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ARAŞTIRMA MAKALESİ **RESEARCH ARTICLE**

Machine Learning-Based Prediction of NPSH, Noise, and Vibration Levels in Radial Pumps Under Cavitation Conditions

Radyal Pompalarda Kavitasyon Koşulları Altında ENPY, Gürültü ve Titreşim Düzeylerinin Makine Öğrenimine Dayalı Tahmini

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Abstract

Cavitation, a physical phenomenon that detrimentally affects pump performance and reduces pump life, can cause wear on pump elements. Various engineering methods have been developed to identify the initiation and full development of the cavitation process. One such method is the determination of the net positive suction head (NPSH) through a 3% decrease in total head (Hm) at a constant flow rate. In radial pumps, commonly used in agricultural irrigation and industry, cavitation conditions result in a sudden drop in the Hm-Q curve, making it challenging to detect the 3% Hm value drop. This study differs from others in the literature by modelling NPSH, noise, and vibration levels using three machine learning models, specifically artificial neural networks (ANN), support vector machines (SVM), and decision tree regression (DTR). The best-performing model predicts NPSH, noise, and vibration levels corresponding to a 3% decrease in Hm level. The present study determined the NPSH values of a horizontal shaft centrifugal pump at different flow rates and constant operating speed, and the vibration and noise levels were measured for these NPSH values. For each of the NPSH, noise, and vibration levels, ANN, SVM and DTR models were created. The performances of these models were evaluated using criteria such as root mean squared error (RMSE), Mean Absolute Error (MAE) and mean absolute percentage error (MAPE). In addition, Taylor and error box diagrams were created. The ANN model and DTR yielded high accuracy predictions for NPSH values (R^2 = 0.86 and R^2 = 0.8, respectively). The ANN model provided the best prediction performance for noise and vibration levels. By entering the level of 3% drop in the Hm value of the pump as external data input to the ANN model, $NPSH_3$, noise, and vibration levels were determined. The ANN models can be effectively employed to determine $NPSH_3$, noise, and vibration levels, particularly in radial flow pumps, where detecting 3% reductions in manometric height value is challenging.

Keywords: Centrifugal pumps, Net positive suction head (NPSH), Vibration, Noise, Machine learning

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Öz

Kavitasyon, pompa performansını olumsuz etkileyen ve pompa ömrünü azaltan fiziksel bir olgudur ve pompa elemanlarında aşınmaya neden olabilir. Kavitasyon sürecinin başlangıcını ve tam gelişimini belirlemek için çeşitli mühendislik yöntemleri geliştirilmiştir. Bunlardan biri, sabit bir debi hızında toplam basınç düşüşü (%3 Hm) ile emmedeki net pozitif yük (ENPY) değerinin belirlenmesidir. Tarım sulaması ve endüstride yaygın olarak kullanılan radyal pompalarda, kavitasyon koşulları Hm-Q eğrisinde ani bir düşüşe yol açarak %3 Hm değer düşüşünü tespit etmeyi zorlaştırır. Bu çalışma, yapay sinir ağları (ANN), destek vektör makineleri (SVM) ve karar ağacı regresyonu (DTR) olmak üzere üç makine öğrenmesi modeli kullanarak ENPY, gürültü ve titreşim seviyelerini modellenmesiyle literatürdeki diğer çalışmalardan farklılık gösterir. En iyi performans gösteren model, %3 Hm düşüşüne karşılık gelen ENPY, gürültü ve titreşim seviyelerini tahmin eder. Bu çalışma, yatay şaftlı santrifüj pompada farklı debi hızlarında ENPY değerlerinin belirlendiği ve bu ENPY değerleri için titreşim ve gürültü seviyelerinin ölçüldüğü bir çalışmadır. ENPY, gürültü ve titreşim seviyeleri için ANN, SVM ve DTR modelleri oluşturulmuştur. Bu modellerin performansları kök ortalama kare hatası (KOKH), ortalama mutlak hata (OMH) ve ortalama mutlak yüzde hatası (OMYH) gibi kriterler kullanılarak değerlendirildi. Ayrıca Taylor ve hata kutu diyagramları oluşturulmuştur. ANN modeli ve DTR, ENPY değerleri için yüksek doğrulukta tahminler sağlamıştır (sırasıyla R^2 = 0.86 ve R^2 = 0.8). ANN modeli, gürültü ve titreşim seviyeleri için en iyi tahmin performansını sağlamıştır. Pompa Hm değerindeki %3 düşüş seviyesini ANN modeline harici veri girişi olarak kullanarak, $ENPY_3$, gürültü ve titreşim seviyeleri belirlenmiştir. ANN modelleri, özellikle radyal akış pompalarında manometrik yükseklik değerlerinde %3'lük azalmaların tespit edilmesinin zor olduğu durumlarda, $ENPY_3$, gürültü ve titreşim seviyelerini belirlemek için etkili bir şekilde kullanılabilir.

Anahtar kelimeler: Santrifüj pompalar, Emmedeki net pozitif yük (ENPY), Titreşim, Gürültü, Makine öğrenimi

1. Introduction

Centrifugal pumps play a significant role in energy conversion and liquid transfer in various sectors such as agriculture, industry, and other industrial fields (Dong et al., 2019). However, the performance of pump applications can be adversely affected by cavitation (Brennen, 2011). Cavitation is a physical phenomenon that results in the wearing of pump elements and a serious reduction in pump life (Yüksel and Eker, 2009). Cavitation can also lead to cavitation erosion, which is a form of wear and tear that can be harmful to pumps. Cavitation erosion occurs when vapor bubbles form in places where the pressure decreases, and then rapidly collapse when they pass into a high-pressure zone, causing damage to the pump surfaces (Dzhurabekov et al., 2021). This phenomenon occurs when the absolute pressure of the liquid moving in the pump falls below the vaporisation pressure of that liquid at a constant temperature, leading to the formation of vapour bubbles. The collapse of these bubbles generates a high velocity micro-jet that impacts the adjacent inner metal surface, producing wave shock and causing flow pulsation in both radial and axial directions. In the event that the pump operates under cavitation conditions for an extended period, the unsteady flow condition may have detrimental effects on components such as the impeller, volute, bearing, shaft, seal, and other mechanical parts (Sahdev, 2005).

