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A new artificial neural network model integrated with a cat swarm optimization algorithm for predicting the emitted noise during axial piston pump operation

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Abstract. This study presents a new artificial intelligence based methodology to predict the emitted noise of an Axial Piston Pump (APP). The suggested method depends on augmentation of conventional Artificial Neural Network (ANN) via integration with Cat Swarm Optimization (CSO). CSO is used to obtain the optimal structure of ANN. The training and testing of the approach were accomplished using experimental data sets considering six system operating pressures (0.5, 1.0, 1.5, 2.0, 2.5, and 3.0 MPa) and five speed levels (600, 900, 1200, 1500, and 1800 rpm). Two valve seat materials were investigated: polyetheretherket one (PEEK) and 316L stainless steel. A reasonable agreement was observed between the predicted results obtained by the developed method and the experimental data.

1. Introduction

APPs have been shown promising application in hydraulic systems that used to induce hydraulic power from mechanical power due to their advantages over other commonly used pumps such as their high operating pressure and speed.

However, APP has a main drawback as when it operates at higher pressure and displacements, high noise levels and severe vibration are generated[1]. APPs are classified into two main types based on the port type: plate or valve. The APP with port valve has a good abrasion resistance as it is not affected by water contamination which gives it an advantage to be operated under severe conditions in abrasive mediums such as silt-laden water. In a typical APP with port valve, two valves control the water flow: the inflow valve by which water enters the pump and the discharge valve by which water exits the pump. Therefore, APPs with port valve are the optimal choice for hydraulic systems that contain open hydraulic circle in which working fluid has excessive contamination. Moreover, this type of pump averts the use of extra filtration devices to clean the flowing water. In APP with port valve, inlet/outlet flow is controlled using port valves. These valves have a noteworthy effect on the life span, emitted noise, and volumetric efficiency of the pump. Xu et al. [2] proposed a methodology based on vibro-acoustic analyses to optimize the housing of an APP. A finite element model of the cover and housing has been developed to execute the modal analysis. Then, a topology optimization is carried out to obtain the optimal structure of the housing that reduces the frequency response function. The average level of sound pressure is decreased by about 2 dB(A) at operating pressure of 250 bar using the optimized housing. Pan et al. [3] investigated the transmission paths and radiated noise source of

an APP. A finite element model of the APP shell was developed to execute the modal analysis. The vibration performance as well as the excitation forces generated during operation and transmitted to the cover was analysed. The noise transmission path and the main noise source were determined. The sound pressure level was reduced by 1.26 dB (A) at 300 bar discharge pressure. An effort to reduce the sharpness of an APP with a reinforced shell with casting stiffeners has been conducted by Zhang et al. [4]. The sharpness of the APP was decreased by about 6.2% when reinforced shell is used compared with that of the reinforced shell-free APP at 21 MPa discharge pressure. A new design method of valve plate of APP to reduce the emitted noise resulted from the fluid flow and structure vibration has been proposed by Xu et al. [5]. The proposed design method has succeeded to reduce the flow ripple and eliminate the pressure undershoot and overshoot. Zhang et al. [6] proposed a new deposition technique to reduce the generated noise of an APP. This technique depends on depositing a 3 mm layer of a visco-elastic damping material on the external surface of the APP to increase the natural frequency of the APP by about 6%, which consequently decreases the modal displacement as well as the induced noise and vibration. The average level of sound pressure is reduced by about 6.3 dB(A) at 21 MPa discharge pressure. Yin et al.[7]proposed a reliability model to investigate the effects of valve-port on the emitted noise of an APP. The fluctuation in the contact pressure and rotational speed impairs the reliability of the pump. Therefore, it is recommended to preserve the speed of APPs at a constant value.

