Optimisation of industrial oil-flooded screw compressor: A comparative analysis of conventional and soft computing approaches

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ABSTRACT

Screw compressors are widely used in industrial and commercial applications due to their high efficiency, reliability, and durability. However, there is still room for optimisation of such machines to improve energy efficiency and performance. This paper presents a comparative analysis of different optimisation methods for screw compressors, including conventional methods such as the simplex method and soft computing methods such as genetic algorithms, particle swarm optimisation, and Bayesian optimisation. The focus of the paper is on the development, application and evaluation of a novel Bayesian optimisation method for oil-flooded screw compressors. Optimisation targets are rotor profile parameters including the interlobe clearance, radial clearance, and axial clearance. The multi-objective function includes specific power consumption, adiabatic efficiency, volumetric efficiency, and flow. The results of the comparative analysis show that the Bayesian optimisation method outperforms other optimisation methods in terms of time and computational effort, while also achieving a better objective function using a weighted-sum approach. This provides a deeper understanding of the trade-offs between the different objective functions and enables engineers to make more informed decisions about the design and operation of oil-flooded screw compressors.

Keywords: Bayesian, Multi-objective optimisation, Screw compressor, Soft Computing

1. INTRODUCTION

Screw compressors are widely used in industrial and commercial applications due to their high efficiency, reliability, and durability (Kumar, Patil, Kulkarni, & Patil, 2023). Increasing demands for more efficient screw compressors require compressor designs to be adapted according to their duties, capacity, and production capacity. A suitable procedure for screw optimisation of the compressor's shape, size, dimensions and operational parameters is described using different optimisation methods, which implies the most appropriate design for the given compressor application and fluid.

Referring to the various kinds of literature in this field, an optimisation of a refrigeration twin screw compressor considering the rotor geometrical parameters such as the wrap angle, relative length (length to diameter ratio) and the slide valve parameters using the computer program has been presented by (Fleming, Tang, & Anderson, 1994). The optimum rotor geometrical parameters are not only crucial from the compressor efficiency point of view but also for other factors such as female rotor deflection, bearing loads and the rotor contact force. (You, Tang, & Fleming, 1996) talk about the optimisation of lobe combination, relative length and the wrap angle on the factors mentioned above. (Stosic & Hanjalic, 1997) describe the rotor profile generation. It makes use of the conjugacy conditions when solved explicitly and enables a variety of primary arcs to be defined, which allows it to generate a higher efficiency profile. A breakthrough in the optimisation of screw machines using evolution strategy (ES) has been carried out by (Berlik & Helpertz, 2002). The limitations of using the ES in the optimisation of screw machines have been discussed, along with how the unsuitability of the penalty function method led to the extended offspring generation scheme. The problem in optimisation is the number of calculations to be performed to reach the optimum and whether this optimum is the global optimum or not.

Some of the common optimisation methods are listed in this paper on performance optimisation using evolutionary algorithms:(Kumar et al., 2022).

Among all the optimisation methods discussed above, genetic algorithms are widely used, which require only the value of the target function and can also handle discontinuous functions. The only disadvantage is its slow converging nature due to its small seed size. Apart from this, the box complex method is also convenient, requiring only the function value and not the gradient. The disadvantage of this method is that it is less suitable for discrete parameters. (Stosic, Smith, & Kovacevic, 2003) utilise the box complex method to optimise the compressor shape, size, dimension and operating parameters. The application of NURBS (Non-uniform rational B-splines) by (Hauser, Bruemmer, & Kauder, 2008) improves optimisation for complex geometry machines that include profile variation of screw compressors.

On the other hand, (Herlemann, n.d.) highlights the use of a chamber model generator and simulation tool to optimise rotor profiles with the same number of lobe combinations to minimise the energy costs that can be validated experimentally. Last but not least, (Zhang, Gao, Fu, Li, & Lin, 2019) shows the structural parameter optimisation of the twin-screw expander and the influence of geometrical parameters on the thermal performance of the machine. Considering a single-objective function and using the sequential quadratic programming algorithm for optimisation, the impact of leakage on its functional force is also studied.