Cavitation is a phenomenon that relies on both the pump design and operating conditions. To prevent cavitation formation, it is crucial to select the appropriate pump for the installation. The parameter that determines whether the pump will operate with cavitation or not is the positive head at the suction port, also known as the NPSH. In centrifugal pumps, cavitation is a critical factor that restricts the pump inlet (suction) pressure, rotational speed, and consequently, the dimensions, weight, and cost of the pump. Furthermore, cavitation also limits the mechanically and hydraulically stable and reliable operating range. To ensure cavitation-free operation, it is necessary to guarantee that the NPSH value determined based on the system, installation, pumped liquid, and operating conditions, denoted as NPSHm, is greater than the pump-specific NPSHg value with a specific tolerance (Delale et al., 2020).

The detection and prevention of cavitation in pumps require a thorough understanding of the onset and full development of this phenomenon. A considerable number of studies have focused on investigating cavitation in kinetic pumps, as well as water turbines, as revealed by the literature (Al-Obaidi and Towsyfyan, 2019; Bordoloi and Tiwari, 2017; Čdina, 2003; Durdu et al., 2021; Kan et al., 2022; Panda et al., 2018). Recently, researchers have attempted to identify cavitation by utilizing machine learning models (Arendra et al., 2020; Bordoloi and Tiwari, 2017; Matloobi and Riahi, 2021; Panda et al., 2018; Wang, et al., 2019; Wang et al., 2020) . However, given the unpredictable nature of cavitation, an accurate numerical estimation of the resulting noise and vibration is not feasible. To detect the onset and full development of cavitation, various engineering methods have been proposed, among which determining the net positive suction head (NPSH) through measuring the 3% decrease in total head (Hm) at a constant flow rate represents a critical value beyond which cavitation is fully developed. The method necessitates a specialized test stand and a series of measurements at various flow rates, following the ISO 3555 standards.

The early detection of cavitation is essential for ensuring the reliability and efficiency of pumps and extending their service life. Effective detection requires the characterisation of cavitation, and the selection of an appropriate indicator. The analysis of signals acquired from sensors, such as those measuring vibration, pressure, and noise, is a widely used technique for cavitation detection (Sun et al., 2020). Previous studies have shown that the acoustic emission of background noise during pump operation can be used to detect incipient cavitation (Escaler et al., 2006; Neill et al., 1997) analysed various signals to determine the cavitation condition for hydraulic turbines. Čdina (2003) developed an electrical control system for preventing cavitation by initiating an alarm, shutdown, or control signal based on noise signal reception. The research in this area is generally focused on cavitation prevention based on manometric height, noise, and vibration data.

Radial pumps are commonly used in agriculture and industry, and under cavitation conditions, there is a sharp decline in the Hm-Q curve (Keskin, 2002). As a result, determining the 3% decrease in Hm value becomes difficult. To address this issue, some studies have utilized artificial neural networks or other machine learning algorithms to predict cavitation in (Arendra et al., 2020; Matloobi and Riahi, 2021; Wang et al., 2020; Wang et al., 2019; Yong et al., 2009). Unlike these previous studies, the present study focuses on predicting the NPSH, noise, and vibration levels associated with the 3% decrease in Hm using an artificial neural network model.

The present research focuses on the determination of NPSH values for a horizontal shaft centrifugal pump operating at various flow rates. Concurrently, vibration and noise levels corresponding to different NPSH values at various flow rates were measured. Machine learning models including ANN, SVM and DTR were generated to predict NPSH, vibration and noise levels under a constant pump speed. The predictive success of each model is discussed based on metrics such as R^2, RMSE, MAE, MAPE, error values, and Taylor diagrams. Taylor diagrams were utilized to assess the results obtained from the models in terms of standard deviation and correlation. The external input data for the best-performing model was adjusted to the level of 3% decline in the manometric height of the pump, and subsequently, the NPSH, noise and vibration values were forecasted.

2. Materials and Methods

The present study utilized a 3" nominal diameter horizontal shaft, stepless centrifugal pump, and the pump performance evaluations were conducted at the Sedat Çalışır Pumping Plant, affiliated with the Department of Agricultural Machinery and Technologies Engineering of Selçuk University. The pump speed was monitored by employing a mechanical/optical tachometer to measure the electric motor shaft speed, where a linear relationship exists between the frequency of the electrical network f (Hz) and the electric motor speed n (rpm), while the number of electric poles is denoted by P (Hanson et al., 1996). In order to alter the speed of the pump, a frequency control device (FCD) with the technical specifications FCD, ATV61, 31 kW, 380/480V HD 37 N4 was utilized. The flow rate was measured by employing an electromagnetic flow meter of type S MAG 80, capable of working with a flow rate of 1-280 m^3 h^{-1}, while the negative pressure was determined via a glycerine type vacuum meter and the positive pressure by utilizing a glycerine type manometer. Furthermore, the noise level measurements were carried out by employing a Jetnorl brand S4001 type digital sound level meter capable of measuring within the range of 30-130 dBA, whereas the vibration measurements were executed by employing a Time brand digital TV110 type vibration meter operating within the frequency range of 50-10000 Hz.