Recently, artificial intelligence based methods such as ANN and different metaheuristic optimization algorithms and their hybrid combinations have been used to optimize and predict the performance of different mechanical systems [8-15]. Ye et al. [16] used genetic algorithm, as a metaheuristic optimization tool, to minimize the noise of an APP which used as an objective function. A dynamic pump model was established considering the phenomena of cavitation and air-release. A comprehensive parametric investigation was carried out to analyse the effects of the valve plate design parameters on the induced noise. The average level of sound pressure is reduced by about 1.6 dB(A) at 15 MPa discharge pressure. Karkoub et al.[17]developed a feed-forward ANN model to predict the steady-state and dynamic behaviour of an APP. The pump speed was used as the input of the ANN, while the pressure was used as the output. Huayong et al. [18] used aback propagation ANN to obtain the emitted noise of APP for four materials of port plates. The ANN inputs were the operating pressure, flow rate, oil bulk modulus, and oil temperature, while the output was the noise level.

Based on the abovementioned survey, most of previous studies carried on APPs investigated dynamics of moving parts, fluid dynamics, application of visco-elastic damping material, valve plate optimization, and housing optimization. Few studies have been investigated the effects of port valve material on the pump lifespan, pump efficiency, and generated noise. There are two main materials used in port valve fabrication: polymeric and metallic. Polymeric port valves have superior sealing characteristics and high machinability compared to metallic ones. On the other hand, metallic port valves are recommended for severe operating conditions with high pressure due to their superior mechanical properties such as strength and rigidity. However, precision fabrication techniques is required to enhance the sealing capabilities of metallic port valves which results in increasing the cost of the pumps with metallic port valves.

2. Objective and approach
The main aim of this study is to develop an accurate model to predict the generated noise of an APP. Experiments were conducted on an APP experimental setup under different operating pressures and speeds. Two different valve seat materials were considered: PEEK and 316L. A modified version of ANN was proposed in which CSO was used to optimize the ANN structure. The performance of the proposed ANN-CSO model was compared with that of conventional ANN model using different statistical criteria.

3. Experimental setup

An APP with a port valve is used in this study. This pump is composed of two main components: driving components (case, shaft, swash plate, slipper, and bearing) and flowing components (discharge valve, inflow valve, piston, and cylinder). The valves used in this APP are disc-type poppet valves. This type of valve could be utilized to minimize pressure loss in comparison to ball and cone types. Due to the high salinity of seawater, different pump parts should be made of cost-effective materials with excellent anticorrosion characteristics, suchpolymers, alloy steel, and titanium alloys. PEEK is a well-known polymeric material which has good mechanical properties such as high modulus of elasticity, high tensile strength, creep resistance, and corrosion resistance. Titanium alloys have excellent corrosion resistance, low density, and outstanding strength. Stainless steels alloys have enhanced cavitation erosion resistance. In the current experimental setup,TC4 titanium alloy has been chosen as valve spool material for both of discharge and inflow valves. Meanwhile, PEEK and 316L stainless steel have been chosen as valve seat materials to figure out their role on the generated noise.

