JSCDM

JOURNAL OF SOFT COMPUTING AND DATA MINING
e-ISSN: 2716-621X

Vol. 7 No. 3 (2026) 28-38
https://publisher.uthm.edu.my/ojs/index.php/jscdm

Comparative Analysis of Data Normalisation Techniques: A Case of Reservoir Water Level Monitoring

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DOI: https://doi.org/10.30880/jscdm.2026.07.03.003

Article Info

Received: 25 November 2025
Accepted: 19 October 2026
Available online: 1 November 2026

Keywords

Data normalisation, neural network, reservoir monitoring, Min-Max, Z-score, Decimal Scaling

Abstract

Reservoir water level data may vary with seasonal rainfall, reservoir operations and extreme hydrological events. This study compares four normalisation techniques applied to 3,287 daily observations from the Timah Tasoh Reservoir between 1 January 1999 and 31 December 2007: Min-Max (binary), Min-Max (bipolar), Z-score and Decimal Scaling. The original water levels ranged from 26.81 to 30.00 m, with a skewness of −0.878 and an excess kurtosis of 0.327. Using descriptive statistics and Pearson correlation, we compared the resulting scales and statistical characteristics of the transformed observations. Strengths, weaknesses, opportunities and threats (SWOT) analysis was also used to summarise the practical characteristics of each technique. The study identified 23 observations meeting the $|Z| > 3$ outlier criterion. Min-Max normalisation mapped the observed range to 0–1 or −1 to 1, while Decimal Scaling divided each water level by 100. All four transformations had a reported Pearson correlation of 1.000 with the original observations, consistent with their positive linear formulas. The techniques produced different scales but preserved the ordering of observations. No forecasting algorithm was trained or tested, so the results do not establish which technique would yield the best predictive accuracy. The comparison provides statistical information to guide preprocessing choices for future reservoir forecasting studies.

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1. Introduction

Reservoirs are artificial or natural water storage systems that regulate water resources for purposes such as irrigation, hydropower generation, flood mitigation, and domestic supply. One of the most important operational parameters is the reservoir water level. Monitoring reservoir water levels is vital because changes can affect water supply, hydropower generation, flood control, and environmental sustainability [1,2].

Machine learning techniques such as neural networks have been used for reservoir water level forecasting [2]. Machine learning has also been studied in petroleum reservoir exploration and prediction [3]. The performance of neural network models depends not only on the learning algorithm but also on the quality of the input data and its preparation before training [4]. Data normalisation is a common preprocessing technique that makes features with different numerical scales more comparable during learning [5,6]. Neural networks can model complex nonlinear relationships, but their performance is also influenced by network design and the training process [7,8]. Input scaling is therefore one consideration when preparing data for a neural network.

Normalisation transforms data to a defined numerical range or expresses observations relative to summary statistics [5,6]. The effect of extreme values depends on the method used. Although normalisation is widely adopted in machine learning, the selection of a technique is often based on convention or software defaults rather than the statistical characteristics of the dataset. In practice, different methods transform data in different ways and respond differently to extreme observations. A comparative evaluation can therefore help researchers select a preprocessing method before developing predictive models.

The effectiveness of a normalisation technique also depends on its compatibility with the neural network architecture, including its activation functions. Sigmoid, Tanh, and other activation functions respond differently to their inputs [9,10]. Min-Max normalisation produces values within a specified interval, while Z-score normalisation and Decimal Scaling transform observations without imposing the same fixed interval. The suitability of these methods for a particular neural network must be evaluated in the context of its data and model design.

Reservoir water level data can be affected by seasonal rainfall, reservoir operations, droughts, and flood events. These factors can lead to varying dispersion and extreme observations. There is no single normalisation method that works for all reservoir datasets. A method suited to one dataset may not be equally suitable for another with different statistical characteristics. It is therefore important to understand the properties of different normalisation methods before developing predictive models for reservoir monitoring.

Normalisation has been examined in medical and classification datasets [11-15]. However, findings from those applications do not establish which method is preferable for reservoir water level data. Kachapornkul et al. [2] developed a machine learning approach to reservoir water level forecasting, but few comparisons have examined how different normalisation methods affect the statistical characteristics of reservoir water level observations. This gap requires further investigation.