The centrifugal irrigation pump was driven by an 11 kW Watt brand EFF2 class electric motor with a speed of 2960 rpm, a current of 34 A, a voltage of 380/660 V, and a torque of 60.9 Nm. The pump was directly coupled to the motor. During the experiments, the water temperature and ambient temperature were recorded as 13°C and 10°C, respectively. The measurements were conducted at a constant speed of 2960 rpm (50 Hz) and at various flow rates, namely 13.9, 12.5, 11.1, and 9.7 l/s. The measurements of the pump's operating characteristics and the subsequent calculations were carried out according to the ISO 2548 standard (Anonymous, 2002).

The determination of the NPSHp curve that reflects the cavitation characteristics of the pump was conducted through simultaneous control of the suction and discharge valves (Eryılmaz, 2004). Initially, the valves were adjusted to any position except for being fully open or fully closed, and the pressure values corresponding to a certain flow rate (Q1) were obtained. The value of the total manometric height (Hm) was calculated using the standard equation and positioned on the vertical axis of the graph as H1. By utilizing the following equation, the NPSHp value was calculated, and the values at the same point were placed on the horizontal axis, resulting in the acquisition of the Q1 point. Afterwards, the outlet valve was slightly opened, and the flow rate was gradually increased. To bring the flow back to the Q1 value, the inlet valve was slightly reduced while the total manometric height and Q1 point were obtained using the equation in (1). This process was repeated until the head was at least three percent lower than the initial reading.

$$NPSH=H_1+\frac{P_a-P_v}{\rho g} \qquad \text{(Eq.1)}$$

$$H_1=\frac{P_e}{\rho g}+V^2/2g \qquad \text{(Eq .2)}$$

The present paragraph describes the measurements and standards used for evaluating the vibration and noise levels of the horizontal shaft centrifugal pump. The pressure values of atmospheric pressure (Pa), evaporation pressure of pump water (Pv), vacuum in suction line (Pe), and water inlet velocity (V) are specified. The vibration levels were assessed in three axes of the housing containing the pump shaft, and the composite vibration vectors were computed. The ISO 2372 standard was applied for evaluating the vibration acceleration. The vibration and noise measurements were performed in triplicate at each flow rate value and for all total manometric height (Hm) values acquired for that particular flow rate. The noise measurements adhered to the TS 2709-10, TS 2773, and EN ISO 1680 standards, and were conducted within the area encompassing 1 m diameter of the pump. The research employed the approaches outlined in Cucit et al. (2018); Çalışır et al. (2006a); Çalışır et al. (2006b, 2007) for assessing the vibration and noise levels.

2.1. Machine Learning

Machine learning involves the creation of computer programs that can access data and utilize it to learn autonomously (Pattnaik et al., 2021). This method emphasizes the input and the solution to the problem in order to discover the optimal algorithm that leads to the solution. Machine learning is an application of artificial intelligence, which allows systems to learn and improve from experience without explicit programming (El Guabassi et al., 2021). In machine learning algorithms, models are constructed with the aim of achieving the desired prediction in the most efficient and quickest manner, with the highest probability (Gültepe, 2019).

2.1.1 Artificial neural network

The Artificial Neural Network (ANN) is composed of a multilayer perceptron structure, including input, hidden, and output layers. Learning algorithms commonly employed in ANNs encompass radial basis function networks, perceptron algorithms, backpropagation, and elastic backpropagation (Liakos et al., 2018). These learning algorithms operate as a machine learning mechanism that updates the weights between each node by learning the correlation between input and output variables (Shin and Cho, 2021)

The neural network model follows two primary processes. The first process is a feed-forward process that computes the output value by considering the input variables, variables in the hidden layer, relationships between each variable (connectivity, weight), and transfer functions. The second process is a backpropagation process that rectifies the relationship between the variables using the error between the output value computed from the model and the actual value to ensure accurate calculation. In the neural network, each node has a weight that reflects the significance of its signal. It receives an input signal and calculates the information according to the relevant equation (Shin and Cho, 2021).

2.1.2 Decision Tree regression

Decision trees are machine learning models that take the form of a tree-like structure and can be used for classification or regression (Liakos et al., 2018). In a decision tree, each node in the tree represents a test on an attribute or feature, and each branch represents the outcome of the test. The process of creating a decision tree involves recursively splitting the dataset into subsets based on the value of a particular attribute or feature until a stopping criterion is met (Loh, 2011; Pekel, 2020). During the training phase, the algorithm evaluates the fitness of each attribute or feature to serve as a decision node by calculating the error between the predicted values and the actual values, using a predefined fitness function. The attribute or feature that results in the lowest error is selected as the decision node (Pekel, 2020). Subsequent splits are performed in the same manner until a stopping criterion, such as a predefined tree depth or minimum number of instances at a node, is reached.

2.1.2 Support vector machine regression

The Support Vector Machine (SVM) is a frequently employed machine learning method for the characterization and classification of data, using information derived from their characteristics (Shin and Cho, 2021). SVM operates as a binary classifier by creating a linear separation hyperplane to differentiate between data samples. The most common SVM algorithms encompass Support Vector Regression, Least Squares Support Vector Machine, and Successive Projection Algorithm-Support Vector Machine (Liakos et al., 2018). The foundation of the SVR algorithm lies in the ε-insensitive function and the kernel function (Takeda et al., 2007). SVR functions transform the data into a higher dimensional feature space to achieve a non-linear learning algorithm in the original low dimensional space (Geng et al., 2020).

