Annals of Optimization With Applications

www.anowa.reapress.com

Ann. Optim. Appl. Vol. 1, No. 2 (2025) 38-44.

Paper Type: Original Article

Calculating the Best Efficiency Point of a Piston Diaphragm Pump Using a Metaheuristic Algorithm

Hamid Ahmadi*

Ferdowsi University of Mashhad; ahmadi742@gmail.com.

Citation:

Received: 12 September 2024	Ahmadi, H. (2025). Calculating the best efficiency point of a piston
Revised: 24 November 2024	diaphragm pump using a metaheuristic algorithm. Annals of optimization with
Accepted: 10 January 2024	applications, 1 (2), 38-44.

Abstract

Piston diaphragm positive displacement pumps are widely used in various industries dealing with high-viscosity fluids, such as aluminum production. They are considered among the most effective equipment for generating extremely high pressures in abrasive liquids. However, operating these devices at their optimal performance point poses a significant challenge. In the present study, the pump's performance was simulated using input and output data to derive a functional model of the pump. Subsequently, the optimal operating point was identified using the Multi-Verse Optimization (MVO) metaheuristic algorithm. The obtained optimal point was compared with the recommended point provided in the pump's characteristic curves and theoretical information from the manufacturer's manual. The results indicate the effectiveness of the proposed model and the optimization process.

Keywords: Single-objective optimization, Metaheuristic algorithm, Multi-verse optimization, Reciprocating pump.

1|Introduction

One of the main challenges in industrial systems is operating equipment at its optimal performance point. For devices such as centrifugal and reciprocating pumps, performance curves are typically provided by the manufacturer. However, in more complex pumps—such as piston-diaphragm models—these curves are often less accurate. Moreover, due to the presence of numerous parameters and the effects of operational time, identifying the optimal operating point becomes increasingly difficult. Additionally, factors such as large volumes of data and system constraints turn this into an NP-hard problem, which in many cases cannot be solved using classical optimization methods.

In computational complexity theory, NP is a complexity class used to categorize decision problems. NP refers to a set of problems that can be solved in polynomial time using a non-deterministic Turing machine [1]. In essence, an NP problem may not be solvable in a reasonable time, but if a solution is given, its validity can be

🖂 Corresponding Author: ahmadi742@gmail.com

(i)(i)

Licensee System Analytics. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0).

verified in polynomial time. However, NP-Hard problems are not only unsolvable in a reasonable time, but even verifying a proposed solution is computationally infeasible within practical time limits.

In the present study, using the input and output data of a piston-diaphragm pump, a functional model of the pump was first identified using MATLAB's System Identification toolbox. Given the complexity of the pump's performance function, finding suitable input values that lead to operation at the optimal point is not feasible through conventional means. Therefore, the Multi-Verse Optimization (MVO) metaheuristic algorithm was utilized for optimization purposes [2], [3].

The case study involves the TZPM 1600 GEHO pump, a critical component of the Iran Alumina Complex [4]. Any failure of this pump results in production downtime and financial losses of approximately 1.75 billion rials per hour. The pump has a volumetric capacity of 112 cubic meters per hour, operates at a pressure of 92 bar, and consumes 485 kilowatts of power. Its drive system includes a large bearing, crankshaft, connecting rod, and a piston rod assembly. The end of the piston rod sits within a smaller bearing that enables rotational and reciprocating motion, thereby transferring force to the cylinder piston assembly.

The pump contains three chambers responsible for generating the discharge pressure. A schematic diagram of the pump is shown in *Fig. 1*.

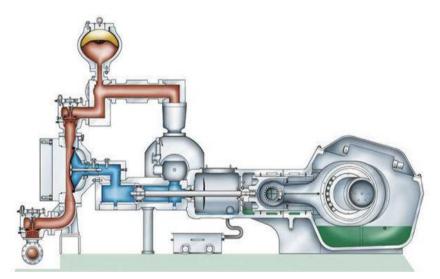


Fig. 1. Schematic of the pump and the output pressure diagram (Blue line).