Apart from the works of literature on the optimisation of screw compressors, there are some papers which talk about the optimisation of the centrifugal compressor as well as heat pump using Neural Networks. This paper (Kim, Choi, & Kim, 2009) presents the design optimisation of a centrifugal compressor impeller using a radial basis Neural Network method. The four variables defining the impeller hub and shroud contours are selected as the design variables which need to be optimised The results show an improvement in the isentropic efficiency by 1%. In another paper (Massoudi, Picard, & Schiffmann, 2022), the author describes an automated design framework based on multiobjective optimisation to evaluate the robustness of turbocompressors.

Bayesian optimisation has also been used to optimise screw compressors. For instance, (Kumar, Patil, Kovacevic, & Ponnusami, 2024) used Bayesian optimisation to optimise the design parameters of a screw compressor for air systems. The authors found that the optimised design resulted in a 2% reduction in the specific power consumption.

This paper presents a comparative analysis of different optimisation methods for an industrial oil-flooded screw compressor, including conventional methods such as the simplex method and soft computing methods such as genetic algorithms, particle swarm optimisation, and Bayesian optimisation. The paper also focuses on the development and application of a novel Bayesian optimisation methodology for the optimisation of an industrial oil-flooded screw compressor manufactured at Kirloskar Pneumatic Company Limited (KPCL), Pune, India. The optimisation parameters are the rotor profile parameters, including the interlobe clearance (*GAPI* in μm), radial clearance (*GAPR* in μm), and axial clearance (*GAPA* in μm). The objective function is multi-objective, including power consumption (P in kW) and volumetric flow rate (Q in m^3/min).

The paper is structured as follows: Section 2 offers a comprehensive overview of the innovative optimisation approach. In Section 3, the modelling and optimisation formulation is presented, detailing the impact of each input parameter on screw compressor performance and the objective functions. Section 4 presents the results obtained from various optimisation algorithms, comparing them based on performance and computational time. Lastly, Section 5 summarizes the key findings and implications of the study, along with recommendations for future research.

2. INNOVATIVE OPTIMISATION APPROACH

This section discusses the development of two innovative optimisation frameworks created during this research. These frameworks provide advanced approaches to optimisation, addressing complex challenges in the field. The two frameworks are as follows:

1. Evolutionary Framework: This framework leverages an evolutionary approach and incorporates a chamber model for calculating thermodynamics performance. It is designed to address multi-objective optimisation challenges (Kumar et al., 2022).
2. Bayesian Framework: The Bayesian framework combines the chamber model and a machine learning model for thermodynamics performance calculation. It also focuses on multi-objective optimisation, offering an innovative and robust solution (Kumar et al., 2024).

Both optimisation frameworks are designed to be flexible and adaptable, allowing users to integrate various optimisation algorithms to suit their specific needs. The primary optimisation algorithms employed by these frameworks are the Genetic Algorithm and Bayesian optimisation, which are capable of handling both single and multi-objective optimisation functions. This versatility enables these tools to effectively solve a wide range of optimisation problems. The thermodynamics solver used in both frameworks is the chamber model approach, which is thoroughly explained in this paper (Kumar et al., 2022).

2.1 Evolutionary framework: Chamber model

A Genetic Algorithm (GA) is a population-based optimisation technique used to find solutions to complex problems. In the context of screw compressor optimisation, a GA can be employed to adjust compressor parameters for optimal performance.

The genetic algorithm optimizes by iteratively evolving the population towards better solutions. Over time, it explores the parameter space to identify optimal compressor settings.

The equations associated with a genetic algorithm are as follows:

- Fitness function: $f(x)$, where x represents a chromosome (a set of parameter values).
- Crossover operator: $C(x_1, x_2)$, which combines two parent chromosomes, x_1 and x_2, to create offspring.
- Mutation operator: $M(x)$, which applies small random changes to a chromosome x to introduce diversity.
- Selection mechanism: The selection method is based on fitness values and may use techniques like roulette wheel selection, tournament selection, or others.