In this paper, we apply four normalisation techniques to reservoir water level data: Min-Max (binary), Min-Max (bipolar), Z-score, and Decimal Scaling. We compare the statistical characteristics of the resulting values and examine how each technique responds to the data distribution and extreme observations. We do not train or test any forecasting algorithm, so the study does not assess the effects of these techniques on prediction accuracy.

2. Literature Review

Data preprocessing plays a significant role in the performance of machine learning models. Data normalisation is a common preprocessing method because it places input variables on more comparable numerical scales before model training. When variables have substantially different scales, those with larger numerical values can have a disproportionate influence on learning. Muhammad Ali and Faraj [6] described normalisation and standardisation as methods for preparing data with different scales. Patro and Sahu [5] discussed normalisation as a preprocessing stage, while Li et al. [4] examined the importance of training data quality in a neural network application. These studies support careful preparation of input data before model development.

There are several common normalisation techniques, each with a different transformation strategy. Min-Max normalisation maps observations to a fixed interval, typically between 0 and 1 (binary) or between −1 and 1 (bipolar). Nancy et al. [11] examined Min-Max normalisation using Alzheimer's disease data. Muhammad Ali [16] investigated its effect on K-nearest-neighbour regression and found that the results varied across datasets and similarity measures.

Z-score normalisation expresses each observation relative to the dataset mean and standard deviation. It allows variables measured on different scales to be compared in terms of their distance from their respective means. Whendasmoro and Joseph [15] examined its effect on K-nearest-neighbour classification. Because the transformation uses the mean and standard deviation, extreme observations can affect the standardised values. Decimal Scaling is a simpler approach that divides every observation by a selected power of 10 [6]. It reduces numerical magnitude but does not account for the distribution or reduce the relative influence of extreme observations.

No normalisation method can be assumed to perform best in every modelling task. Singh and Singh [12] compared methods across classification settings and found that the choice of normalisation affected performance. Izonin et al. [13] investigated several normalisation methods in medical data classification. In a separate study of breast cancer classification using K-nearest neighbours, Henderi et al. [14] reported a better accuracy of 98% with Min-Max normalisation and 97% with Z-score normalisation. Muhammad Ali [16] found that the effect of Min-Max normalisation on K-nearest-neighbour regression varied with the dataset and similarity measure. Together, these findings indicate that normalisation methods should be evaluated for the specific dataset and modelling task.

Input preparation is also relevant when neural networks are used. The scale and distribution of input variables are among the considerations in model design and training. Kanwar et al. [7] discussed neural network design issues, while Uma et al. [8] examined challenges and techniques associated with neural network training. Wang et al. [17] surveyed deep learning methods for motor imagery electroencephalogram (EEG) classification. Their survey illustrates another neural network application, but it does not provide experimental evidence that normalisation improves reservoir forecasting.

The choice of activation function is another aspect of neural network design. Sigmoid, Tanh, and ReLU respond differently to their inputs. Kaloev and Krastev [9] compared activation functions, while Lau and Lim [10] reviewed adaptive activation functions. Stursa and Dolezel [18] compared ReLU and saturated linear activation functions in an approximation task, and Thomas et al. [19] examined activation functions in nodule classification. Castillo-Bolado et al. [20] investigated the design and independent training of reusable neural modules. These studies address activation functions or network design; they do not directly compare Min-Max, Z-score, and Decimal Scaling for reservoir data.

Reservoir water level data presents a distinct preprocessing challenge because water levels can vary with rainfall, seasonal flows, reservoir operations and extreme hydrological events. Abdul Mokhtar et al. [21] used an adaptive neuro-fuzzy inference system to model reservoir water release decisions, while Wan Ishak et al. [1] modelled expert decision-making in reservoir operations. Kachapornkul et al. [2] developed a machine learning approach to water level forecasting. Although these studies demonstrate uses of reservoir data, they do not determine which of the four normalisation techniques examined here is most suitable.

Although normalisation methods have been studied in medical data, classification, regression, and other machine learning applications [11-20], those results do not directly establish how the normalisation methods affect reservoir water level observations.