3. Results and Discussion

3.1. Experimental results

At the optimal operational speed of the pump (2960 rpm), the hydraulic system achieved an efficiency of 38.5%, a flow rate of 13.5 l s-1, and a manometric height of 46.3 m. At this speed point, the specific speed of the pump was computed as nq=19.2 (ns=70.5), thereby indicating that the pump belongs to the category of radial flow pumps. *Figure 1* presents the variation of manometric height, noise level, and vibration values in relation to NPSH at a constant speed of the pump. The Hm value remained constant up to a specific NPSH level, after which there were sudden drops in the Hm value. These sudden decreases in manometric height were also observed in the works of other researchers, including Coutier et al. (2003); Kaya (2020); Salvadori et al. (2015). Notably, these sudden drops were more noticeable at flow rates of 11.1 and 9.7 l s^{-1} in our study. (Kaya, 2020) also reported that sudden drops were observed at low flow rates.

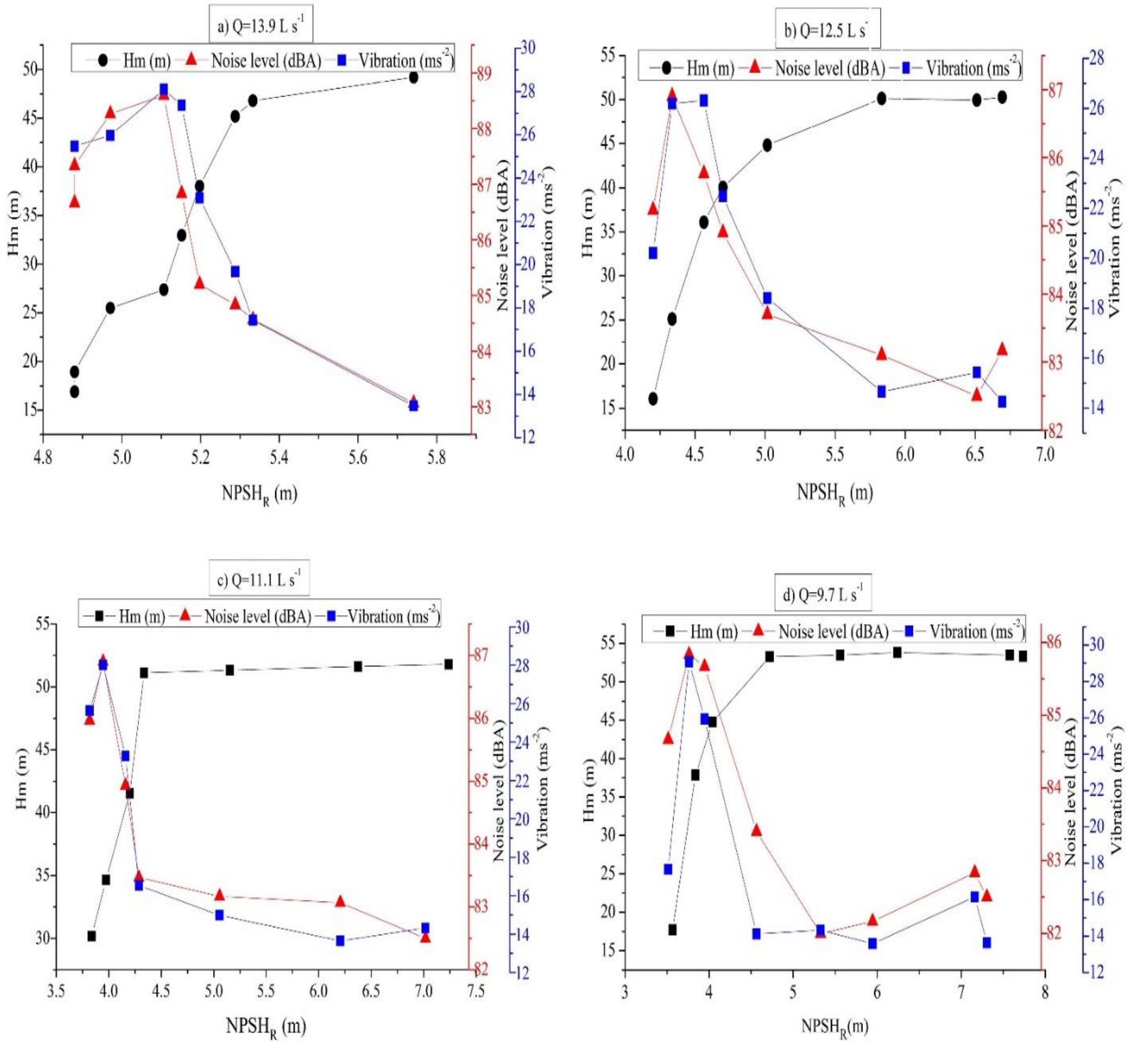

Figure 1. Hm, noise and vibration values depending on $NPSH_R$ variation at 2960 min^{-1} rpm of the pump

The results of the experiment indicate that, at constant speed and flow rate values of the pump, noise and vibration levels increased significantly beyond a certain level of NPSH, as depicted in *Figure 3.* This suggests that the pump was operating in a cavitated state (Čdina, 2003). According to Čdina (2003), the sound frequency of a cavitated pump differs from that of a non-cavitated one. The noise levels of the pump were measured at 83.8-82.9-83.0 and 82.5 dBA for flow rates of 13.9-12.5-11.1 and 9.7 l s^{-1}, respectively, with a decrease in the Hm value of up to 3%. Conversely, the average noise levels after the 3% reduction in the Hm value of the pump were 86.8-85.3-85.9 and 85.4 dBA, respectively. The vibration levels measured until the 3% reduction zone of the Hm value of the pump were 15.45-14.78-14.77 and 14.36 m s^{-2} for flow rates of 13.9-12.5-11.1 and 9.7 l s^{-1}, respectively. Following the 3% drop zone of the Hm value, the average vibration levels of the pump were determined as 25.45-22.78-25.6- and 24.2-mm s^{-2}, respectively. As evident from these results, cavitation significantly affected the noise and vibration levels of the pump. Cavitation is typically accompanied by structural vibration and noise, with a specific sound frequency or broadband peak corresponding to the 3% load drop due to cavitation (Čdina, 2003; Čudina and Prezelj, 2008; 2009; Kan et al., 2022). It is essential to accurately measure the noise and vibration levels associated with this 3% reduction. However, measuring the 3% reduction in radial type pumps used in the study proved to be a challenging task. To overcome this issue, the subsequent part of the study determined the optimal model performance by applying a machine learning algorithm to NPSH, noise, and vibration levels. The machine learning algorithm was employed to estimate the values corresponding to the 3% reduction in the Hm value over the best model.

