Pamukkale Univ Muh Bilim Derg, XX(X), XX-XX, 20XX

Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi

Pamukkale University Journal of Engineering Sciences

Reliability based particle swarm optimization for obtaining optimal dimensions of boom crane lifting mechanism

Vinç bom kaldırma mekanizmasının optimum boyutlarını elde etmek için güvenilirlik tabanlı parçacık sürü optimizasyonu

Ömer Sinan Şahin[1], Ahmet Çatal[2], Kerem Çoban[2], Oğuzhan Taş[2][1]

[1]Department of Mechanical Engineering, Faculty Of Engineering And Natural Sciences, Konya Technical University, Konya, Türkiye.
ossahin@ktun.edu.tr

[2]Hidrokon Konya Hidrolik Makine Sanayi & Tic. A.ş.
ahmet.catal@hidrokon.com, kerem.coban@hidrokon.com, oguzhan.tas@hidrokon.com

Received/Geliş Tarihi: 24.04.2025 Revision/Düzeltme Tarihi: 21.08.2025 doi: 10.5505/pajes.2025.27860
Accepted/Kabul Tarihi: 01.09.2025 Research Article/Araştırma Makalesi

Abstract

Articulated Mobile Cranes are specially designed systems intended for lifting and transporting loads of varying weights and dimensions. The physical dimensions of these systems may vary depending on their field of application and specific technical requirements. Such variations can have significant impacts on both lifting capacity and operational speed. Dimensional changes may lead to undesirable deviations within the safety limits established during the design phase. Therefore, in order to optimize the dimensions of these mechanisms, the statistical nature of manufacturing and measurement errors must be carefully assessed. In this study, the dimensional optimization of crane boom lifting mechanisms was performed based on reliability analysis by combining Monte Carlo Simulation with the Particle Swarm Optimization method to determine the optimal mechanism dimensions. According to the results obtained, it was found that the lambda values for different operating modes are primarily influenced by the geometric parameter (ψ) and, to a lesser extent, by the cylinder speed (vc). Depending on the selected parameters, the lambda value was observed to vary between 0.35 and 0.55.

Keywords: Knuckle Joint Crane, Lifting Mechanism, Reliability, Monte-Carlo Simulation, Particle Swarm Optimization

Öz

Araç üstü mobil vinçler, farklı ağırlık ve boyutlardaki yükleri kaldırmak ve taşımak amacıyla özel olarak tasarlanmış sistemlerdir. Bu sistemlerin fiziksel boyutları, kullanım alanlarına ve farklı teknik isteklere bağlı olarak değişkenlik gösterebilir. Bu durum hem kaldırma kapasitesi üzerinde hem de hareket hızı üzerinde önemli etkiler yaratabilir. Boyutsal değişimler, tasarım aşamasında belirlenmiş güvenlik sınırları içerisinde istenmeyen sapmalara neden olabilir. Bu yüzden, bu mekanizmaların boyutlarını optimize etmek için üretim ve ölçüm hatalarının istatistiksel doğasının dikkatli biçimde değerlendirilmesi gerekir. Bu çalışmada, vinç bom kaldırma mekanizmalarının boyutsal optimizasyonu amacıyla Monte Carlo simülasyonu ile Parçacık Sürü Optimizasyonu yöntemi birlikte kullanılarak, mekanizmanın optimum boyutları güvenilirlik temelli olarak belirlenmiştir. Elde edilen sonuçlara göre, farklı çalışma modları için lambda değerlerinin, öncelikle geometri parametresinden (ψ) ve daha az ölçüde silindir hızından (vc) etkilendiği ve seçilen parametrelere göre lambda değerinin 0,35-0,55 arasında değiştiği tespit edilmiştir.