3. Methodology

The study used water level observations for the Timah Tasoh Reservoir in Perlis. Further information on the Timah Tasoh Reservoir and its basic characteristics is available from the Department of Irrigation and Drainage Malaysia [22]. The water level data are for the daily observations from 1 January 1999 to 31 December 2007. For data processing, the corresponding MS Excel serial date codes (36161- 39447) were used. In total, 3,287 daily observations were provided and water levels ranged from 26.81 m to 30.00 m. The long monitoring period allows for the natural fluctuations in reservoir water levels due to seasonal rainfall, reservoir operations and other environmental factors. We find that this data is reliable for testing the behaviour of different normalisation techniques in real reservoirs.

Data processing and normalisation were done using Microsoft Excel 365. Before applying the normalisation techniques, the data were sorted according to Excel date codes to preserve the chronological sequence of observations. The data were then checked for missing or incomplete records. No missing values were found and we concluded that the dataset was complete and could be applied directly to analyse without having to clean the data.

In this study, we considered four standard normalisation methods. The normalisation methods were implemented in Microsoft Excel using the standard mathematical equations that are summarised in Table 1.

- Min-Max Normalisation (Binary): The data is shifted from 0 to 1.
- Min-Max Normalisation (Bipolar): The data is shifted from -1 to 1.
- Z-score Normalisation: The data is standardised to have a mean of 0 and a standard deviation of 1.
- Decimal Scaling: Decimal Scaling transforms each observation using $x' = x/10^j$, where x is the original water level and j is the smallest nonnegative integer for which the maximum absolute transformed value is less than 1. Since the maximum absolute value in this dataset is 30.00 m, $j = 2$, and each observation is divided by 100.

Unlike many previous studies that evaluate normalisation using machine learning performance, this study focuses on statistical characteristics of normalised data. The comparison includes changes in data distribution, descriptive statistics, sensitivity to extreme observations, and the suitability of each normalisation method for

reservoir water level data. By comparing the normalised data in different ways, we better understand how different normalisation methods transform the original data before it is used to train neural networks.

All the analyses were carried out using Microsoft Excel 365 with built-in statistical functions MIN, MAX, AVERAGE, STDEV.P, SKEW, KURT, and CORREL, and formula-based Z-score calculations. We used descriptive statistics, correlation analysis, outlier analysis, descriptive comparison, and strengths, weaknesses, opportunities, and threats (SWOT) analysis to assess the normalisation methods and their suitability for reservoir water level data.

Descriptive statistics were first calculated to assess the original and normalised data. The different measures were minimum, maximum, range, mean, standard deviation, skewness and kurtosis. These statistics were used to determine the impact of each normalisation method on the data distribution and if the overall characteristics of the original data were retained from the transformation.

To assess the relationship between the original data and the transformed data, Pearson's correlation coefficient was calculated for each normalisation method. The high correlation indicates that the normalisation process preserved the overall pattern of the original data even when the size of the data was changed.

Outliers were identified by the Z-score ($|Z| > 3$) criterion [23]. The number of outliers in each normalised data set was then compared to see how different normalisation techniques handled extreme data. This also showed how different methods react to unusual values that are common to reservoir water level data.

A descriptive comparison was also carried out in order to analyse the practicality of different normalisation techniques. The comparison was done considering the scaling range, compatibility with commonly used neural network activation functions, sensitivity to outliers and general suitability of the reservoir water level data. Finally, we conducted qualitative SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis to summarise the advantages, limitations, potential applications and challenges of each normalisation method. The overall research methodology adopted in this study is shown in Figure 1.

Table 1 *Normalisation methods*

Method	Formula		Output Range
Min-Max (Binary)	$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$	(1)	0 to 1
Min-Max (Bipolar)	$x' = 2 \times \frac{x - x_{min}}{x_{max} - x_{min}} - 1$	(2)	–1 to +1
Z-score	$x' = \frac{x - \mu}{\sigma}$	(3)	Unbounded
Decimal Scaling	$x' = \frac{x}{10^j}$	(4)	$\|x'\| < 1$

In Equations (1)-(4), x is an original water level observation and x' is its normalised value. The terms $x_{\min}$ and $x_{\max}$ are the minimum and maximum observed water levels, respectively; μ is the mean; and σ is the population standard deviation. For Decimal Scaling, j is the smallest nonnegative integer such that the maximum absolute transformed value is less than 1. The maximum absolute value in this dataset is 30.00 m, so $j = 2$ and each observation is divided by 100.