2 | Problem Statement

To develop a mathematical model, the pump's performance function must first be identified. For this purpose, various datasets—including the input flow rates of all three pump chambers and the pump's output pressure—were examined over six months. After filtering out irrelevant data (Such as periods of upstream or downstream shutdowns, pipeline leaks, and component failures), a total of 800 data points were used for model estimation, and 200 data points were reserved for model validation.

A visual of the pump simulation environment and the pressure diagram is shown in *Fig. 2*, while a schematic representation of the process for deriving the pump's performance function is depicted in *Fig. 3*. Data analysis was conducted using the system identification toolbox in MATLAB, and the toolbox interface is presented in *Fig. 4*.

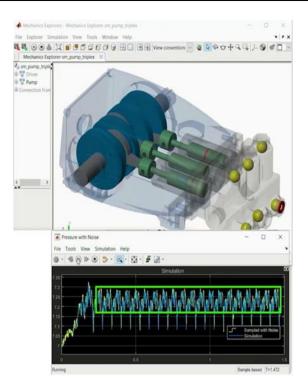


Fig. 2. Pump simulation and output pressure diagram.

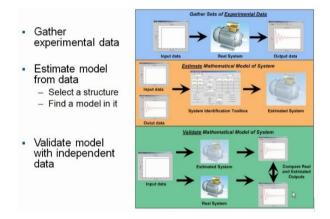


Fig. 3. Steps for estimating the equipment's performance function.

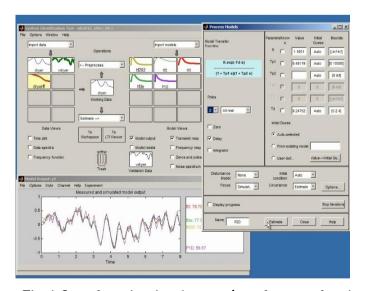


Fig. 4. Steps for estimating the pump's performance function.

(5)

After several stages of analysis, an exponential function with a 99% goodness of fit was identified as the pump's performance function, as shown in Eq. (1).

$$P = 11.8 \times \exp(-0.35 \times \sqrt{\sum(x^2)/3)} + 2.2/\exp(\sum \cos(2\pi x))/3),$$
(1)

In Eq. (1), P represents the pump's output pressure, and x denotes the input pressures of the pump, measured in bars.

To better understand and visualize the problem, the mathematical model was reformulated as a minimization problem. Given that the optimal output pressure recommended by the pump manufacturer is 92 bar, the objective function of the problem is defined as follows:

Objective:

$$\mathbf{F} = \min 92 - \mathbf{P}. \tag{2}$$

s.t.

0

$$P = 11.8 \times \exp(-0.35 \times \sqrt{\sum(x_i^2)/3}) + 2.2/\exp(\sum \cos(2\pi x_i))/3),$$
(3)

$$0 \le x_i \le 5,$$
 for all $i \in \{1,2,3\},$ (4)

F is the objective function, defined as the minimization of the inverse of the output pressure. Given that the input pressure of each chamber is supplied by a feeder pump with a pressure of 5 bar, the input pressure will always range between 0 and 5 bar Eq. (4).

Naturally, the output pressure cannot assume negative values Eq. (5). This study deals with a constrained single-objective optimization problem, and to solve it, the MVO algorithm has been employed.

The MVO algorithm, which is a population-based metaheuristic, is inspired by the theory of multiple parallel universes and was first introduced by Mirjalili et al. [5].

The algorithm has demonstrated effective performance in optimizing various static, dynamic, deterministic, and stochastic functions.

3 | Results

To solve the problem, the algorithm was first coded in MATLAB and executed on a five-core processor with 8 GB of RAM. After 1,500 iterations and a runtime of 72 seconds, the optimal solution was obtained using the MVO algorithm.

The termination condition for the program was reaching the maximum number of iterations defined in the main loop.

The convergence criterion for the problem was the objective function approaching zero, and the convergence graph is presented in *Fig. 5*.

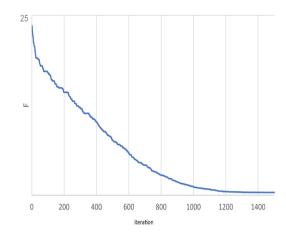


Fig. 5. Convergence of solutions vs. number of iterations.