Anahtar kelimeler: Mafsallı Bomlu Vinç, Kaldırma Mekanizması, Güvenilirlik, Monte Carlo Simülasyonu, Parçacık Sürü Optimizasyonu

1 Introduction

Mobile cranes are machines designed specifically for lifting and transporting loads, usually equipped with either wheeled or tracked chassis. These cranes are widely utilized across industries like construction, heavy industry, energy, and maritime sectors. These cranes can lift a range of loads from elevated or confined spaces, utilizing their long arms and lifting mechanisms, which are powered by hydraulic and mechanical forces. Due to their portability, mobile cranes can be easily relocated to different sites and tailored to suit their carrying capacity. Optimizing both weight and capacity is essential for maximizing the efficiency of these machines, lowering fuel consumption, boosting maneuverability, and improving transportation safety. Optimizing the dimensions of a boom crane's lifting mechanism is crucial for enhancing its efficiency, safety, and overall performance. The crane's boom, which acts as the main load-bearing arm, must be carefully designed and optimized in terms of length, angle, and material composition to effectively lift and transport heavy loads. Proper dimensional optimization ensures that the crane operates within its intended capacity, preventing overloading that could result in mechanical failures, safety hazards, or even catastrophic accidents. By fine-tuning these dimensions, the crane can achieve optimal lifting power and stability while maintaining its range of motion and precision.

Dimensional optimization also offers a significant advantage in terms of fuel efficiency and cost-effectiveness. Cranes tailored for specific lifting tasks operate more efficiently, reducing unnecessary energy consumption and minimizing excessive movements. For example, an optimized boom with the correct lifting angle reduces strain on the engine and hydraulic systems, helping to extend the crane's service life while lowering maintenance costs. Moreover, adjusting the weight distribution and improving the structural integrity of the boom can help minimize stress on critical components, further boosting operational durability. By designing the lifting mechanism with precise dimensions, the crane is less likely to experience issues such as tipping or imbalance, which can arise if the boom is too long or improperly configured for the load.

[1]Corresponding author/Yazışılan Yazar

Ensuring proper balance and stability during lifting helps minimize the risk of accidents, protecting both workers and equipment. Through advanced simulation and computational modeling, engineers can predict the crane's performance in various conditions, allowing them to fine-tune its dimensional parameters for an optimal design that ensures safe and efficient operation across diverse environments. Particle Swarm Optimization (PSO) is an evolutionary algorithm inspired by nature, making it a powerful tool for solving optimization problems. In PSO, a swarm of particles (candidate solutions) navigates through the solution space to find the optimal answer. Each particle keeps track of its best previous position and aims to move toward it, while the entire swarm's memory is shaped by the best solution found collectively. By incorporating both cognitive and social elements, PSO promotes faster and more accurate convergence. This method is capable of optimizing multiple parameters simultaneously, efficiently avoiding local minima and leading to a global solution. The PSO algorithm, introduced by Kennedy and Eberhart [1], is known for requiring less computational time compared to other optimization algorithms. As a result, it has been successfully applied to solve a wide range of problems [2-7]. The algorithm begins by defining unknown parameters, referred to as particles, and assigning them random positions. These particles move through the search space to minimize an objective function. The fitness of each particle is evaluated based on the objective function, which is used to update both the best position of the individual particle and the best position found by all particles collectively at each computational step.

Particle Swarm Optimization is a commonly used metaheuristic algorithm for solving optimization problems. The method is simple, easy to implement, and converges quickly [8]. It has been extensively applied in structural reliability analysis [9-11]. Dimensional optimization of a lifting mechanism, combining Particle Swarm Optimization (PSO) with Monte Carlo simulation, provides an effective solution to the challenges posed by measurement and manufacturing errors in dimensions. The PSO algorithm is used to determine the optimal design parameters for the mechanism, considering factors such as load capacity, efficiency, and structural integrity. However, real-world applications often face complications due to inaccuracies in dimensions arising from measurement or manufacturing deviations. To address these uncertainties, Monte Carlo simulation is used to perform probabilistic analysis, simulating various scenarios with different error distributions to evaluate the impact of dimensional inaccuracies on the mechanism's performance and reliability. By merging PSO's optimization capabilities with Monte Carlo's ability to model and mitigate the effects of dimensional variations, the resulting lifting mechanism becomes more robust, ensuring consistent performance despite real-world errors. This integrated approach enhances both the accuracy and resilience of the design, making it less sensitive to production variability. Monte Carlo Simulation is an analytical method that utilizes random sampling, often employed to model uncertainties and randomness. The simulation creates multiple solution scenarios by using numerous random samples to explore all potential outcomes of a given problem. Monte Carlo simulation is especially powerful for analyzing nonlinear, complex, and uncertain systems. By generating a large number of random samples, it can simulate the behavior of a system and deliver statistically reliable results. The integration of PSO and Monte Carlo simulation improves the accuracy and reliability of solutions for optimization problems. While PSO navigates the solution space, Monte Carlo simulation offers more realistic results by accounting for uncertainties and randomness within the system. This is particularly useful in engineering and manufacturing, where measurement errors and uncertainties frequently occur. These errors may originate from several factors, including material properties and the production process, which could influence the precision of the design. While PSO determines the optimal parameters during the solution process, Monte Carlo simulation addresses uncertainty and measurement errors in these parameters, leading to more robust and reliable results.

