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APPLYING MULTILAYER PERCEPTRON AND DATA FILTERING FOR PRELIMINARY SECOND-HAND SHIP PRICE ESTIMATION

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Abstract: This research investigates the use of a Multilayer Perceptron (MLP) neural network combined with Z-score filtering for preliminary estimation of second-hand ship prices of bulk carriers and tankers. A simplified dataset containing only deadweight tonnage (DWT) and sale price was preprocessed to remove outliers and improve normality. A single MLP architecture with an automatic hidden layer configuration was implemented in the DataMelt environment using WEKA through Jython scripting. Model evaluation showed moderate predictive performance (correlation ≈ 0.50 ; $R^2 \approx 0.25$), indicating that even minimal input features can provide rough cost estimates for early-stage procurement decisions. The findings confirm the potential of neural networks for maritime price forecasting while emphasizing the need for richer datasets to improve accuracy.

Keywords: MLP, WEKA, bulk carrier, tankers, price estimation.

1. INTRODUCTION

Cost estimation and price analysis remain areas of extensive research [Gresia et al., 2023; Singh, 2019]. In particular, estimating second-hand ship prices is crucial in maritime economics due to its influence on fleet procurement and investment decisions [Pruyn et al., 2011]. Azhar [2021] argues that purchasing of second-hand vessels offers faster and more cost-effective solutions compared to newbuilding, and proposes a multi-method approach combining market price, comparative vessels, and physical pricing techniques. Econometric analysis by Tsolakis et al. [2003] introduces an Error Correction Model to capture short- and long-term price dynamics, showing that variables such as newbuilding rates, time charter rates, and orderbook size significantly influence second-hand prices, with effects varying across ship segments. Additionally, Koç Ustali et al. [2024] apply the SWARA method to evaluate 25 criteria that include economic factors, ship characteristics, and buyer-seller attributes to provide insights for market players to manage financial risks and improve decision-making. These

studies collectively demonstrate the complexity of second-hand ship valuation and the need for robust, data-driven models.

Machine learning methods have increasingly been applied to ship price forecasting. A novel approach was proposed by Bal et al. [2025], using Baltic Exchange indices and algorithms including XGBoost, which achieved the highest accuracy among tested models. Support vector regression (SVR) has also been applied to newbuilding ship price forecasting across different vessel types and markets, demonstrating superior predictive performance compared to standard Autoregressive Integrated Moving Average (ARIMA) time-series models [Syriopoulos et al., 2021]. The complex dynamics of vessel pricing are further explored by Tsatsaronis et al. [2026], who employ machine learning techniques, including k-means clustering to classify investor behavior in the sale and purchase market, revealing distinct investment profiles and strategies across different market participants. These findings underscore that ship prices are shaped not only by vessel characteristics but also by broader market cycles and investor behavior.

This research aims to determine general trends in second-hand ship prices of bulk carriers and tankers based on historical market data retrieved from Lee [2023]. A Multilayer Perceptron (MLP) neural network is applied to capture non-linear relationships and improve prediction accuracy. The study also examines whether ship prices can be estimated using only deadweight tonnage (DWT), offering a simplified model for early procurement decisions.

2. METHODS

This section describes the methodological framework adopted to achieve the research objectives, an approach that combines statistical preprocessing techniques. First, Z-score filtering is applied to detect and manage outliers, improving the reliability of the input data.

Z-score filtering is a well-established technique for detecting and removing outliers, ensuring data reliability and improving data quality in complex environments. Its effectiveness has been demonstrated across multiple domains, including transportation and logistics [Peng et al., 2024; Perurivenkata et al., 2019; Yaro et al., 2023]. For instance, Z-scoring combined with linear regression has been applied to identify temporal outliers in road traffic data, enabling early detection of unusual incidents or sensor failures [Mondal & Rehena, 2020]. Similarly, automated traffic signal performance measures utilize Z-score thresholds to flag anomalies in traffic volume data, enhancing the accuracy and usability of ATSPM systems for engineers and planners [Wang et al., 2023]. In production logistics, research emphasizes that outlier handling should not only focus on exclusion but also interpretation, as indiscriminate removal of outliers can lead to a loss of valuable information. A distinction must be made between an outlier as a defect and an outlier as a special

datum, which can be achieved through interpretation methods [Hochkamp et al., 2022]. Furthermore, Z-score normalization has been successfully integrated into advanced filtering approaches for infrared small target detection under heavy cloud interference, reducing false alarms and improving detection performance in aerospace and security applications [Peng et al., 2024]. These studies confirm that Z-score-based methods are valid, practical, and enhance the precision of data-driven systems across diverse applications.