GAs are beneficial in screw compressor optimisation because they can efficiently explore complex parameter space, making them suitable for finding optimal configurations. They can handle both single and multi-objective optimisation tasks, offering flexibility in achieving various optimisation goals.

The evolutionary framework employed in this study offers a diverse range of optimisation algorithms, including simplex search, Genetic Algorithm (GA), Accelerated Genetic Algorithm, and Covariance Matrix Adaptation Evolution Strategy (CMA-ES). This comprehensive framework provides a detailed explanation of its design approach and comparative analysis of the various optimisation algorithms, including simplex search, along with a case study on optimisation. The framework's capabilities are thoroughly discussed in research paper (Kumar et al., 2022), which presents a thorough examination of the evolutionary framework's workings and its applications in optimisation problems.

2.2 Bayesian framework: Chamber model

The Bayesian Optimisation (BO) framework represents a potent tool for optimising complex, black-box functions, particularly when evaluations are expensive. It marries a probabilistic model, often a Gaussian Process, with an acquisition function that guides the search for the optimal solution. BO undertakes an iterative journey through the function's domain, making strategic decisions on where to sample next based on the model's predictions of function behaviour. This framework is particularly useful for predicting screw compressor performance and parametric optimisation, as demonstrated in Kumar et al.'s 2024 research paper (Kumar et al., 2024). The Bayesian framework is leveraged to provide a comprehensive range of optimisation algorithms, including Bayesian Optimisation (BO), Nelder-Mead (Luersen & Le Riche, 2004), Powell (Powell, 1994), Conjugate Gradient (Nazareth, 2009), Constrained optimisation By Linear Approximations (COBYLA) (Tröltzsch, 2016), Particle Swarm Optimisation (PSO) (Marini & Walczak, 2015), and Broyden-Fletcher-Goldfarb-Shanno (BFGS) (Liu & Nocedal, 1989).

2.3 Optimisation procedure

The framework's development incorporated batch scripting and Python programming. For both the Evolutionary and Bayesian optimisation frameworks, the SCORG (Screw Compressor Rotor Grid Generation) software from PDM Analysis was employed. SCORG is an industry-leading tool for grid generation and performance analysis of positive displacement screw machines, conducting thermodynamic calculations through a multi-chamber model (Kovacevic, Rane, & Analysis, 2024). This model uses conservation equations of mass and internal energy for control volumes. The following outlines the steps involved in creating this programming framework:

1. Run the SCORG Solver:
    - Execute the solver using a batch file.

- Input initial parameters (suction pressure, discharge pressure, temperature, rotor speed).

2. Optimisation Setup:
   - Choose parameters to optimize (profile, geometry, or fluid).
   - Modify corresponding batch files accordingly.
3. Parameter Bounds and Initial Values:
   - Define lower and upper bounds for each parameter.
   - Specify initial values for optimisation.
4. Optimisation Method:
   - Select an optimisation method (e.g., Bayesian, Nelder-Mead, PSO, Powell, etc.).
5. Optimisation and Data Collection:
   - Start a timer to measure optimisation time.
   - Perform the optimisation.
   - Collect evaluations and objective values.
   - Display the optimisation result, total evaluations, optimal parameters, and time taken.

2.4 Design approach

The design approach employed in this research involves two distinct methods for multi-objective optimisation:

- Pareto-design: This approach is employed to explore and understand the trade-offs among competing objectives. It seeks to maximize, minimize, or target specific output responses, allowing the identification of numerous optimal designs, each equally valid but geared towards different objective preferences.
- Weighted-sum approach: In this approach, multiple objectives are aggregated into a single-objective function by assigning weight functions to each output. This method aims to strike a balance between various objectives. The governing equation and its explanation are provided in the research paper (Kumar et al., 2022).