Manufacturing and measurement uncertainties are critical factors that can significantly influence design accuracy. In production processes, factors such as tolerances, material variations, and slight machine calibration errors can all impact the precision of the design. These errors, particularly in complex systems, can compromise the accuracy and reliability of the results. Monte Carlo simulation models these random errors and simulates the system's behavior under different scenarios. When combined with PSO, this approach allows for a deeper understanding of how uncertainties affect the system, enabling the creation of more reliable, real-world designs. Therefore, the integration of these two techniques provides more robust and accurate optimization solutions, resulting in more realistic engineering outcomes.

Reliability problems are typically formulated as nonlinear programming problems subject to constraints [12, 13], which can be quite complex. Given that randomness is valuable for finding a global solution [14], metaheuristic approaches have become more popular than gradient methods for solving structural optimization problems.

Coelho [15] developed an efficient particle swarm optimization algorithm based on Gaussian distribution and chaotic sequences to address reliability–redundancy optimization problems. Liu et al. [16] introduced a reliability-based design optimization method to tackle the CFRP battery box lightweight design challenge.

Liu et al. [17] proposed a modified particle swarm optimization algorithm to address the reliability redundancy optimization problem, while Malhotra et al. [18] applied PSO for software reliability prediction.

In practical engineering applications, various sources of uncertainty frequently arise due to inconsistencies in material properties, manufacturing processes, and measurement techniques [19-23]. Accordingly, the consideration of uncertainties in engineering design has garnered increasing attention in recent years [24-26]. For example, Xian et al. [27] introduced a comprehensive analytical framework for stochastic optimization of nonlinear viscous dampers used in energy-dissipating systems, which was successfully applied to uncertainty-based optimization in suspension bridge applications.

With the growing complexity of engineering systems, the presence of diverse and interacting uncertainties has become inevitable, often resulting in challenges related to their identification and quantification [28]. If such uncertainties are not properly accounted for, ensuring the reliability and safety of engineering systems becomes increasingly difficult [29-32].

In this context, the Reliability-Based Design Optimization (RBDO) methodology has been widely employed to enhance the safety and robustness of complex mechanical systems [33]. RBDO seeks to maintain system reliability within acceptable bounds while optimizing performance-related objective functions [34].

This study focuses on optimizing the dimensions of a three-limb mechanism used to position the movable arm in mobile cranes. The goal is to achieve minimum acceleration and maximum moment arm by incorporating dimensional uncertainty through the Monte Carlo approach, integrated with the PSO technique.

2 Modeling and Method

Figure 1 shows the schematic representation of lifting mechanism widely used in knuckle joint boom cranes.

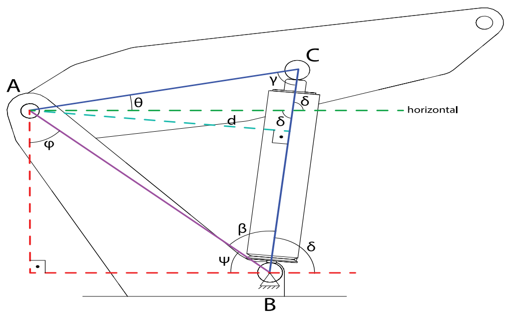

Figure 1. Schematics of lifting mechanism used in knuckle joint boom cranes

By using geometric relations, the following equations can be obtained

$$\Psi + \theta + \beta = 180 = \pi \quad (1)$$
$$\sigma + \theta = \gamma \quad (2)$$
$$\beta + \theta + \gamma = \pi - \Psi = Fixed \quad (3)$$
$$\beta = \pi - \Psi - \gamma - \theta \quad (4)$$