In this study Z-score normalization is employed, and the formula for Z-score normalization is defined as follows (1):

$$Z_i = \frac{X_i - u}{\sigma} \quad (1)$$

where: u – mean value of raw data, σ – standard deviation of X , X_i – individual observation (raw data), and Z_i – the normalized data, i.e., the normalized score for observation i . It indicates the position of the raw data relative to the mean value, which is expressed as a multiple of the standard deviation [Peng et al., 2024].

WEKA is a widely used open-source machine learning workbench that provides a comprehensive collection of algorithms and preprocessing tools for data mining and knowledge discovery [Frank et al., 2009]. It offers an intuitive graphical interface and supports advanced experimental setups, making it a standard tool in academic and applied research. WEKA has evolved to include modern capabilities, such as GPU acceleration for large-scale datasets [Cassales et al., 2025], Python integration through WekaPyScript for flexible algorithm development [Beckham et al., 2016], and deep learning support via WekaDeeplearning4j, enabling GUI-based training of neural networks like MLPs, convolutional, and recurrent models [Lang et al., 2019]. These features ensure WEKA remains a robust platform for implementing classification, regression, and neural network models in scientific studies. The basics of neural networks are presented in Haykin [2009].

However, the use of the WEKA script for MLPs was demonstrated by both Morariu et al. [2017] and Rungrattanaubol et al. [2011], showing the effectiveness of Multilayer Perceptron (MLP) neural networks in different domains. Morariu et al. used WEKA's Knowledge Flow environment to implement MLP for automatic document classification, applying feature selection with Information Gain and showing that fine-tuning hidden layer neurons improves accuracy. Similarly, Rungrattanaubol et al. applied MLP to predict injury severity in road traffic accidents using hospital survey data, integrating the model into the EDEN environment for interactive exploration. These studies confirm MLPs versatility for classification tasks and its practical implementation in accessible tools like WEKA and EDEN.

3. RESULTS

The DataMelt software was used during this research, a versatile computational environment designed for scientific data analysis, mathematical modeling, and statistical computations. It supports multiple scripting languages, including Python/Jython, BeanShell, Groovy, JRuby, and Matlab/Octave, within the Java and Android ecosystems. Unlike many other platforms, DataMelt leverages the Java programming language for enterprise-level scientific computing. The environment is a continuation of earlier projects: jHepWork (1995–2013) and SCAVis (2013–2015), with full compatibility retained from jHepWork version 3.9. DataMelt Code is based on Chekanov [2024, 2016, 2010]. Further details on DataMelt are available on datamelt.org. Other statistics in this research were calculated using Statistica Software.

3.1. DATA SET

The dataset used in this study is based on second-hand ship Sale & Purchase (S&P) transaction records originally compiled by [Lee, 2023]. The original dataset comprises 3,335 records – 2,108 bulk carrier samples and 1,227 oil and chemical tanker samples, covering transactions from January 2018 to July 2022, sourced from Clarksons Research. The data includes such variables as vessel name, IMO number, ship type, deadweight tonnage, age, sales date, and sales price. For the purpose of this study, the data was digitized from the graphical representations published in Lee [2023], extracting only two variables: DWT and sale price. This digitization process resulted in 1030 observations, as only data points clearly legible from the published figures were extracted.

Figure 1 illustrates the empirical relationship between deadweight tonnage and the sale price of second-hand bulk carriers and oil tankers, based on digitized data from [Lee, 2023], while Figure 2 presents the original graph from [Lee, 2023]. The overall distribution suggests a positive association between vessel size and market value. However, several observations deviate significantly from the main trend, particularly smaller vessels with disproportionately high prices. These anomalies likely reflect non-standard determinants, such as vessel age, technological enhancements, or short-term market fluctuations. The processed dataset exhibits substantial variability, with a standard deviation of approximately \$21.8 million and a mean deviation of \$14.5 million, indicating a wide dispersion of sale prices. This high variability supports the presence of extreme observations, which will be addressed through outlier detection using Z-score analysis.