The weighted-sum design approach is favoured for multi-objective optimisation, employing equal weights for each objective. This equal weighting ensures that each output function holds equal importance, making it easier to compare the performance of different optimisation algorithms.

This approach facilitates a more comprehensive exploration of the multi-objective optimisation space, allowing for a nuanced understanding of the trade-offs between competing objectives, and simplifying the comparison of algorithmic performance.

3. MODELLING AND OPTIMISATION

The study aims to optimise the KAS-300 compressor block, a gear-driven, oil-flooded screw compressor with a 22 kW power rating. This compressor features a built-in volume ratio of 4.6 and is designed to operate at pressure ratios of 7.5, 8.5, 10, and 13, with tip speeds ranging from 15 to 45 m/s. Due to its proprietary nature, detailed specifications of the compressor's size and profile are not disclosed. Experimental testing of the KAS-300 compressor block was carried out at the Centre for Compressor Technology, City, University of London (Kumar et al., 2024). The obtained data was used to create a digital model of the KAS-300 in SCORG software (Kovacevic et al., 2024), which serves as the physics solver for optimisation. This SCORG-enhanced KAS-300 model is employed for the thermodynamic calculations needed in the chamber model optimisation process.

3.1 Input functions

The developed optimisation framework targets profile clearances, which are crucial for the performance of screw compressors. This study focuses on optimising three essential profile parameters:

1. Interlobe Clearance (GAPI) in μm: This parameter refers to the space between the male and female rotor lobes, making it a critical parameter. A smaller interlobe clearance reduces gas leakage, improving volumetric and adiabatic efficiency. However, excessively small clearances can result in rotor contact, potentially causing damage and reducing the compressor's lifespan.
2. Radial Clearance (GAPR) in μm: This parameter determines the distance between the rotor lobes and the compressor housing, affecting gas leakage and friction within the compressor.
3. Axial Clearance (GAPA) in μm: This parameter determines the distance between the rotor lobes and the compressor housing in the axial direction, influencing gas leakage and friction within the compressor.

The range of input parameters for optimisation, representative of typical screw compressor operating conditions, is presented in Table 1.

Table 1: Optimisation bounds for input variables

Profile Parameters	Bounds
GAPI	(10 - 150) μm
GAPR	(10 - 150) μm
GAPA	(10 - 150) μm

3.2 Objective functions

After selecting the parameters that require optimisation, the user must choose objective functions from the list of performance parameters, depending on whether single-objective or multi-objective optimisation is the goal.

Performance parameters:

1. Power (P) in kW: Power consumption directly affects the operating costs and energy efficiency of a screw compressor. Minimizing power consumption is vital for cost-effective and sustainable operation.
2. Flow (Q) in m^3/min: Mass flow rate is the mass of gas delivered per unit time. It is obtained from the mass of the gas in the working chamber just before opening the discharge port multiplied by the rotational speed and number of cycles per revolution of the male rotor.

$$\dot{m} = mz_1 \frac{n}{60} [kg/sec] \tag{1}$$

   The volume flow rate is always normalised to the suction conditions.

$$\dot{V} = \frac{60\dot{m}}{\rho_o} [m^3/min] \tag{2}$$

   The flow rate represents the compressor's capacity. Optimizing flow ensures that the compressor can meet the desired output requirements efficiently.

3. Volumetric Efficiency (ETAV): It is the ratio of the volume flow rate and the theoretical capacity of the machine. It reflects the compressor's ability to draw in and compress air. Improving volumetric efficiency contributes to enhanced performance and reduced energy consumption.

$$\eta_v = \frac{\dot{V}}{\dot{V}_t} * 100[\%] \tag{3}$$

4. Adiabatic Efficiency (ETAK): It is the comparison of actual indicated power and theoretical adiabatic power for the compression. It quantifies how well the compressor converts energy to compression without heat loss. A higher adiabatic efficiency signifies better energy utilization.

