembarking passengers, and/or loading and unloading goods. A port includes terminals and berths equipped with facilities for navigation safety and security, as well as supporting port operations, and functions as a hub for both intra- and intermodal transportation. [3]

Cargo Port

In the context of cargo transportation, a cargo port refers to a type of port specifically designated for the handling of freight, including bulk cargo, general cargo, and containers. Cargo ports are equipped with infrastructures such as cargo docks, warehouses, stacking yards, and handling equipment including cranes and conveyors, all designed to facilitate efficient and secure cargo operations. According to the United Nations Conference on Trade and Development (UNCTAD), cargo ports are essential nodes in global supply chains, supporting international trade flows and economic development through the provision of reliable and competitive logistics services. [4]

Bulk Cargo

Bulk cargo refers to goods transported in large quantities without packaging and is generally divided into two main categories: dry bulk and liquid bulk. Dry bulk includes solid commodities such as coal, iron ore, cement, fertilizers, sugar, and grains, which are typically handled in massive volumes using mechanical processes.

Based on trade volume, dry bulk is further classified into major bulk—including coal, iron ore, and wheat—which dominate global maritime trade, and minor bulk, comprising commodities such as bauxite, sugar, and fertilizers. [4]

The handling of dry bulk cargo in ports requires specialized infrastructure such as conveyor systems, grab cranes, hoppers, and adequate open storage areas or stockpiles. Due to its unpackaged nature, dry bulk cargo is prone to spillage, dust pollution, and environmental degradation, thereby necessitating control mechanisms such as drainage systems and water-spray technologies to suppress airborne particles. [5]

In port operations, dry bulk plays a crucial role as an indicator of industrial demand, being directly linked to sectors such as energy, construction, and agriculture.

However, managing bulk cargo poses several challenges, including market volatility, port capacity limitations, and operational risks, all of which underscore the importance of data-driven monitoring systems and early warning mechanisms to detect unusual fluctuations in cargo volume.

Therefore, the development of anomaly detection systems based on bulk cargo trends is essential to improving the efficiency, resilience, and responsiveness of port logistics. [6][7]

Dry Bulk Port Facilities

Dry bulk ports play a critical role in global trade by facilitating the efficient handling of unpackaged commodities such as coal, iron ore, grain, cement, and fertilizers. These ports are specifically designed to accommodate the high-volume, continuous flow of dry bulk materials, which require specialized infrastructure and equipment to ensure safe, cost effective, and environmentally responsible operations. The performance of a dry bulk port is largely determined by the adequacy and integration of its facilities, which must support not only cargo handling but also vessel maneuvering, storage, and logistical coordination.

a. A dry bulk terminal is the core facility for handling unpackaged commodities like coal and iron ore. It integrates ship unloading, temporary storage, and land transport, supported by equipment such as conveyors, hoppers, and stacker-reclaimers to ensure efficient bulk handling. According to Stopford, mechanized handling in dry bulk terminals plays a crucial role in improving port throughput and operational reliability. [6]
b. The berth is where bulk carriers dock and transfer cargo. It must support heavy equipment like grab cranes and continuous unloaders and provide basic ship services such as water supply and waste handling.
c. The stockpile, or open storage yard, is used to store dry bulk materials either before loading onto ships or after unloading. The strategic placement of stockpiles relative to conveyor networks significantly impacts the efficiency of cargo movement within the terminal.
d. The approach channel is the navigable waterway that provides access for ships entering and exiting the port. In dry bulk ports, the channel must be adequately deep and wide to accommodate bulk carriers, which often have large drafts. Maintaining navigational safety is paramount, requiring well-marked channels with buoys, navigation lights, and regular dredging to ensure minimum depth requirements are met.
e. The anchorage area is a designated zone outside the harbor basin where ships can anchor while awaiting berth allocation or completing administrative formalities. In dry bulk operations, where loading and unloading can be time-consuming, anchorage areas serve as essential buffer zones. They must offer shelter from sea currents and adverse weather to ensure the safety of anchored vessels. Well-managed anchorage reduces congestion within the port and contributes to smoother scheduling of vessel traffic. [4]
f. A turning basin provides maneuvering space for vessels to rotate or align before approaching or departing from the berth. This is especially critical for large bulk carriers that require wide turning radii and have limited maneuvering capabilities. A properly sized and strategically located turning basin ensures safe and efficient vessel operations, preventing collisions with infrastructure or other vessels.
g. The harbor basin is the calm water area within the port where ships berth, maneuver, and conduct cargo operations. It must be protected from ocean waves and swells to allow safe and uninterrupted operations. Adequate water depth is essential to accommodate deep-draft dry bulk carriers, while its layout must support the deployment of heavy handling equipment at the quay. The effectiveness of a harbor basin directly influences port safety and operational performance.