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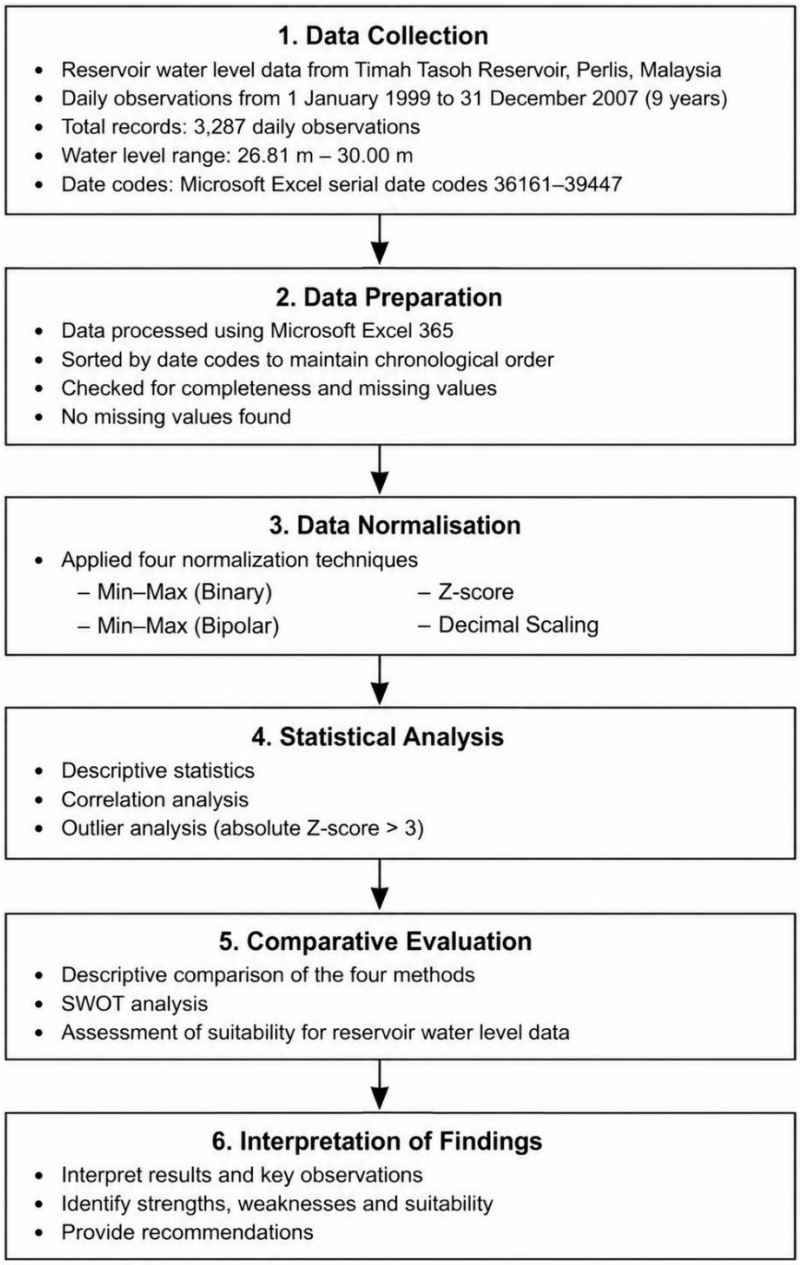


Fig. 1 *Workflow for preparing and comparing normalisation methods for Timah Tasoh Reservoir water level data*

4. Findings

Table 2 summarises the original and normalised data. Over the nine-year observation period, the recorded reservoir water levels ranged from 26.81 m to 30.00 m, a difference of 3.19 m.