The results show that with input pressures of 4.9, 4.8, and 4.6 bar in the first to third chambers, respectively, the output pressure reaches 89.8 bar. The design pressure of the pump is 92 bar, as specified in the equipment catalog by the manufacturer. The value obtained through the MVO algorithm is, therefore, very close to the recommended design value. To evaluate the performance of the MVO algorithm, the problem was also solved using MATLAB's optimization toolbox, which employs the Genetic Algorithm (GA) [6], [7]. The parameters used in this toolbox and its environment are shown in *Fig. 6*.

A Optimization Tool	>	×
<u>F</u> ile <u>H</u> elp		
Problem Setup and Results	Options	
Solver: ga - Genetic Algorithm Problem Fitness function: @F Number of variables: 3 Constraints:	Population Population Population type: Ouble vector Population size: Use default: 50 for five or fewer variables, otherwise 200 Specify: [200 Creation function: Ouble default: [] Specify: [nitial population: Use default: [] Specify: [nitial corres: Use default: [] Specify: [nitial range: Use default: [] Specify: [] [] Specify: [] Specify: [] Specify: [] Specify: [] Specify: [] [] Specify: [] [] Specify: [] [] Specify: [] [] []	
Current iteration: Qlear Results	Scaling function: Rank Selection Selection function: Stochastic uniform	

Fig. 6. MATLAB optimization toolbox interface.

To understand the context under which the MVO and GA were compared, the primary parameters used for their execution are presented below in *Table 1*.

Parameter	MVO	GA
Number of iterations	1500	1500
Population size	200	200
Platform/toolbox	Coded in MATLAB4	MATLAB's optimization toolbox1
Computational environment	Five-core processor, 8 GB RAM4	Five-core processor, 8 GB RAM4

Table 1. Comparison of key optimization parameters for MVO and GA.

The solution obtained using the GA, which took 138 seconds, indicated that with input pressures of 4.8, 4.8, and 4.7 bar in the first to third chambers, respectively, an output pressure of 87.4 bar was achieved.

To compare the results from the two optimization methods and assess the responses, a suitable approach is to compare them with the manufacturer's recommended value. For this purpose, the Root Mean Square Error (RMSE) index was used in this study, and the calculation formula is presented in Eq. (6).

RMSE =
$$\sqrt{\frac{1}{n} \sum_{i=1}^{n} (X_i - Y_i)^2}$$
, (6)

In Eq. (6), X_i represents the predicted values, and Y_i denotes the observed values. A lower RMSE value indicates less error and a more acceptable solution. The effectiveness of the MVO and GA in optimizing the pump's performance was evaluated based on key metrics compared to the manufacturer's recommended output pressure of 92 bar. The comparison of the results obtained from both algorithms is detailed in *Table 2*. The findings demonstrate that the MVO algorithm outperforms the GA in terms of accuracy and solution quality.

 Table 2. Comparison of optimization results (Output pressure, error, RMSE, and solution time) for MVO vs. GA.

Optimization Method	Output Pressure (Bar)	Error (%)	RMSE	Solution Time (Seconds)
MVO	89.8	2.4	1.56	72
GA	87.4	5.0	3.26	138
Manufacturer's recommended value	92	0	0	N/A

4|Discussion and Conclusion

Operating industrial equipment like piston-diaphragm pumps at peak performance is a complex challenge [8]. For devices such as the TZPM 1600 GEHO pump at the Iran Alumina Complex, the task of identifying the optimal operating point is particularly difficult due to numerous parameters, the influence of operational time, large data volumes, and inherent system constraints. These factors contribute to classifying this optimization problem as NP-hard, rendering classical optimization methods often inefficient or infeasible. The critical nature of this pump, where failure incurs significant financial losses, underscores the importance of finding effective optimization solutions.