3.2. Machine learning modelling and performances

In typical machine learning models, the data set is divided into training and test sets, with the majority of the data being used for training and a smaller portion reserved for testing. Splitting the data is a crucial step in machine learning to evaluate model performance and determine its suitability for real-world applications. Testing the model on the held-out data is the best approach to assessing its accuracy. The commonly used split is 75% for training and 25% for testing. However, a better way to evaluate the accuracy of the model is to test it on the data that was not used during training (Salem et al., 2022).

Various error metrics are used to assess model performance and measure the relationship between predicted and actual values (Güven, 2022). Three commonly used measurement methods are root mean square error (RMSE), relative root mean square error (RRMSE), and coefficient of determination (R2). RMSE measures the difference between predicted and observed values, while RRMSE or normalized RMSE enables a direct comparison between different meta-models and output variables with different units. R2 is used to assess model performance by determining the proportion of variance in the response variable explained by the independent variables (Shahhosseini et al., 2019). The algorithms were implemented and evaluated using the R statistical programming language.

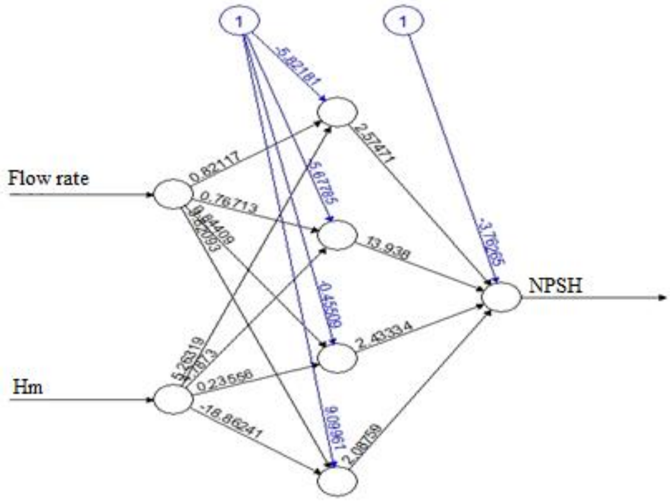

Figure 2. Neural network model applied to NPSH

The present study employs artificial neural network (ANN) models to process the data, which are first normalised. In the literature, several data normalisation techniques have been proposed, such as Minimum, Maximum, Median, Sigmoid, and Z-Score rules (Jayalakshmi and Santhakumaran, 2011). The Z-Score rule is utilised in this study as it generates a statistically normal distribution and indicates the position of each data point in terms of the standard deviation. The standard value represents how far the data point is from the mean, where negative values indicate that the data point is below the mean, and positive values indicate that the data point is above the mean (Cho, 2020).

The ANN models implemented in this study are composed of four hidden layers. The threshold value of 0.04 and learning rate value of 0.05 are determined to yield the best outcomes. *Figure 2* presents an overview of the network model applied to NPSH. The error values of the ANN models of NPSH, noise, and vibration data are determined as 3.76, 1.28, and 0.43, respectively, and the number of steps is found to be 578, 229, and 286, respectively.

The input variables of the artificial neural network models were the flow rate and Hm, while the output variables were NPSH, noise and vibration. For each model, 24 data points were allocated for training, and 8 data points were allocated for the test set. The support vector machine regression algorithm was used to create the NPSH, noise, and vibration models with specific parameters, such as SVM-Type: eps-regression, SVM-Kernel: radial, cost: 1, gamma: 0.5, and epsilon: 0.1. The number of support vectors was determined as 15, 16, and 18 for the NPSH, noise, and vibration models, respectively. *Table 1* presents the parameters used for the decision tree regression models.

Table 1. Decision tree regression models

	Minsplit	cp	Maxdepth	Terminal nod	Decision nod
NPSH	12	0.01	5	3	1
Noise	4	0.01	5	11	9
Vibration	3	0.01	5	15	13

The ANN model yielded the highest performance among the models created for NPSH prediction, as illustrated in *Figure 3*. The prediction performances of the ANN and DTR models were found to be comparable. The coefficient of determination (R^2) values for the ANN, SVM, and DTR models were 0.86, 0.37, and 0.8, respectively, while the corresponding root mean square error (RMSE) values were 0.55 m, 1.28 m, and 0.7 m, respectively. The MAPE values of the models were 6.09, 15.1 and 8.7, and the MAE values were 0.4 %, 1.1 % and 0.65 %, respectively. The success of the SVM model in predicting NPSH was found to be markedly low.

The prediction performance of the models for the vibration level of the pump were evaluated using R^2, RMSE, MAE and MAPE values. Among the models, the ANN model achieved the highest R^2 value of 0.86, indicating that the model was able to explain 82% of the variance in the data (*Figure 4*). The RMSE, MAE and MAPE values of the ANN model were also the lowest at 2.1 m s^{-2}, 0.42% and 8.77%, respectively. The SVM model achieved an R^2 value of 0.69, while the DTR model had an R^2 value of 0.57. However, the SVM and DTR models had higher RMSE and MAE values compared to the ANN model. Therefore, the ANN model was found to be the most successful in predicting the vibration level of the pump.