Liquid Bulk Port Facilities

Liquid bulk ports serve as essential nodes in the global transportation network, enabling the safe and efficient movement of large volumes of liquid commodities such as crude oil, petroleum products, chemicals, liquefied natural gas (LNG), and edible oils. Due to the hazardous and often volatile nature of these cargoes, liquid bulk ports require highly specialized infrastructure and strict safety protocols. The design and operation of these ports are governed by international standards and best practices to prevent spills, contamination, and fire hazards. Key facilities typically include dedicated berths with loading arms or hoses, tank farms for storage, pipeline systems, vapor recovery units, firefighting installations, and control centers for monitoring and emergency response. Understanding the function and integration of these facilities is crucial for managing the operational complexity and environmental risks associated with liquid bulk handling.

a. The liquid bulk terminal is the central facility for handling the loading and unloading of un-containerized liquid cargo, such as crude oil, chemicals, and LNG. It connects berths with storage tanks and includes systems for transfer, storage, and monitoring. Operations rely on specialized equipment to ensure safety, efficiency, and environmental compliance.
b. Liquid bulk berths are designed for mooring tankers and enabling secure cargo transfer via marine loading arms or hoses. They include spill containment systems and structural reinforcements to support hazardous operations. Ship services such as waste handling and safety checks are also conducted at the berth.
c. Tank farms store liquid cargo temporarily in above-ground tanks, often equipped with pressure relief, vapor control, and fire protection systems. Their design must prevent contamination and ensure safe handling of volatile or reactive substances.
d. Pipelines system connects the berth to the tank farm and are constructed to handle high-pressure liquid transfer. They include safety valves, corrosion protection, and cleaning systems to prevent leakage and maintain product integrity.
e. Marine loading arms or hoses enable controlled cargo transfer between ship and shore. These are designed with swivel joints, emergency release systems, and often vapor recovery connections, especially for volatile or toxic cargoes.
f. Firefighting infrastructure in liquid bulk ports must be robust and multi-layered. Facilities typically include foam-based fire suppression systems, hydrants, fire monitors, fixed and portable extinguishers, and gas detection alarms. Emergency response plans are mandatory and regularly rehearsed, and personnel must be trained in handling hazardous material incidents.
g. Waste handling and spill response equipment for the handling of oily water, slops, and chemical waste generated during port operations.

Recurrent Neural Network

Recurrent Neural Networks (RNNs) are a class of artificial neural networks specifically designed to handle sequential data by incorporating temporal dynamics through recurrent connections. Unlike feedforward neural networks, RNNs maintain a memory of previous inputs via internal states, making them particularly well-suited for tasks involving time series, natural language processing, and speech recognition. The ability of RNNs to "remember" previous inputs gives them a unique advantage in capturing dependencies across time steps, which is essential for modeling the structure of sequential data.

One of the fundamental strengths of RNNs lies in their capability to learn temporal dependencies and patterns across variable-length sequences. As Mandic and Chambers emphasize, "Recurrent neural networks provide a natural framework for processing sequential data and are able to approximate dynamic systems with high accuracy." [8]

However, standard RNNs are often plagued by issues such as vanishing or exploding gradients, which hinder learning over long sequences. To mitigate these problems, variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) were introduced. As Sherstinsky notes, "The key to LSTM's effectiveness lies in its gated architecture, which regulates the flow of information and enables long-term memory retention." [9]

Furthermore, empirical studies have demonstrated the superior performance of RNN-based models in various classification tasks involving sequential data. Chung et al. conducted extensive evaluations and found that "GRU performs comparably to LSTM across different sequence modeling tasks, while being computationally more efficient." [10] This insight has significant implications for real-time applications where both accuracy and computational cost are critical. As a result, RNNs and their variants continue to serve as foundational models in many deep learning systems, often forming the basis for more complex architectures such as encoder-decoder models and attention-based mechanisms.