All four normalisation methods produced a Pearson correlation of 1.000 with the original dataset. This result is expected because each method applies a positive linear transformation to the water level values. Although the transformed values have different scales, their relative order and linear relationship with the original values are preserved.

The original dataset had a skewness of −0.878, indicating a moderately negatively skewed distribution. Water levels tended to be concentrated toward the higher end of the observed range, with a tail extending toward lower levels. The excess kurtosis was 0.327, slightly above the normal-distribution reference value of zero. This is consistent with somewhat heavier tails, although kurtosis alone cannot determine the number of extreme observations.

Outliers were classified using the Z-score ($|Z| > 3$), and 23 observations were classified as outliers. These values were found between 26.81 m and 27.20 m, which are very low reservoir water levels. If these observations constitute only a fraction of the dataset, then they may have an effect on the normalisation methods, especially the ones based on minimum and maximum values.

The effects of these outliers were different in the four different normalisation methods. Min-Max normalisation was the most affected since the minimum observation is the lower boundary of the transformation. The remaining data is then compressed into a relatively narrow interval and the distance between observations is even smaller. Z-score normalisation is less affected by the overall scale because the scale is based on the mean and standard deviation. Nonetheless, the outliers were clearly distinguishable as large negative deviations from the mean. Decimal Scaling divided every observation by 100, reducing its numerical magnitude while preserving the relative differences between observations. It therefore did not reduce the relative influence of extreme values. Min-Max (bipolar) normalisation mapped the observed water levels to a range from −1 to 1. Zero represents the midpoint of the observed minimum and maximum, which is not necessarily the dataset mean. However, the transformation of the data also depends on the minimum and maximum values, so it was still sensitive to the extreme low observations.

In Table 3 we compare the four normalisation methods. The comparison is based on three practical reasons that are relevant to the data: compatibility with common neural network activation functions, sensitivity to outliers, and correctness of the data for reservoir water levels. Since each normalisation method uses a different transformation, its suitability is influenced by the statistical characteristics of the dataset as well as by the learning model. We see that none of the normalisation techniques is universally superior.

Min-Max (Binary) normalisation is suitable for Sigmoid activation functions because the transformed values are in the range 0 to 1. However, because of the minimum and maximum observations, it is very sensitive to outliers. Even a small number of extreme values can compress the remaining observations into a much smaller range. The Min-Max (Bipolar) normalisation is similar but rescales the data from -1 to 1. This range may be appropriate if an intended model requires inputs between −1 and 1; its effect on model performance was not tested in this study. The extreme values are preferred by Min-Max and thus it is more prone to outliers.

However, Z-score normalisation uses the mean and standard deviation of the data to standardise. This means that the transformed values represent the distance of each observation from the mean rather than a fixed number of observations. The resulting values express each observation's distance from the mean in standard deviation units. Extreme observations can affect both the mean and the standard deviation. Decimal Scaling is the simplest of the four methods. It reduced the numerical magnitude of each water level observation by dividing it by 100, without taking the data distribution into account. The method is very fast but does not do much to reduce the effect of extreme observations and is suitable for relatively consistent data sets.

A qualitative SWOT analysis was performed to evaluate the practicality of each normalisation technique on reservoir water levels. The analysis evaluated their strengths, weaknesses, potential applications and possible limitations. The results are summarised in Table 4.

Overall, the SWOT analysis complements the descriptive comparison. Min-Max (Binary) normalisation is simple to implement, and the bounded values are quite suitable for Sigmoid activation functions. Its main drawback is that it is sensitive to very extreme observations and can significantly reduce the variance in the rest of the data after normalisation has been performed. Min-Max (Bipolar) normalisation has the same properties but with a symmetrical range between -1 and 1. This is more suited to Tanh-based neural networks and datasets that are richer in the areas where deviations around the centre are of more interest. However, it is still affected by high or low observations.

Z-score normalisation gives us a different perspective by describing observations as the mean and standard deviation. In this way, we can retain meaningful differences between observations and the differences in scale of measurement is less influential. But when there are very large outliers, they may increase the standard deviation and decrease the separation among most observations. Decimal Scaling is still the easiest method to implement and requires minimal computational effort. At the same time, since it changes only the numerical size of the data and does not change the distribution of data or the difference due to outliers it doesn't change the data distribution.