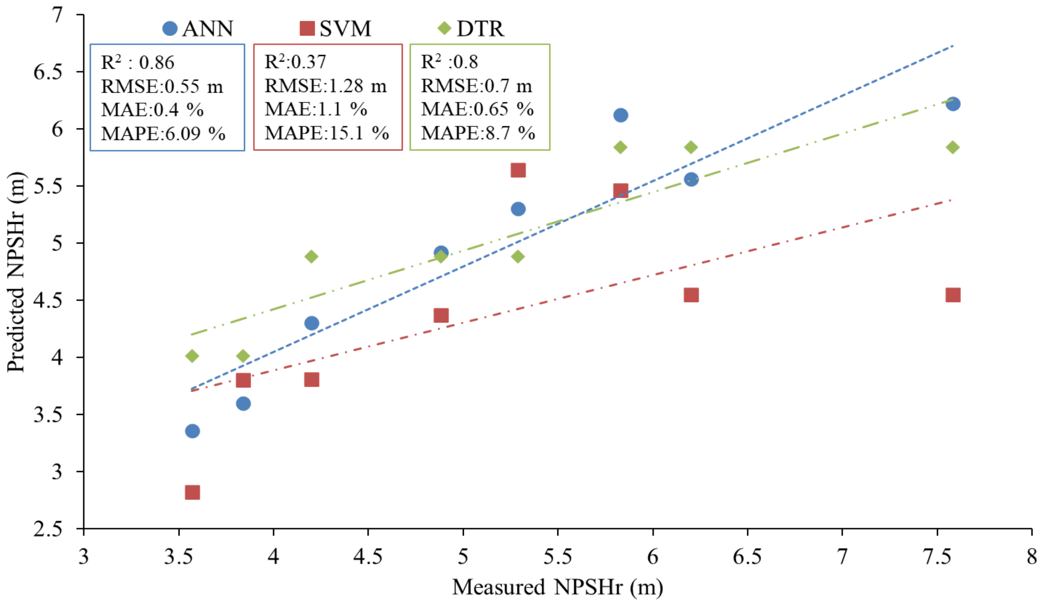

Figure 3. Performance of models created for NPSH estimation

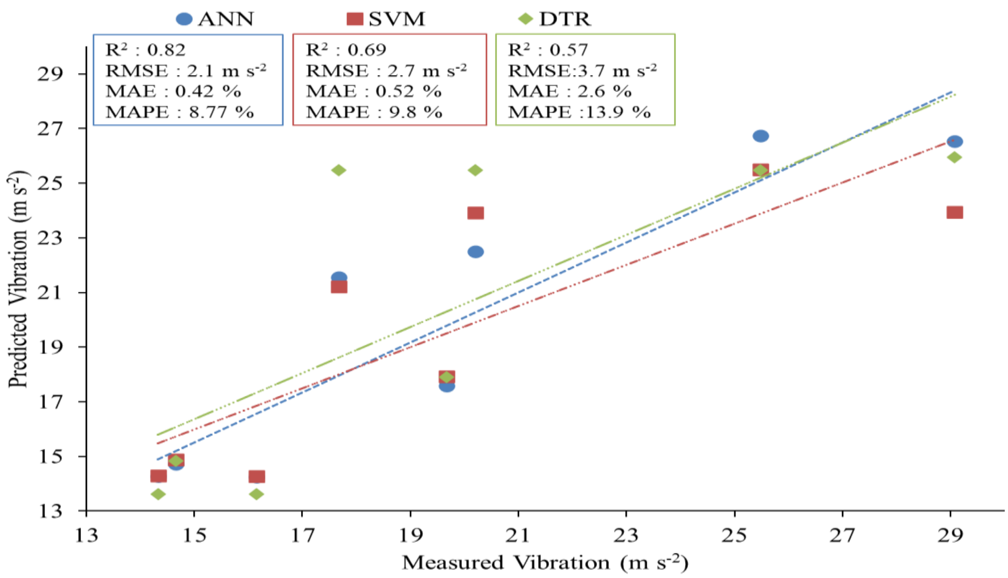

Figure 4. Performance of models created for vibration estimation

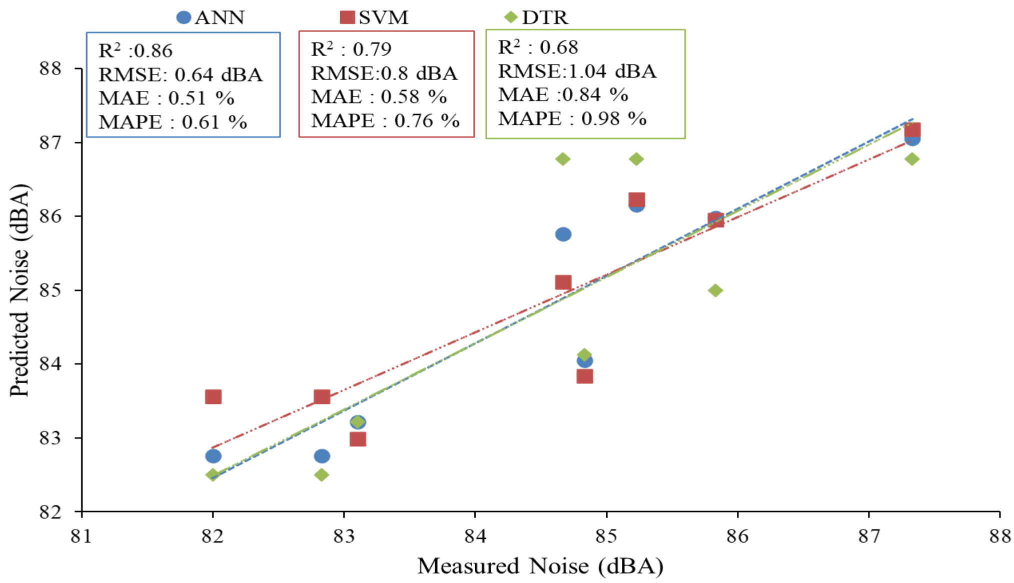

Figure 5. Performance of models created for noise estimation

The R^2 values for the prediction performances of artificial neural network (ANN), support vector machine (SVM), and decision tree regression (DTR) models with respect to the noise level of the pump were determined as 0.86, 0.79, and 0.68, respectively, as depicted in *Figure 5*. The corresponding root mean square error (RMSE) values for these models were measured as 0.64 dBA, 0.8 dBA, and 1.04 dBA, while the mean absolute error (MAE) values were calculated as 0.51%, 0.58%, and 0.84%, respectively. Notably, the ANN model exhibited the most successful prediction performance among the models evaluated. In terms of noise level prediction, the SVM model outperformed the NPSH model. Furthermore, the ANN model demonstrated superior performance in predicting the vibration level of the pump compared to the other models considered.

The errors in the NPSH, vibration, and noise prediction values for the models are presented in *Figure 6*. According to these graphs, the models generally underestimated the NPSH predictions compared to the actual values (*Figure 6a*). Specifically, the models performed poorly in predicting the 26th data point. The error values for the vibration level of the models varied, either being low or high, depending on the test data (*Figure 6b*). The least accurate prediction for the vibration level was observed for the 32nd test data point. Furthermore, the models generally overestimated the noise level prediction compared to the actual value. Upon an overall examination of the graphs, it can be observed that the ANN model achieved the highest level of success in terms of error values.