A schematic diagramand a photograph of the experimental setup are presented in figure 1. The inlet pressure was 0.01 MPa and adjusted via a water tank and a loading valve. The flow rate was controlled by adjusting the motor speed by an inverter. The pressure of the inlet line was measured by a pressure gauge with accuracy of $\pm 0.25\%$ of full scale and a measuring range of 0–4 MPa. The flow rate was measured using a flow meter device with accuracy of $\pm 0.5\%$ of full scale and measuring range of 0–50 L/min. The level of the generated noise was measured by a sound level meter with accuracy of ± 0.5 dB which located at 1 m from the pump. The noise is measured according to A-weighted sound pressure level technique. In the current study, the effects of valve seat material (316L and PEEK), motor speed (600, 900, 1200, 1500, and 1800 rpm), and pressure (0.5, 1, 1.5, 2, 2.5 and 3 MPa) on the level of the emitted noise are investigated.
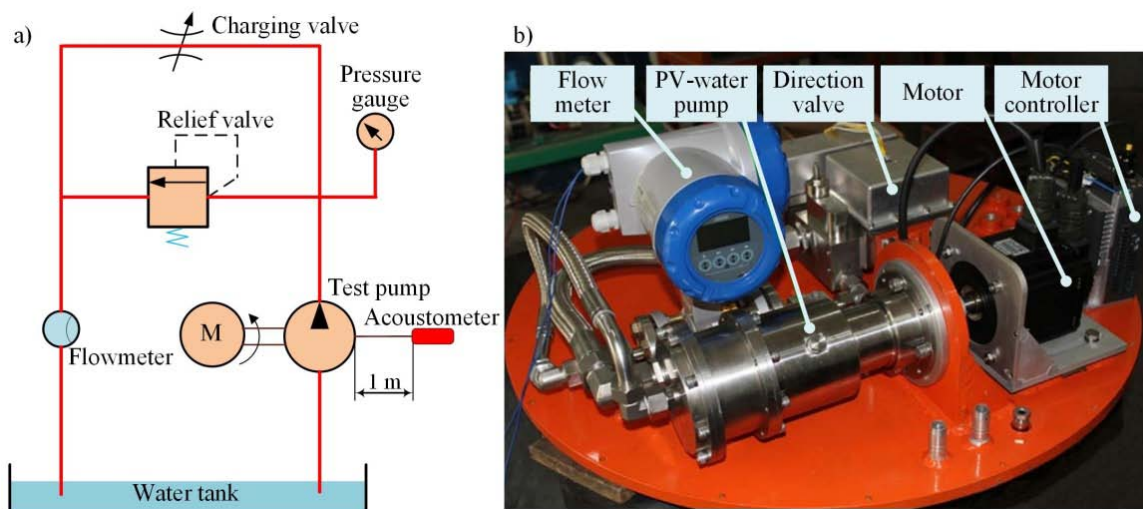
Figure 1. a) A schematic diagram; b) A photograph of the experimental arrangement[19].

4. The proposed approach

The proposed approach depends on improving the performance of the ANN through integration with CSO as a metaheuristic optimization method to find the optimal structure of ANN. ANN is intelligent computing tool which simulate the learning behaviour of the human brain. The performance of ANNs models is highly affected by the learning process. Multilayer perceptron (MLP) is a feed forward neural networks (FFNNs) which utilizes a supervised learning algorithm. MLP is composed of three main layers (figure 2 (a)): the input layer in which the input factors enter the network, the hidden layer in which data is processed, and the output layer. The neurons in different layers of MLP are organized

in a one-directional manner. These interconnections are represented by weights defined by real numbers in the interval [-1.1]. The following equation can be used to describe each layer in an MLP:

$$O_i^{(\ell)} = \varphi(u_i^{(\ell)}) = \varphi\left(\sum_{j=1}^{n_\ell} O_j^{(\ell-1)} w_{j,i}^{(\ell)} + w_{0,i}^{(\ell)}\right), \quad 1 \le \ell \le L \tag{1}$$

Wherein $\varphi(.)$ denotes the activation function used in the layer. The commonly used activation functions are classified as linear and non-linear (tangent hyperbolic). The linear activation functions are recommended for input and output layers, while the non-linear activation function is recommended for the hidden layers. The index ℓ denotes the layer in a network of L hidden and output layers, n_ℓ is the number of neurons of layer ℓ, O_i^ℓ denotes the ineuron output in the layer ℓ, $w_{j,i}^{(\ell)}$, $1 \le \ell \le n_{\ell-1}$ are the weights of the interconnection of neuron i of layer ℓ with the neurons j of the layer $\ell - 1$, and $w_{0,i}^{(\ell)}$ is the neuron i bias of the layer. The output vectors of the layer $\ell = 0$ and layer $\ell = L$ are $O^{(0)} = x$ and $O^{(L)} = y$, respectively. These vectors have lengths of n_0 and n_L and represent the input and the output vector of the network, respectively.