Table 2 *Summary of analysis*

Aspect	Finding
Date Range	01 Jan 1999 – 31 Dec 2007
Dataset	3,287 records (daily reservoir water level data)
Water Level (m)	Min = 26.81 m, Max = 30.00 m, Range = 3.19
Skewness	-0.878
Kurtosis	0.327 (excess kurtosis) → Slightly positive
Outliers (Z>3 or Z<-3)	23 counts
Correlation (Original vs Transformed)	1.000 for all methods

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Table 3 *Descriptive comparison of normalisation methods*

Method	Potential compatibility with model inputs	Effect of extreme observations	Interpretation for reservoir water level data
Min-Max (binary)	Maps the observed minimum to 0 and maximum to 1; may be considered when an intended model requires inputs in this interval.	An extreme minimum or maximum can place most other observations within a narrower part of the interval.	Provides a bounded representation of observed water levels. The suitability of this range for forecasting requires model testing.
Min-Max (bipolar)	Maps the observed minimum to −1 and maximum to 1; may be considered when an intended model requires inputs in this interval.	Like binary Min-Max, it depends on the observed minimum and maximum. Changing the output interval does not remove sensitivity to extreme values.	Places the midpoint of the observed range, rather than necessarily the mean, at zero.
Z-score	Expresses observations in standard deviation units relative to the mean; outputs are not bounded.	Extreme observations can affect both the mean and standard deviation used in the transformation.	Shows how far each water level lies from the dataset mean. It does not remove outliers or require a normal distribution.
Decimal Scaling	Divides every observation by the same power of 10; the resulting interval depends on the original data.	Preserves the ordering and proportional relationships between observations, including extreme values.	Offers simple rescaling when a specific bounded interval or mean-centred scale is not required.

Table 4 *SWOT analysis of normalisation methods*

Method	Strengths	Weaknesses	Opportunities	Threats
Min-Max (binary)	Simple transformation with outputs between 0 and 1 for the observed dataset.	Depends on the observed minimum and maximum; extreme values can compress other observations within the interval.	Can be evaluated for models whose inputs are intended to lie between 0 and 1.	Future observations outside the fitted range may transform to values outside 0–1 unless the scaling procedure addresses them.
Min-Max (bipolar)	Simple transformation with outputs between −1 and 1 for the observed dataset.	Remains sensitive to extreme minimum and maximum values; zero represents the range midpoint, which may differ from the mean.	Can be evaluated for models whose inputs are intended to lie between −1 and 1.	Future observations outside the fitted range may transform to values outside −1 to 1.
Z-score	Expresses observations relative to the mean in standard deviation units; does not impose a fixed interval.	The mean and standard deviation can be affected by extreme observations.	Can help identify observations that are unusually far from the dataset mean.	A change in the data distribution may make statistics calculated from the original dataset less representative of future observations.
Decimal Scaling	Easy to calculate; reduces numerical magnitude while preserving ordering and proportional relationships.	Does not centre the data or reduce the relative influence of extreme observations.	Can be evaluated where simple rescaling meets the intended application's input requirements.	The selected power of 10 may no longer give the intended magnitude if future observations differ substantially from those used to select it.

5. Discussion

The results show that the four normalisation techniques transform reservoir water level data in different ways. The choice of method should reflect the statistical characteristics of the data and the requirements of any intended prediction model. Reservoir water levels can be affected by seasonal rainfall, reservoir operations, and extreme

hydrological events, resulting in different patterns of variation. Because this study compares the statistical properties of normalised data without training a forecasting model, it does not establish which method would produce the most accurate forecasts.

Previous work has shown that data preparation and normalisation are relevant to machine learning [4-6,12]. While many studies compare normalisation methods using model performance, this study examines their statistical behaviour when applied to reservoir water level observations. The resulting distributions and the relative influence of extreme observations are discussed below. Table 5 presents recommendations based on the characteristics of the reservoir data, and Figure 2 provides a framework for choosing a preprocessing method before model development. These recommendations concern the transformed data; they have not been validated through forecasting experiments.