$$\eta_{ad} = \frac{P_{ad}}{P} * 100[\%] \tag{4}$$

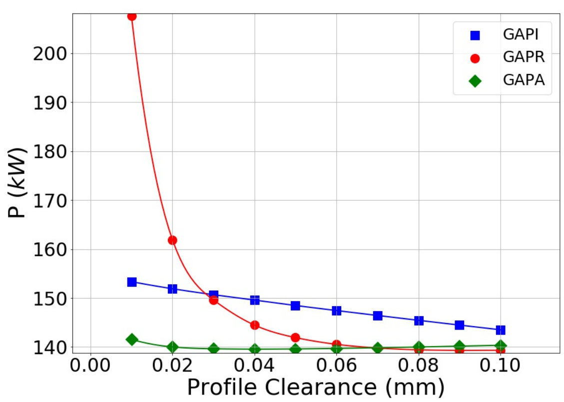
5. Specific Power Consumption (SPC) in $kW/m^3/min$: It is the power required to deliver a unit quantity of mass of the gas . It is calculated as the ratio of the compressor power and volume flow rate. Reducing SPC is critical for sustainability and cost-effectiveness, as it leads to more efficient operation and lower energy expenses.

$$SPC = \frac{P}{\dot{V}}[kW/m^3/min] \tag{5}$$

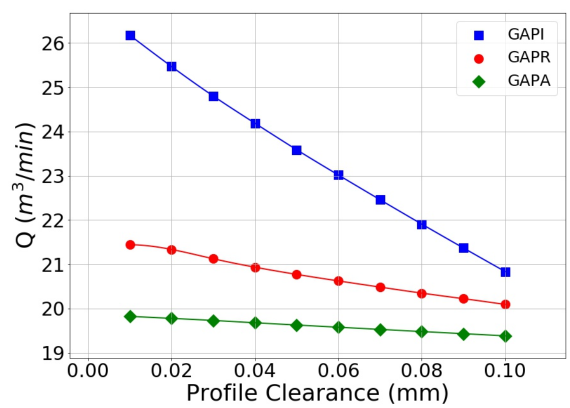
4. RESULTS AND DISCUSSION

4.1 Effect of input variables on objective functions

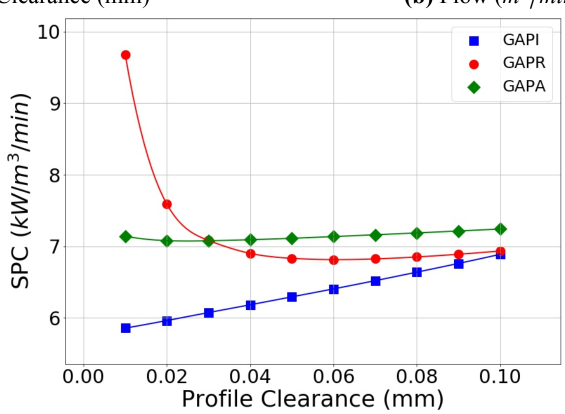
To optimise the performance of the screw compressor, it is essential to understand the impact of input variables on the objective functions. Figure 1 illustrates the effect of profile clearances on the performance of the screw compressor under a pressure ratio of 8.5. As shown in the figure, as clearances increase, compressor performance decreases. This is primarily attributed to two key factors:



(a) Power (kW) vs. Profile Clearance (mm)



(b) Flow (m^3/min) vs. Profile Clearance (mm)



(c) SPC ($kW/m^3/min$) vs. Profile Clearance (mm)

Figure 1: Effect of profile clearance on screw compressor performance at a pressure ratio of 8.5

- Increased gas leakage: Larger clearances permit more gas to escape between the rotor lobes and the compressor housing. This reduces the trapped and compressed gas, resulting in lower volumetric efficiency.
- Increased turbulence and friction: Larger clearances can also lead to heightened turbulence and friction within the gas flow, diminishing the adiabatic efficiency of the compressor.

As clearances increase, compressor performance decreases. However, excessively reducing clearances, leads to exponential performance deterioration. Lower clearances increase oil drag and may cause wear and tear, potentially impacting the compressor's reliability and longevity.