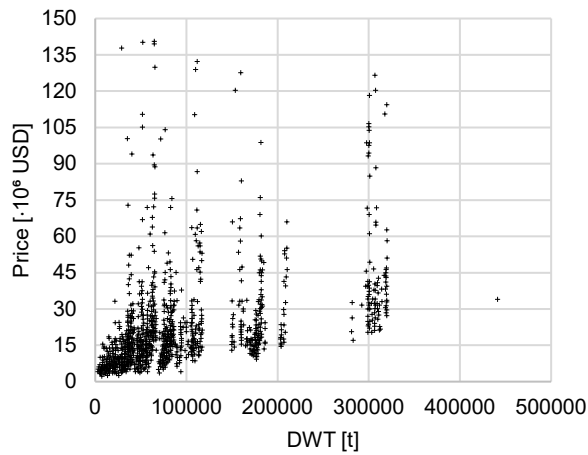


Figure 1. Scatter plot of relationship between ship size (DWT) and sale price

Source: based on digitized data [Lee, 2023].

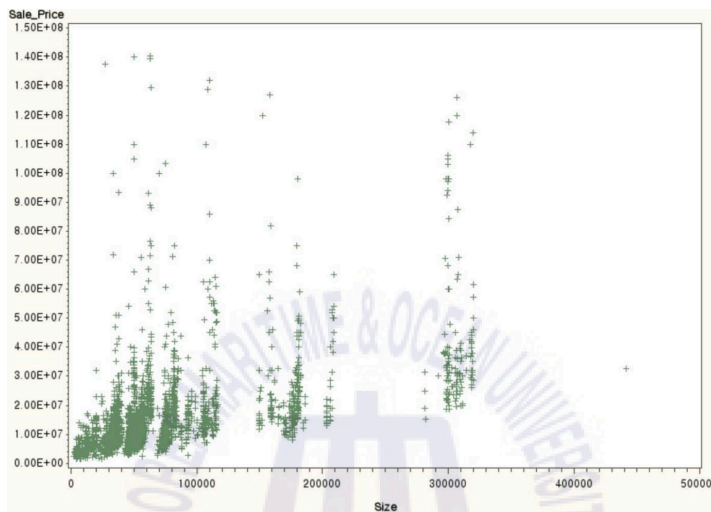


Figure 2. Scatter plot of relationship between ship size (DWT) and sale price

Source: original set [Lee, 2023, p. 50].

3.2. APPLICATION OF Z-SCORE FILTERING

Given the substantial variability in sale prices (standard deviation $\approx$ \$21.8 million), Z-score analysis was applied to identify and remove extreme outliers. The implementation was carried out in the DataMelt environment through a Jython script by author for this research, utilizing existing DataMelt libraries for statistical analysis.

The script calculated the mean and standard deviation of ship prices, computed Z-scores for each observation, and excluded data points exceeding the specified threshold. Threshold values of Z-score ranging from 3 to 1 were tested, as shown in Figure 3, which illustrates the effect of different Z-score thresholds on dataset size. Applying the strictest threshold equal to 1 reduced the dataset to 923 observations from the original 1030 observations, significantly minimizing the influence of anomalous points. The threshold of Z-score equal to 1 was selected with the intention of retaining only observations concentrated around the central tendency of the dataset, as may be observed in Figures 1 and 2, where the majority of ship price data was clustered around lower values, while a small number of significantly higher-priced observations deviated substantially from this central cluster.