Table 5 *Practical guidance for selecting a normalisation technique*

Data or application characteristic	Method to consider	Reason and qualification
The intended model requires inputs between 0 and 1.	Min-Max (binary)	Maps the observed range to 0–1. Check the effect of extreme values and how future values outside the fitted range will be handled.
The intended model requires inputs between −1 and 1.	Min-Max (bipolar)	Maps the observed range to −1 to 1. Zero corresponds to the midpoint of that range, not necessarily the dataset mean.
Observations need to be expressed relative to the dataset mean.	Z-score	Expresses values in standard deviation units. Check whether extreme observations substantially affect the mean and standard deviation.
Only a reduction in numerical magnitude is required.	Decimal Scaling	Divides all values by the same power of 10. It preserves their relative relationships and does not reduce the relative influence of outliers.
The dataset contains extreme observations.	Examine the observations before choosing a method.	Determine whether the observations are valid measurements. None of the four transformations, by itself, removes their influence.
The method is intended for a forecasting model.	Compare suitable candidate methods through model testing.	Use the same model architecture, data split and performance measures. The present statistical comparison cannot establish which method gives the best forecasts.

Min-Max normalisation maps the observed water levels to a specified interval. This may be useful when an intended model requires inputs within a particular range. Min-Max normalisation has been examined using Alzheimer's disease data [11], breast cancer classification [14], and K-nearest-neighbour regression [16]. Those studies demonstrate its use in other settings but do not establish its performance for reservoir forecasting. Because the transformation uses the minimum and maximum values, an unusually high or low observation can compress the remaining values into a narrower part of the chosen interval. Research on anomaly detection provides general context for identifying unusual observations [23], although it does not compare normalisation methods for this dataset. Min-Max normalisation may therefore be appropriate when the observed water level range is reasonably representative of the values that an intended model would encounter.

Z-score normalisation expresses each water level relative to the dataset mean and standard deviation. Unlike Min-Max normalisation, it does not restrict the transformed values to a fixed interval. It does, however, standardise their measurement scale. Whendasmoro and Joseph [15] examined Z-score normalisation in a K-nearest-neighbour task, while Henderi et al. [14] compared it with Min-Max normalisation for breast cancer classification. These findings do not establish how Z-score normalisation would affect reservoir forecasting accuracy. In the present dataset, Z-score values show how far observations lie from the mean in standard deviation units. Extreme water levels can affect both the mean and the standard deviation, so Z-score normalisation does not remove their influence.

Decimal Scaling divides every observation by the same power of 10. For this dataset, each water level value was divided by 100. The method reduces numerical magnitude while preserving the ordering of observations and the ratios between their values [6]. Differences between values are also divided by 100. Decimal Scaling therefore does not reduce the relative influence of extreme observations. It may be useful when simple rescaling is sufficient, but it does not account for the data distribution.

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These statistical comparisons are relevant to reservoir applications, but determining the suitability of a method for a predictive model requires model testing. A future forecasting study could evaluate the techniques using the same model architecture, data split, and performance measures to determine whether the statistical differences observed here affect predictive accuracy.