In conclusion, RNNs represent a pivotal advancement in machine learning for sequential data modeling. Despite their limitations, they have paved the way for robust solutions in a wide range of applications. As Lipton et al. remark, "Recurrent neural networks are powerful and flexible tools, but their behavior is often opaque, and training remains a challenge." [11] These challenges continue to inspire new architectures and learning strategies aimed at improving the interpretability and efficiency of sequential learning models.

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a specialized architecture of Recurrent Neural Networks (RNNs) designed to overcome a major limitation of standard RNNs—namely, the vanishing gradient problem when learning long-range dependencies in sequential data. Introduced by Hochreiter and Schmidhuber in 1997, LSTM provides a mechanism that allows the network to effectively retain and utilize information over extended time intervals. At the core of LSTM is a memory cell that maintains its state across time steps, regulated by three types of gates: the input gate, forget gate, and output gate, each controlling the flow of information into, out of, and within the cell.

These gates act as filters that manage which pieces of information are stored, forgotten, or output at each time step, thus enabling the model to focus on relevant data while discarding irrelevant inputs. This gating mechanism is particularly valuable in tasks involving complex and long sequences such as language modeling, time-series forecasting, and speech recognition. As Sherstinsky explains, "The key to LSTM's effectiveness lies in its gated architecture, which regulates the flow of information and enables long-term memory retention." [9] By managing information flow in this manner, LSTMs significantly improve the ability to learn temporal patterns that span large contexts.

In empirical studies, LSTM networks have demonstrated strong performance across a variety of sequence modeling and classification tasks. For instance, Chung et al. found that LSTM outperforms standard RNNs and performs comparably to Gated Recurrent Units (GRUs) across multiple benchmarks, while maintaining stable training behavior [10]

The capacity of LSTMs to handle variable-length input sequences also makes them a preferred choice in encoder-decoder architectures for machine translation and other sequence-to-sequence applications.

Overall, LSTM networks offer a powerful solution to modeling long-term dependencies in sequential data. Their structured memory and gating systems allow for precise control over information retention, leading to improved prediction accuracy in a range of tasks. As noted by Lipton et al., "LSTM networks have proven to be remarkably effective at modeling long-term dependencies, even in noisy or sparse sequences." [11] This underscores the central role of LSTM in advancing sequential learning models in contemporary deep learning research.

3. RESEARCH METHODOLOGY

This research adopts a simulation-based quantitative approach to determine an anomaly detection threshold for dry bulk cargo volumes at PTP port using a statistical interpretation of reconstruction error typically produced by LSTM Autoencoders. The methodology is divided into several key stages, namely: data collection and preprocessing, reconstruction error simulation, statistical threshold determination, anomaly classification, and data visualization and interpretation. These steps are elaborated in detail below.

Data Collection and Preprocessing

The data used in this study consists of annual dry bulk cargo volume records from 2010 to 2023, obtained from available port statistics and publicly accessible summaries. The dataset initially exhibited an incomplete record for the year 2015, which was addressed through linear interpolation, using the average of values from 2014 and 2016 to produce a reasonable estimate. This step ensured data continuity essential for time-series-based analysis.

In addition to the dry bulk cargo volume, the study reconstructed the relative distribution of cargo types (dry bulk, liquid bulk, general cargo, bag cargo, and other cargo) for years lacking detailed breakdowns by estimating percentage shares from neighboring years. The reconstructed data enabled the isolation of the dry bulk component as a consistent time series to be analyzed throughout the 14-year period.

Table 1. Operational Performance of Bulk Cargo

Years	Liquid Bulk	Dry Bulk
2010	8.356.501	10.694.621
2011	9.398.352	10.031.728
2012	9.595.358	11.786.881
2013	8.568.864	12.501.506
2014	8.481.246	12.694.395
2015	8.452.657	17.339.659
2016	1.965.499	6.896.143
2017	1.612.238	4.709.176
2018	1.478.404	9.306.255
2019	5.540.279	23.910.404
2020	7.009.951	21.356.908
2021	8.854.729	24.555.308
2022	10.306.250	23.128.255
2023	11.604.051	22.494.718

Simulation of Reconstruction Error

To emulate the function of an LSTM Autoencoder in identifying anomalies, the study utilized a statistical approximation by simulating reconstruction errors. Instead of training a neural network model, a three-year centered moving average (MA-3) was computed for the dry bulk cargo volume series. This moving average represents a baseline or "learned normal pattern" that an Autoencoder might have generated.