These factors underscore the importance of optimising profile clearances to achieve optimal compressor performance.

4.2 Optimisation comparison

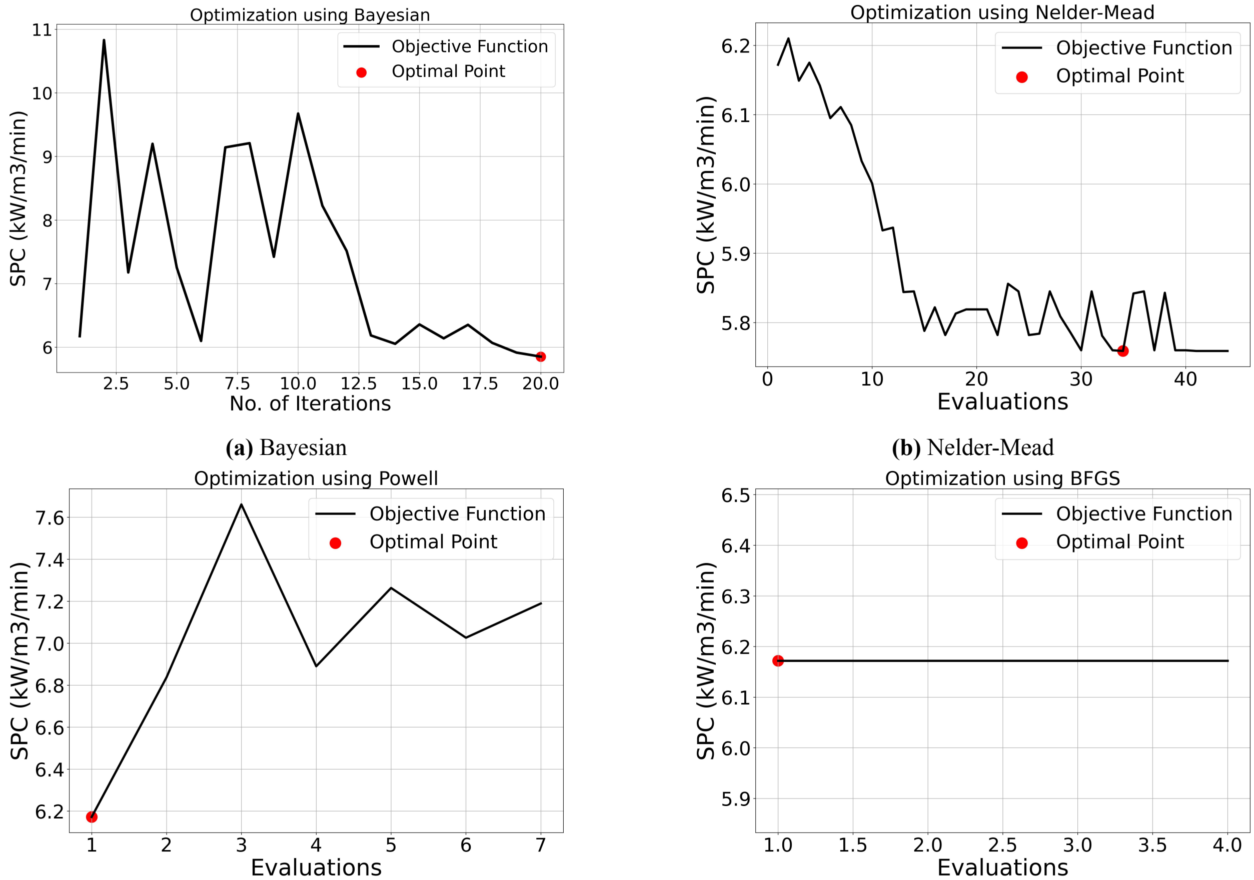
This section provides a detailed comparison of the optimisation algorithms evaluated in this study, summarized in Table 2. The table showcases the performance outcomes for Bayesian Optimisation, Nelder-Mead, Powell, Particle Swarm Optimisation (PSO), and Evolutionary Optimisation using a Genetic Algorithm (GA). Each algorithm's performance is measured as a percentage change relative to the baseline KAS-300 compressor performance, which is presented without optimisation. The sign in the tabular column indicates the direction of change in performance parameters compared to the KAS-300 (Baseline) with no optimisation. A negative sign indicates a deterioration in performance, while a positive sign indicates an improvement. This notation helps to quickly identify the impact of optimisation on key performance metrics, such as flow, power consumption, and specific power consumption.