CSO algorithm is a swarm technique which simulates the behaviour of cats. This behaviour can be categorized into two modes, the seeking and tracing. The CSO algorithm starts by defining its parameters then generating a set of N solutions with dimension D. The next step is to compute the objective function for each cat and assign the mode for each cat (seeking, and tracing). The cats update their positions based on the mode of each cat. Then the best cat is determined based on the best fitness value. The previous steps are performed until the stop conditions met. The cats in the seeking mode, construct Seeking Memory Pool (SMP) copies (which called candidates) of the current cat. Then, the value of Self Position Consideration (SPC) parameter is used to determine either all the candidate solutions are updated randomly when SPC is false, or one of the candidate solutions doesn't updated and the rest are updated when the SPC is true. The next step in the seeking mode is to update the selected dimension based on the value of the Seeking Range of the selected Dimension (SRD). Therefore, the fitness function of each cat is computed then candidate is selected to exchange the original structure according to the probability Pro_i that defined as the following equation:

$$Pro_i = \frac{|F_i - F_{max}|}{F_{max} - F_{min}} \tag{2}$$

Where F_{max}, F_{min} are the maximum and minimum value of the fitness for all candidates, respectively. The F_i is the fitness of i-th candidate. In the tracing mode, the CSO begins by computing the fitness function for each cat then determine the best solution. Then the velocity of each cat is updated using the following equation:

$$v_i = v_{i,d}^t + R \times C_1 \times \left(x_{b,d}^t - x_{i,d}^t\right), d = 1,2,\dots,D \tag{3}$$

Thereafter, the position of i-th cat is changed using the following equation

$$x_i = x_i + v_i \tag{4}$$

where the $v_{i,d}^t$ represents the velocity of the i-th cat at the dimension j during the iteration t. $x_{b,d}^t$ is the best position at the t-th iteration, while C and R are constant and random number respectively. The final steps of the CSO are given in Algorithm 1.

Algorithm 1: Cat Swarm optimization
1) Generate a set of N cats and determine the initialize position and velocity for each of them
2) Randomly select N × MR cats and put them into tracking mode, and the rest in seeking mode.
3) For each cat update its position based on its mode (seeking or tracking).

4) Assess the cats based on fitness value and determine the best cat which has the best value of fitness.
5) Check if the terminal conditions are met or not Return the best cat.

In general, the proposed hybrid ANN-CSO approach starts by creating the structure of the ANN and creating a random population which contains N solutions. Each generated solution defines the neurons weights of the ANN. To assess the accuracy of the obtained solutions, the RMSE is computed according to the following formula:

$$\text{Fit}_i = \text{Root mean square error (RMSE)} = \sqrt{\frac{\sum_{j=1}^{Ns}(y_j - \hat{y}_j)}{N}} \tag{5}$$

Where $\hat{y}_i$ and y_i are the predicted value and its corresponding target value, respectively. The following stage is to obtain the best solution with the minimum RMSE.

5. Results and discussions

Based on the conducted experiments, APP with valve seats made of PEEK has a lower noise level compared with that with 316L valve seats as shown in figure 2 (b). Moreover, the generated noise is increased by increasing the speed and/or the pressure. Experimental data is used to train the ANN models; in which 70% of the data are used to train the models and 30% are used to test the model validity. The results obtained by CSO-ANN showed a reasonable agreement with the experimental data compared with that obtained by ANN model. Different statistical criteria are used to assess the performance of the proposed models such as coefficient of determination R^2, mean absolute error (MAE), mean relative error (MRE), Root mean square error (RMSE), overall index (OI), and coefficient of residual mass (CRM). The lower values of RMSE, CRM, MRE, and MAE and approaching of R2, OI values to 1 indicate a better performance of the model. To assure the stability of the proposed approach, it was executed 20 times and the average value was used as the final output. The present results revealed the outperform of the ANN-CSO model over ANN model to predict the emitted noise of APP with different valve seat materials for both of training and test processes as tabulated in table 1. Figure 2 (c,d) shows the QQ-plot of the predicted and the target values of the emitted noise. A reasonable agreement between the predicted and experimental datasets could be realized for all the examined materials of the valve seat and for all investigated models. However, ANN-CSO has a better agreement compared with ANN, which indicates the ability of CSO to enhance the accuracy of ANN via determining the optimal ANN structure.