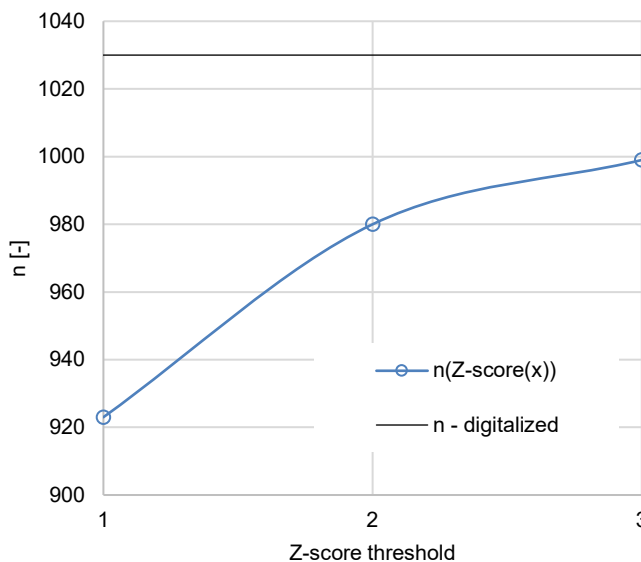


Figure 3. Effect of Z-score threshold on dataset size after filtering, where: $n(Z\text{-score}(x))$ denotes the number of observations retained after applying the z-score filter

Source: own study.

Figure 4 visualizes the filtering effect, where excluded data points are marked in red and retained points in blue.

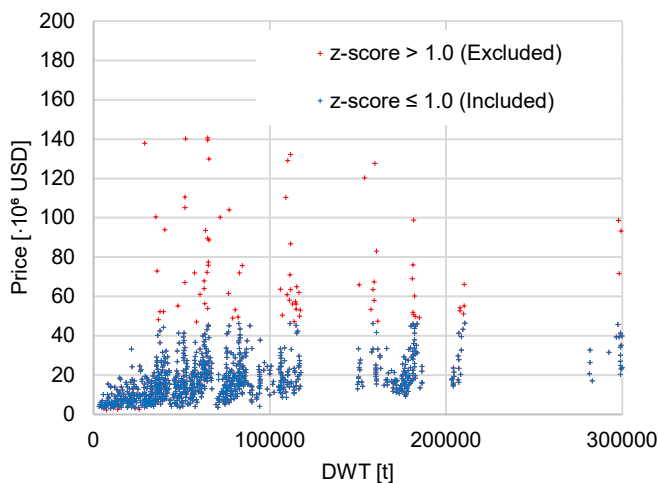


Figure 4. Scatter plot of ship size (DWT) and sale price, showing original data points (red) excluded by z-score filtering and retained points (blue) used for analysis

Source: own study.

After applying the Z-score filtering, the standard deviation of ship prices decreased from 21 783 313.63 to 10 189 276.79, and the mean deviation dropped from 14 478 490.56 to 8 186 730.09. This represents a reduction of approximately 53% in standard deviation and 43% in mean deviation, confirming the effectiveness of the filtering process. The substantial decrease in variability indicates that extreme outliers were successfully removed, producing a more homogeneous dataset. This step is critical for improving the reliability and accuracy of subsequent machine learning modeling. It is acknowledged that this strict threshold may remove some legitimate high-value market observations, not only erroneous data points; however, the primary objective of this study was also the preliminary price estimation for typical vessels rather than modeling of extreme market events. The Z-score filter was applied exclusively to the sale price variable – DWT values were retained as recorded. For further analysis using the Multilayer Perceptron (MLP) algorithm, only the filtered dataset was utilized.

In addition, normality was evaluated using descriptive statistics and probability plots using Statistica software. The dataset ($n = 1030$) exhibited skewness of 2.55 and kurtosis of 7.93, indicating a highly skewed distribution. After Z-score filtering, the dataset contained 923 observations, skewness decreased to 0.74 and kurtosis to -0.09 , values consistent with a near-normal distribution. The P-P plot (Figure 5) further confirms the improvement in normality, with the filtered data aligning closely with the theoretical normal line.

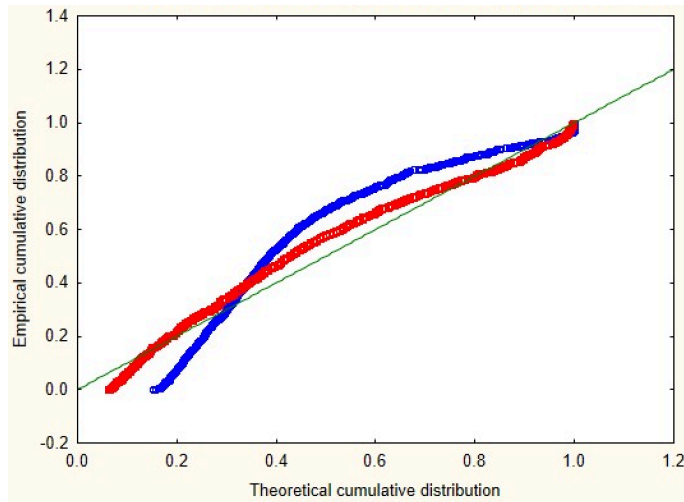


Figure 5. Probability–Probability (P–P) plot showing empirical cumulative distributions of the dataset before filtering (blue) and after z-score filtering (red), compared to the theoretical normal distribution