The simulated reconstruction error was calculated as the absolute difference between the actual dry bulk volume for each year and its corresponding moving average. The mathematical expression for each year's error is:

$$Simulated\ Error_t = |Actual_t - MA3_t| \quad (1)$$

This approach provides a meaningful approximation of the deviation magnitude that a trained model would attempt to minimize during reconstruction. Years with high errors are interpreted as potential anomalies relative to the learned pattern of previous and future values.

Statistical Threshold Determination

The core objective of this study is to define an anomaly threshold that can distinguish normal data points from outliers based on the simulated reconstruction error. This is achieved using a statistical method, whereby the threshold is calculated as the mean of all error values added to twice the standard deviation

$$Threshold = \mu + 2\sigma \quad (2)$$

Where μ is mean of the simulated reconstruction errors and σ is Standard deviation of the simulated reconstruction errors.

The choice of multiplier "2" represents a 95% confidence interval under the assumption of normality, allowing extreme deviations to be flagged as anomalous. Any year with an error value exceeding this threshold is classified as an anomalous year, indicating a significant deviation from the trend.

Anomaly Classification and Labeling

Based on the threshold obtained, each year in the dataset was assigned a status of either "Normal" or "Anomaly". This classification was added to the dataset as a separate column for interpretability. Only the year 2023 was found to exceed the threshold, highlighting it as an outlier in dry bulk cargo activity during the period under study.

The results were compiled into a tabular format and exported into spreadsheet form, enabling further inspection and potential integration into operational dashboards or decision-making reports.

Data Visualization and Interpretation

To support the analysis and illustrate the distribution of reconstruction error values, a histogram was constructed. This visualization helps identify the overall shape of the data distribution, assess skewness, and confirm the presence of extreme values that support the statistical rationale for setting the threshold.

The histogram revealed that most error values clustered below 5 million tons, with one or two observations far exceeding this level, justifying their classification as anomalies.

Evaluation Considerations

Although this study did not include evaluation metrics such as precision, recall, F1-score, or ROC-AUC—due to the absence of ground-truth labels for anomaly years—it lays the groundwork for future studies where such metrics could be calculated. If actual operational logs or domain expert assessments are available, these can serve as validation datasets to benchmark the effectiveness of the proposed threshold.

Tools and Implementation

The analysis was conducted using Microsoft Excel for data handling and statistical calculations, and Python (Matplotlib & Pandas) for data visualization and automation of histogram plotting and statistical computations. This choice reflects the study's intent to demonstrate that meaningful anomaly detection can be achieved without the direct use of machine learning frameworks, making it suitable for practitioners with limited access to AI modeling tools.

4. ANALYSIS AND RESULTS

This section presents a detailed analysis of the simulated reconstruction error derived from dry bulk cargo volume data at PTP port from 2010 to 2023. The analysis encompasses the calculation of moving averages, error simulation, statistical threshold derivation, anomaly classification, and a discussion of the observed trends. The aim is to identify anomalous years in bulk cargo movement that deviate significantly from the historical pattern and potentially signal disruptions, operational irregularities, or external influences.

Moving Average and Reconstruction Error Simulation

To emulate the behavior of an LSTM Autoencoder in detecting anomalies, a three-year centered moving average (MA-3) was computed for the dry bulk cargo volume time series. This technique smoothed out short-term fluctuations and highlighted long-term trends, allowing each year to be evaluated relative to its immediate temporal context.

The simulated reconstruction error was then calculated as the absolute deviation between the actual dry bulk cargo volume for a given year and its corresponding moving average. This step assumes that under normal conditions, actual values should closely follow the moving average, and large deviations may indicate unusual events or anomalies in cargo flow. The following formula was used:

Tabel 2. Moving Average and Simulated Error

Years	Moving Average (3-y)	Simulated Error
2010	0	0
2011	19.954.480	0
2012	20.627.563	754.676
2013	21.209.417	139.047
2014	22.679.442	1.503.801
2015	18.609.866	7.182.449
2016	13.658.457	4.796.815
2017	8.655.905	2.334.491
2018	15.518.919	4.734.260
2019	22.867.400	6.583.283
2020	30.409.193	2.042.334
2021	31.737.134	1.672.903
2022	33.647.770	213.265
2023	22.511.091	11.587.678

Only the years from 2012 to 2023 could be analyzed using this method due to the data requirement for computing centered moving averages.