Table 1. Statistical coefficient for performance estimating ANN and ANN-CSO.

| | PEEK | | | | 316L | | | |
| | Training | | Test | | Training | | Test | |
	ANN	ANN-CSO	ANN	ANN-CSO	ANN	ANN-CSO	ANN	ANN-CSO
R^2	0.999549	0.999978	0.998534	0.999955	0.999544	0.999993712	0.998745	0.999726
RMSE	1.48957	0.123499	2.827062	0.49768	1.558615	0.18296066	2.708818	1.266416
MRE	4.13E-05	2.89E-06	0.01156	-0.00024	0.000108	6.64012E-06	0.011173	0.006027
MAE	1.223408	0.050684	2.603294	0.374134	1.317489	0.101587302	2.262728	0.991515
OI	0.935835	0.996733	0.831525	0.98421	0.934328	0.995220697	0.848476	0.950006
CRM	8.94E-12	2.22E-14	0.011807	0.00043	1.09E-11	1.48997E-16	0.010489	0.004939
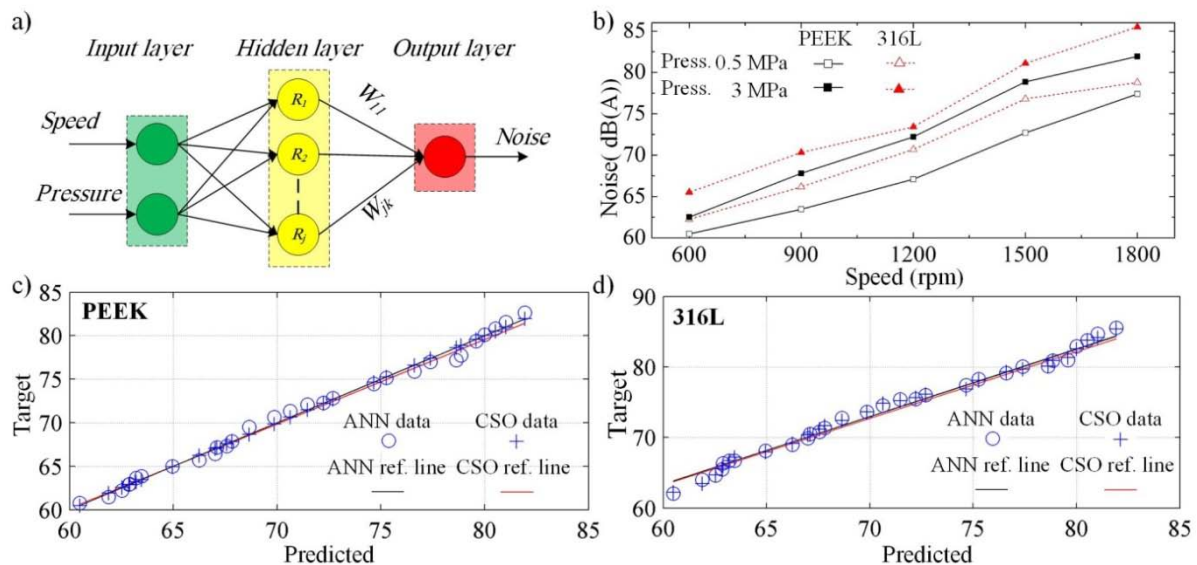
Figure 2. a) MLP ANN; b) Measured noise under the investigated operating conditions for PEEK and 316L as valve seat materials; c) QQ plot for PEEK; d) QQ plot for 316L.

6. Conclusion

A hybrid ANN-CSO model was proposed to predict the emitted noise of an APP for two different valve seat materials (PEEK and 316L) under different operating conditions. The CSO was utilized to determine the ideal ANN structure. ANN-CSO results were compared with conventional ANN model. Both models were trained using experimental data measured during experiments carried out on an APP experimental setup and then tested using another experimental data that have not been used in the training stage. The inputs of the models were speed (600-1800 rpm), and operating pressure (0.5- 3.0 MPa); while the output of the models was the emitted noise. ANN-CSO showed a better performance compared with conventional ANN. Moreover, to reduce the emitted noise of APP it is suggested to use PEEK as a valve seat material and decrease operating speed and pressure.

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