Table 2: Comparative analysis for profile parameters optimisation

Algorithms	**Optimal Clearances** (μm)	**Q** (%)	**P** (%)	**SPC** (%)	**Time Duration** (s)
KAS-300 (Baseline)	(70, 70, 70)	-	-	-	-
Bayesian	(15, 46, 52)	58.34	-5.78	33.19	195
Nelder-Mead	(12, 42, 33)	64.31	-5.35	35.88	845
Powell	(94, 94, 94)	-29.48	0.64	-40.88	67
PSO	(104, 88, 101)	-35.82	2.05	-52.61	55
BFGS	(60, 60, 60)	12.43	-0.33	10.76	1039
Evolutionary (GA)	(14, 44, 43)	60.72	-5.48	34.38	9450

The results indicate that Bayesian Optimisation achieves the optimal solution in the shortest time frame with the fewest iterations. This is followed by Nelder-Mead, which requires more time and iterations to converge to the optimal solution. In contrast, Powell and PSO algorithms showed negative improvements and rapidly converged within seconds of starting the optimisation. Powell's negative improvement could be attributed to slow convergence in high-dimensional spaces, potentially leading to local minima. PSO's premature convergence resulted in suboptimal solutions, but tuning hyperparameters might yield practically optimal results, particularly when optimising screw parameters using the Machine Learning-based solver. The Evolutionary framework using a Genetic Algorithm (GA) resulted in optimal parameters with approximately a 35% improvement in SPC. However, it's worth noting that the time duration for Evolutionary optimisation was relatively longer compared to other Bayesian framework algorithms. A detailed view of the optimisation process, including the objective function versus the number of iterations, is provided in Figure 2.

In summary, Bayesian Optimisation stands out as an efficient choice for obtaining near-optimal solutions with minimal time and iterations. It provides a compelling alternative for solving optimisation problems, as evidenced by this analysis.



(a) Bayesian

(b) Nelder-Mead

(c) Powell

(d) BFGS

Figure 2: Objective Function vs. Number of Iterations

5. CONCLUSIONS

The present study has successfully developed a Bayesian framework utilizing the chamber model for optimising the performance of screw compressors. This framework exhibits versatility, as it is not confined to specific input functions, thus holding the potential to optimise all parameters of screw compressors, including design, geometrical, and fluid parameters. The effectiveness of this framework has been demonstrated through two distinct case studies. Firstly, it has been applied to optimise profile parameters, as presented in this study. Additionally, it has been employed for optimising design parameters, as illustrated in Kumar et al. (Kumar et al., 2024), focusing on the same industrial compressor model, KAS-300. In both instances, Bayesian optimisation has proven superior in computational efficiency and effort.

Future endeavours should extend this optimisation framework to encompass multi-stage screw compressors and undergo experimental validation. This will establish its robustness for optimising both single-stage and multi-stage screw compressors.

NOMENCLATURE

P	power	(kW)
Q	flow	(m^3/min)
SPC	specific power consumption	
		$(kW/m^3/min)$
GAPI	interlobe clearance	(μm)
GAPR	radial clearance	(μm)
GAPA	axial clearance	$(\mu m$

Subscript

v	volumetric
th	theoretical
ad	adiabatic

Abbreviations

BO	Bayesian optimisation
GA	Genetic algorithm
PSO	Particle Swarm optimisation
BFGS	Broyden–Fletcher–Goldfarb–Shanno algorithm

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