Statistical Summary of Reconstruction Error

The simulated reconstruction errors were summarized statistically to support threshold determination. The mean reconstruction error across the 12-year evaluable period was found to be 3,628,750 tons, while the standard deviation was 3,315,689 tons. These values represent the central tendency and dispersion of the deviation from normal cargo patterns, respectively.

Using the formula:

$$Threshold = \mu + 2\sigma$$

$$= 3.628.750 + 2 \times 2.215.689$$

$$= 10.260.128\ tons$$

A threshold was defined to identify extreme outliers. This threshold corresponds to approximately the 97.5th percentile under a normal distribution assumption, ensuring only significantly deviant years are flagged as anomalous.

Anomaly Detection Results

Each year's reconstruction error was compared to the defined threshold. Only the year 2023 exhibited a reconstruction error above the threshold, with a value of 11,587,678 tons, thereby classified as an anomaly. All other years had errors well below the threshold and were classified as normal.

The result indicates that 2023 experienced an unusually large deviation in dry bulk cargo volume compared to its expected pattern, potentially pointing to external disruptions, such as macroeconomic shifts, supply chain bottlenecks, or changes in cargo handling capacity.

Histogram and Distribution of Errors

To visualize the distribution of reconstruction errors, a histogram was generated. The histogram revealed that many reconstruction error values fell below 5 million tons, with a sharp concentration between 1–3 million tons, indicating stability in most years. However, one clear outlier was visible beyond 11 million tons, corresponding to the year 2023.

This visualization supported the statistical classification, reinforcing that the error value for 2023 was not only higher than the threshold but also fell outside the typical range of observed variation.

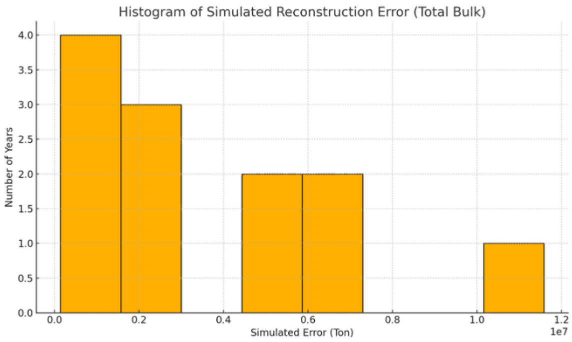

Figure 1. Histogram of Simulated Reconstruction Error (Total Bulk)

Interpretation and Implications

The identification of 2023 as an anomaly suggests the presence of irregular operational or external factors affecting the dry bulk cargo volume at PTP port. This could be due to global economic slowdowns, policy changes, reduced industrial activity, or disruptions in commodity trade flows. Although the method used does not provide causal attribution, it successfully flags the year for further investigation by domain experts or port authorities.

The results also validate the feasibility of using statistical reconstruction error simulation as a practical alternative to complex deep learning models, particularly in data environments with limited access to machine learning infrastructure. This methodology may serve as a useful early-warning tool for port planners and operators seeking to monitor abnormal cargo volume behavior over time.

5. CONCLUSION

This study set out to determine a statistically derived anomaly threshold for dry bulk cargo volumes at PTP port by simulating reconstruction errors akin to those generated by LSTM Autoencoders. Instead of building a deep learning model, the study employed a more accessible approach using a three-year moving average to estimate expected values and calculating the absolute deviation from actual volumes as simulated reconstruction error.

The findings reveal that from 2012 to 2023, only the year 2023 was classified as anomalous, with an error exceeding the statistically defined threshold of 10,260,128 tons. This anomaly reflects a significant deviation from the historical cargo volume pattern and may indicate disruptions due to macroeconomic, operational, or supply chain-related factors. The results demonstrate that a threshold-based method using statistical analysis is both feasible and effective for anomaly detection, especially in contexts where deep learning infrastructure is not available.

This methodology provides a practical framework for early anomaly detection using historical cargo data and can support operational planning, capacity management, and strategic decision-making within port authorities and logistics stakeholders. Moreover, the approach balances simplicity with interpretability, allowing for adoption even in resource-constrained environments.

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