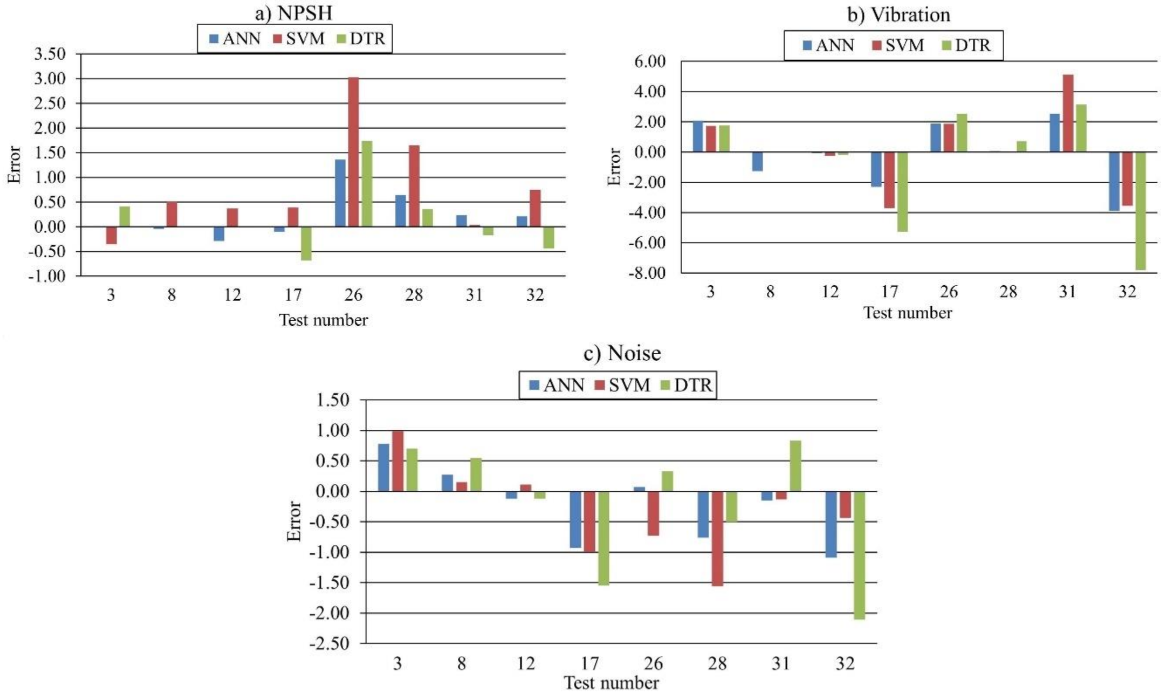

Figure 6. Error diagrams a) NPSH b) Vibration c) Noise

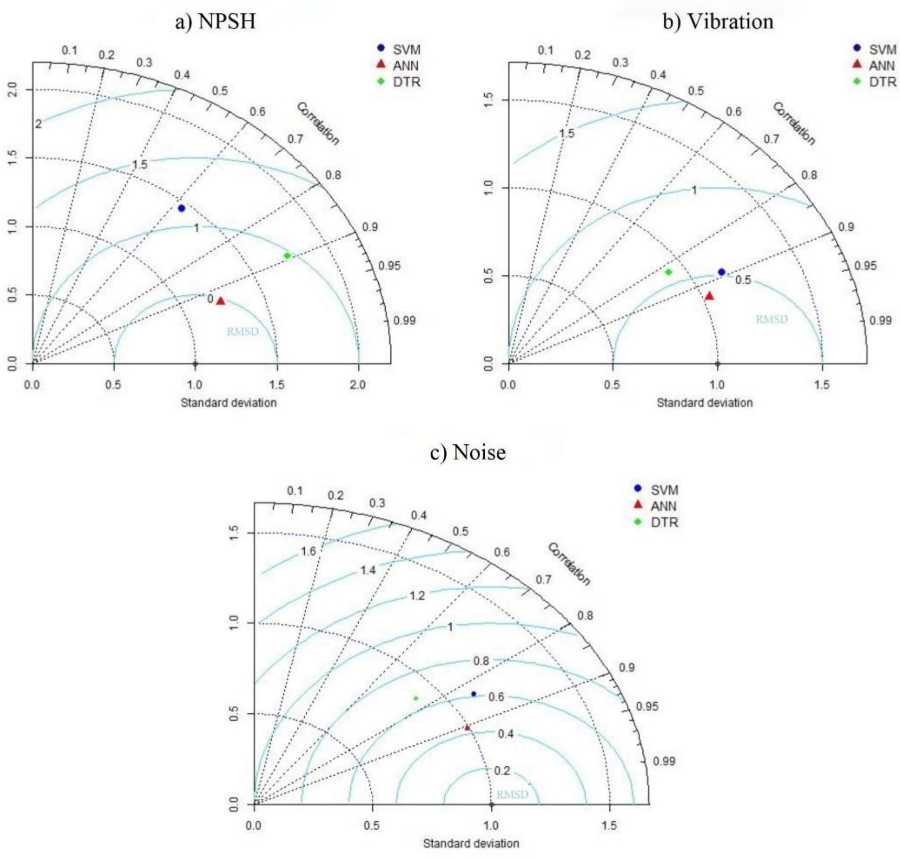

Figure 7. Taylor diagrams of test results a) NPSH b) Vibration c) Noise

Taylor diagrams given in *Figure 7* were used to evaluate the results obtained from the variables with standard deviation and correlation (Demir, 2022; Bayram and Çıtakoğlu, 2023). The NPSH, vibration, and noise values, along with the estimation values derived from SVM, ANN, and DTR models, have been thoroughly analyzed within these diagrams based on statistical criteria including standard deviation, correlation coefficient, and centered root mean square difference (RMSD).

Based on the Taylor diagram presented in *Figure 7*, it is evident that the ANN model displayed the highest level of success among the models for predicting vibration and noise, particularly in relation to NPSH. In *Figure 7a*, it can be observed that while the ANN and DTR models exhibit similar R^2 values for the NPSH predictions, the ANN model surpasses the DTR model in terms of error criteria. ANN gave the best results in terms of the errors of the models of noise and vibration values (*Figure 7b, c*). According to Taylor diagrams, the ANN model gave the best result.

Due to the abrupt reduction in the Hm-Q curve of radial pumps during cavitation, measuring or reading the 3% reduction value of Hm is problematic. Among the machine learning algorithms utilized for the NPSH, noise, and vibration values of the pump, the ANN models that displayed the best performance had the 3% decrease level of Hm value incorporated as external data. During the data input procedure, the flow values were kept constant in the models, and the Hm values were computed by taking 3% reduction of the initial Hm value. Consequently, the $NPSH_3$ values, noise, and vibration levels of the pump were projected from the models and presented in *Table 2*.

Table 2. Prediction of $NPSH_3$, noise and vibration levels via ANN model

Speed (min^{-1})	Flow rate (l s^{-1})	Hm_3 (m)	$NPSH_3$ (m)	Noise (dBA)	Vibration (m s^{-2})
2960	13.9	47.72	5.51	83.4	15.25
2960	12.5	48.79	5.25	83.5	15.47
2960	11.1	50.22	4.22	83	15.66
2960	9.7	51.72	4.1	82.88	16.3