Source: own study.

3.3. THE USE OF MLP

Following the preprocessing steps described in Section 3.2, the filtered dataset was used to train an MLP model for predicting vessel sale prices based on DWT. The reduction in variability and improvement in normality (Figure 5) were essential for stabilizing the neural network training process and minimizing the influence of extreme outliers. The MLP was implemented in the DataMelt environment using Jython and the WEKA library, with a learning rate of 0.15, momentum of 0.1, and 1000 training iterations, and hidden layers set to "a". The automatic hidden layer configuration "a" in WEKA computes the number of hidden neurons as $(\text{number of inputs} + \text{number of outputs}) / 2$. Given the single input variable (DWT) and single output variable (price), this resulted in one hidden neuron in the hidden layer.

The MLP model achieved a root mean squared error (RMSE) of \$8.92 million and a mean absolute error (MAE) of \$6.84 million, with a correlation coefficient of 0.504 and $R^2 = 0.254$. These results indicate that the model explains approximately 25% of the variance in sale prices, which is reasonable given the complexity of market determinants. Compared to the original dataset variability (standard deviation $\approx$ \$21.8 million), the prediction error is substantially lower, confirming the benefit of Z-score filtering in reducing noise and improving model stability. However, the moderate R^2 suggests that additional explanatory variables, such as vessel age or technological features, may be required to enhance predictive performance. Figure 6 shows predicted

(red points) vs. actual prices (blue points), indicating that the MLP approximates the nonlinear relationship between DWT and price, though residual variance remains.

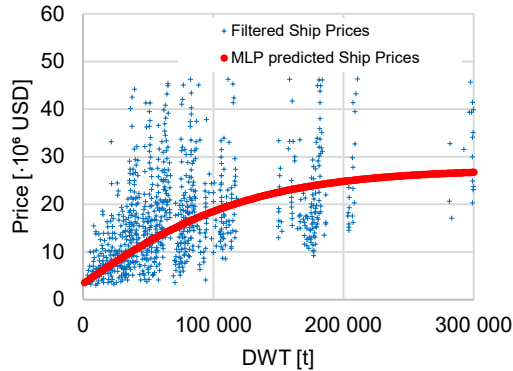


Figure 6. Predicted relationship between DWT and vessel sale price using the MLP model, with actual data points shown in blue

Source: own study.

To derive an analytical approximation, the trained MLP model was used to generate predicted prices for DWT values ranging across the dataset in increments of 1000 t. A third-degree polynomial curve was then fitted to these MLP-generated predictions (Figure 7), yielding Equation 2, which provides a closed-form expression suitable for rapid preliminary estimation of ships price in early-stage design for ships up to 300 000 DWT.

$$PRICE_{USD} = 7.16 \cdot 10^{-16} \cdot DWT^3 - 6.61 \cdot 10^{-10} \cdot DWT^2 + 2.12 \cdot 10^{-4} \cdot DWT - 3.17 \quad (2)$$

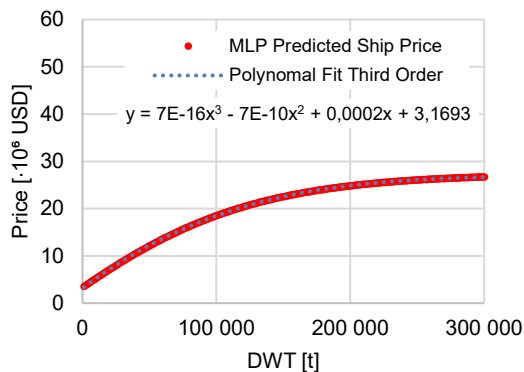


Figure 7. Third-degree polynomial curve fitted to MLP-generated price predictions as a function of DWT

Source: own study.