To address this challenge, our study first developed a functional model of the pump based on six months of historical input and output data (Flow rates from three chambers and output pressure) using MATLAB's System Identification toolbox. The derived performance function, identified as an exponential model with a 99% fitness, enabled the problem to be formulated as a constrained single-objective optimization task aimed at minimizing the difference between the achieved output pressure and the manufacturer's recommended 92 bar. Constraints reflecting physical limits, such as input pressures between 0 and 5 bar and non-negative output pressure, were incorporated.

To solve this constrained single-objective optimization problem, the MVO metaheuristic algorithm was utilized due to its strong ability to handle complex optimization tasks. For comparative evaluation, the GA from MATLAB's Optimization Toolbox was also employed. Both algorithms were executed for 1500 iterations under comparable conditions. The comparative results between the two methods demonstrated that the MVO algorithm significantly outperformed the GA in finding a solution closer to the optimal manufacturer-recommended pressure and in computational efficiency [9].

The comparison showed:

The MVO algorithm produced an output pressure of 89.8 bar, with an error of 2.4% and RMSE of 1.56, bringing the pump's output very close to the 92 bar target. In contrast, the GA resulted in an output pressure

of 87.4 bar, showing a higher error of 5% and RMSE of 3.26. Furthermore, the solution time for MVO was only 72 seconds, compared to 138 seconds for the GA under the same iteration and population conditions.

Hence, MVO outperformed GA both in terms of accuracy and computational efficiency. The success of the MVO algorithm in this application provides a practical and robust method for determining operating parameters that drive the TZPM 1600 GEHO pump's output pressure very near its optimal design value. This is particularly valuable given the NP-hard nature of the problem and the limitations of manufacturer-provided performance curves for complex pumps. The results validate the use of the MVO algorithm as a robust and efficient tool for solving constrained single-objective optimization problems in complex industrial settings, potentially contributing to enhanced operational stability and reduced risk of downtime for critical equipment.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

Funding

This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

- Kleinberg, J., & Tardos, E. (2006). *Algorithm design*. Pearson Education India. https://www.amazon.com/Algorithm-Design-Jon-Kleinberg/dp/0321295358
- [2] Al-Madi, N., Faris, H., & Mirjalili, S. (2019). Binary multi-verse optimization algorithm for global optimization and discrete problems. *International journal of machine learning and cybernetics*, 10(12), 3445– 3465. https://doi.org/10.1007/s13042-019-00931-8
- [3] Jui, J. J., Molla, M. M. I., Ahmad, M. A., & Hettiarachchi, I. T. (2025). Recent advances and applications of the multi-verse optimiser algorithm: A survey from 2020 to 2024. *Archives of computational methods in engineering*, 1–34. https://doi.org/10.1007/s11831-025-10277-w
- [4] Ahmadi, H., Mofrad, M. E., & Sedghi, A. (2023). Risk assessment using fmea to identify potential risks of positive displacement pump failure in aluminum industry: A case study. *16th WCEAM proceedings* (pp. 521–529). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-25448-2_49
- [5] Mirjalili, S., Mirjalili, S. M., & Hatamlou, A. (2016). Multi-verse optimizer: A nature-inspired algorithm for global optimization. *Neural computing and applications*, 27(2), 495–513. https://doi.org/10.1007/s00521-015-1870-7
- [6] Mirjalili, S. (2019). Genetic algorithm. In *Evolutionary algorithms and neural networks: Theory and applications* (pp. 43–55). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-93025-1_4
- [7] Lambora, A., Gupta, K., & Chopra, K. (2019). Genetic algorithm-a literature review. 2019 international conference on machine learning, big data, cloud and parallel computing (COMITCON) (pp. 380–384). IEEE. https://doi.org/10.1109/COMITCon.2019.8862255
- [8] Krimpenfort, H., Ricks, B., & Schermann, E. (2017). The largest piston diaphragm pump in the world: From drawing board to operational experience. *Paste 2017: Proceedings of the 20th international seminar on paste and thickened tailings* (pp. 115–124). University of Science and Technology Beijing. https://doi.org/10.36487/ACG_rep/1752_13_Krimpenfort
- [9] Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International journal of forecasting*, 22(4), 679–688. https://doi.org/10.1016/j.ijforecast.2006.03.001