The artificial neural network model yielded a range of 5.51-4.1 m for the $NPSH_3$ value. At this point, the pump exhibited an average noise level of 83.19 dBA and an average vibration level of 15.67 ms^{-2}. Prior to reaching the $NPSH_3$ point, the average noise level and vibration level of the pump were determined as 83.01 dBA and 14.56 ms^{-2}, respectively. Notably, a small change of 0.18 dBA was observed between the average noise levels before and after the $NPSH_3$ point. In contrast, a significant difference of 1.11 m s^{-2} was observed between the average vibration levels before and after the $NPSH_3$ point.

4. Conclusions

In summary, this study aimed to model and predict the net positive head (NPH), noise, and vibration levels of a horizontal shaft centrifugal pump in suction using machine learning algorithms such as artificial neural network (ANN), support vector machine regression (SVR), and decision tree regression (DTR). The results revealed that at constant speed and flow rate values, the Hm value followed a constant course until a certain NPSH value, after which sudden decreases in Hm level were observed. The measured noise and vibration levels of the pump were clearly separated before and after cavitation, with average noise values of 85.8 dBA and average vibration levels of 24.4 m s^{-2} during cavitated operation. The ANN model demonstrated the best performance in NPSH prediction (R^2 = 0.86), followed by the DTR model (R^2 = 0.8), whereas the SVR model was found to be less successful in NPSH prediction. Both ANN and DTR models were found to be suitable for NPSH prediction, with the ANN model exhibiting the most favorable performance in predicting the noise and vibration levels of the pump during the NPSH test. Moreover, it was determined that the change in vibration level can be used to monitor the beginning of cavitation before the NPSH3 value, which is difficult to detect through a 3% reduction in manometric height value. Hence, the ANN model can be effectively used to determine NPSH3, noise, and vibration levels, particularly in radial flow pumps.

Ethical Statement

There is no need to obtain permission from the ethics committee for this study.

Conflicts of Interest

We declare that there is no conflict of interest between us as the article authors.

Authorship Contribution Statement

Concept: Orhan N., Kurt M., Kırılmaz H., Ertuğrul M.; Design Orhan N., Kurt M., Kırılmaz H., Ertuğrul M.; Data Collection or Processing: Orhan N., Kurt M., Kırılmaz H.; Statistical Analyses: Orhan N., Kurt M.; Literature Search: Orhan N., Kurt M., Kırılmaz H., Ertuğrul M.; Writing, Review and Editing: Orhan N., Kurt M., Kırılmaz H., Ertuğrul M.

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