4. DISCUSSION

This study demonstrated the effectiveness of data preprocessing and machine learning modeling for predicting second-hand vessel prices based on DWT. The initial dataset (Figure 1) exhibited substantial variability and skewness, with numerous outliers influencing the overall distribution. Applying Z-score filtering (described in Section 3.2) significantly improved data quality by removing extreme observations, reducing the standard deviation by 53% and mean deviation by 43%, as illustrated in Figures 3 and 4. Normality assessment confirmed this improvement, with skewness and kurtosis values approaching zero and the P-P plot (Figure 5) showing close alignment with the theoretical normal distribution, when compared to the original dataset variability (Section 3.1), where the standard deviation was approximately \$21.8 million and decreased to \$10.2 million after z-score filtering.

This confirms that preprocessing not only improved data quality but also enhanced model stability and accuracy relative to the inherent variability of the dataset. The filtered dataset enabled the successful application of an MLP model implemented in the DataMelt environment using WEKA (Section 3.3). The model achieved an RMSE of \$8.92 million and MAE of \$6.84 million, with $R^2 = 0.254$ and a correlation coefficient of 0.504. These results indicate that the MLP captured the nonlinear relationship between DWT and price (Figure 6). In addition, the preprocessing step using Z-score filtering played a critical role in improving model performance. By removing extreme outliers, the dataset's variability was reduced by over 50%, and normality was significantly improved (Figure 5). These changes likely contributed to better convergence of the MLP algorithm and reduced prediction error. Without filtering, the presence of highly skewed data and extreme values would have led to unstable training and substantially higher error metrics.

Machine learning methods have shown growing potential in maritime price forecasting. Syriopoulos et al. [2021] confirmed that SVR outperforms ARIMA in ship price prediction. While a direct MLP-SVR comparison is beyond the scope of this study, both methods demonstrate the value of nonlinear approaches in this domain. However, residual variance suggests that additional explanatory variables, such as vessel age, technology level, and market conditions, are necessary to improve predictive accuracy. This observation is consistent with findings by Tsatsaronis et al. [2026], who demonstrate that vessel prices are shaped by a combination of interrelated factors. Drawing on k-means cluster analysis of 565 dry bulk transactions, the authors identify the following key price determinants:

- freight rate levels,
- supply-side dynamics,
- vessel age,
- vessel size,
- technological and environmental features, such as eco-electronic engines and SOx scrubbers,

- market cycle phase,
- investor nationality and institutional context,
- Environmental, Social and Governance (ESG) [Pangalos, 2023].

Together, these factors illustrate that vessel pricing is not solely driven by physical asset characteristics, but is equally shaped by investor behavior, market cycles, and broader economic dynamics in the sale and purchase market.

5. CONCLUSIONS

The results of this study indicate that an MLP neural network can approximate the relationship between DWT and second-hand ship prices, even when using a highly simplified dataset. The achieved correlation coefficients (≈ 0.50) and R^2 values (≈ 0.25) suggest moderate predictive capability, which is reasonable given the complexity of market determinants and the limited number of input features. These findings confirm that neural networks can serve as a preliminary tool for rough cost estimation during early procurement stages, where quick approximations are valuable.

The application of Z-score filtering significantly improved data quality by reducing variability and enhancing normality, which stabilized the training process and minimized the influence of extreme outliers. This step was critical because the original dataset exhibited high skewness and kurtosis, reflecting market volatility and irregular pricing patterns.

However, the moderate accuracy highlights a key limitation: ship prices are influenced by multiple factors beyond DWT, such as age, condition, technological features, and market cycles. Incorporating these variables into future models could substantially improve predictive performance. Additionally, testing alternative machine learning algorithms (e.g., Random Forest, Gradient Boosting) and comparing them with MLP could provide insights into the most effective approach for maritime price forecasting.

Overall, this research demonstrates the feasibility of using neural networks for preliminary ship price estimation and underscores the importance of data preprocessing in achieving reliable results. Future work should focus on expanding the dataset, integrating additional explanatory variables, and exploring hybrid modeling techniques to enhance accuracy and practical applicability.

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