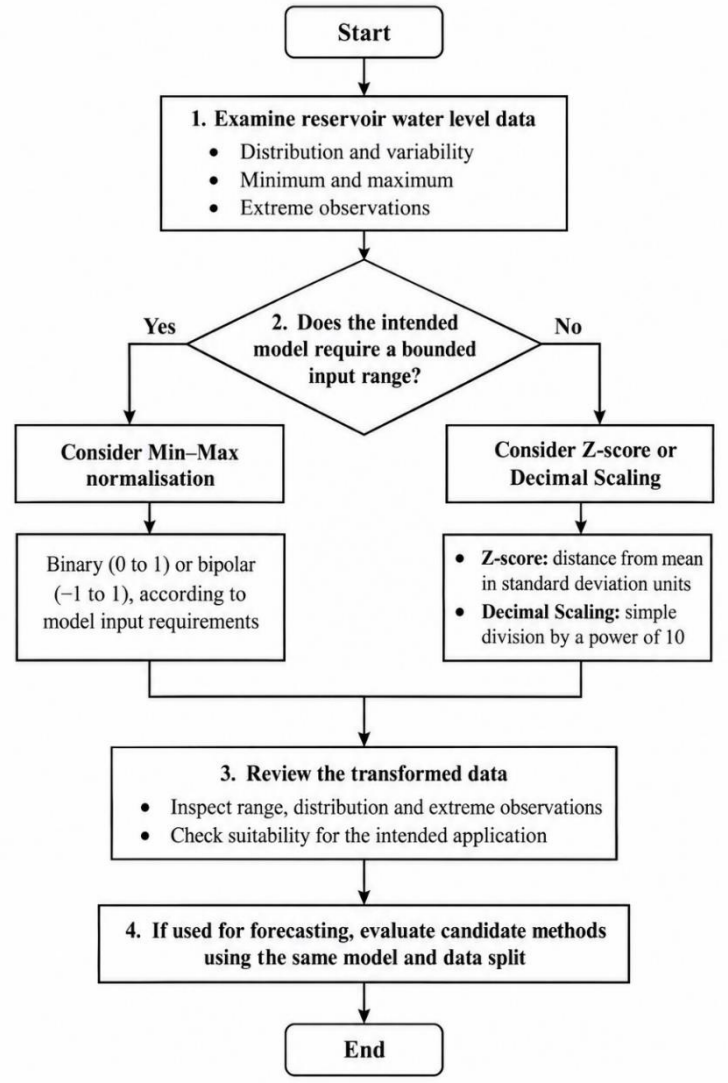


Fig. 2 *Decision framework for considering normalisation methods for reservoir water level data*

6. Conclusion

The findings of this study contribute to the understanding of the characteristics of four commonly used normalisation techniques when applied to reservoir water level data. The findings show that each technique has different strengths and limitations, particularly in relation to data distribution, outlier sensitivity, and compatibility with neural network activation functions. These observations may assist researchers in selecting an appropriate normalisation technique during the data preprocessing stage. Although the proposed guidance is derived from reservoir water level data, the same decision framework may also be applicable to other environmental time-series datasets with similar statistical characteristics. Further validation using additional datasets and neural network models would strengthen the generalisability of these recommendations.

This study was limited to a descriptive comparison of normalisation techniques based on their statistical characteristics and qualitative evaluation. Future research should examine how the normalised datasets perform when used with neural network models, such as Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). Evaluating prediction accuracy, convergence behaviour, training time, and computational performance would provide a more complete assessment of the practical effects of each normalisation technique.

Future studies may also extend the comparison by including additional normalisation methods, such as Robust Scaling, Quantile Transformation, and adaptive normalisation techniques. Another possible direction is to evaluate the methods using reservoir datasets from different geographical locations and hydrological conditions. Such studies would help determine whether the observations reported in this work remain consistent across datasets with different statistical characteristics.

Acknowledgement

The authors would like to thank the Perlis Department of Irrigation and Drainage Malaysia for providing data about reservoir water levels.

Data Available Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to any applicable data-use conditions. Hydrological data may also be requested independently from the Malaysian Department of Irrigation and Drainage (www.water.gov.my) through its Hydrological Data application page, subject to the Department's availability and conditions of use.

Conflict of Interest

There is no conflict of interest in the publication of this article.

Author Contribution

The authors confirm the contribution to this article as follows: ***study conception and design****: Wan Hussain Wan Ishak;* ***data collection****: Wan Hussain Wan Ishak and Fadhilah Mat Yamin;* ***analysis and interpretation of results****: Wan Hussain Wan Ishak, Fadhilah Mat Yamin, Siti Sarah Maidin, and Samuel-Soma M. Ajibade;* ***original manuscript draft****: Wan Hussain Wan Ishak;* ***manuscript review and editing****: Wan Hussain Wan Ishak, Fadhilah Mat Yamin, Siti Sarah Maidin, and Samuel-Soma M. Ajibade. All authors reviewed and approved the final manuscript.*

Declaration of AI Use in Manuscript Preparation

The authors used ChatGPT for grammar checking, correction and language editing. The content generated was reviewed and verified by the authors who take full responsibility for the final submission.

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