Applying the Sinus theorem, we get equations (5), (6) and (7) as follows;

$$\frac{|AB|}{\sin\gamma} = \frac{|AC|}{\sin\beta} \quad (5)$$
$$\gamma = \sin^{-1}\left(\frac{|AB|}{|AC|} . \sin\beta\right) \quad (6)$$
$$\beta + \sin^{-1}\left(\frac{|AB|}{|AC|} . \sin\beta\right) - \pi + \Psi = -\theta \quad (7)$$

Introducing a new parameter as λ=[AB]/[AC], Eq (8) can be obtained;

$$\theta \geq 0 \quad \beta = \tan^{-1}\left(\frac{\sin(\Psi+\theta)}{\lambda - \cos(\Psi+\theta)}\right)$$
$$\theta \leq 0 \quad \beta = \tan^{-1}\left(\frac{\sin(\Psi-\theta)}{\lambda - \cos(\Psi-\theta)}\right) \quad (8)$$

Then, the moments arm (d(θ)) can be expressed as follows

$$d(\theta) = |AB| . \sin\beta$$

This type of mechanism generally operates at very low acceleration. However, it should still be considered during the optimization process. It is assumed that the hydraulic cylinder moves at a constant velocity, it still can cause angular acceleration due to variation of angular positions of members. The angular velocity and angular acceleration are expressed as follows.

$$\dot{\theta} = \frac{d\theta}{dt} = \frac{V_C . \sin\gamma}{|AC|} \quad (9)$$
$$\ddot{\theta} = \frac{d^2\theta}{dt^2} = \frac{V_C}{|AC|} . \cos\gamma . \gamma' \quad (10)$$

Where, dγ/dt and dβ/dt are expressed as;

$$\frac{d\gamma}{dt} = \gamma' = \sin^{-1}(\lambda . \sin\beta) = \frac{\lambda . \cos\beta . (\frac{d\beta}{dt})}{\sqrt{1-\lambda^2 . \sin^2\beta}} \quad (11)$$

Where

$$\dot{\beta} = \frac{d\beta}{dt} = \frac{1-\lambda . \cos(\theta-\Psi)}{1-2\lambda . \cos(\theta-\Psi)+\lambda^2} . \frac{V_C}{|AC|} . \lambda^2 . \frac{V_C}{|AC|} . \lambda . \sin\beta$$

Finally, the angular acceleration of arm member is expressed as follows.

$$\ddot{\theta} = \frac{V_C}{|AC|} . \cos(\sin^{-1}(\lambda . \sin\beta)) . \frac{\lambda . \cos\beta}{\sqrt{1-\lambda^2 . \sin^2\beta}} . \dot{\beta} \quad (12)$$

In this study, the optimization process was carried out in the parameters presented in Table 1, which are the variables used in the PSO algorithm, by taking into account both measurement errors and variations in hydraulic systems for various reasons. For this purpose, a noise term was added to the (ψ) angle selected in the mechanism and the velocity (vc) of the hydraulic cylinder in accordance with the Gaussian distribution. Algorithm parameters are shown in Table 2 while Pseudocode for the solution is presented in Table 3.

Table 1. Mechanism design parameters

Parameter Name	Value	Variation
θ angle (Deg.)	-15 to +83	
ψ angle (Deg.)	+15 to +75	±1%
Cylinder velocity (vc) (m/s)	0.005 to 0.015	±1%

Table 2. Algorithm parameters

Parameter Name	Value
Population Size	30
Number of Iteration	100
Inertial Weight	0.7
c1	1.5

c2	1.5

The velocity of the ith particle, vi, is calculated as follows [1]:

$V_i^{t+1}=\omega.v_i^t+c_1.r_1.(x_{best,i}^t-x_i^t)+c_2.r_2.(x_{best,g}^t-x_i^t)$

The new position of the ith particle is then determined as follows:

$X_i^{t+1}=X_i^t+V_i^{t+1}$

Where

v_i^t: Velocity of i[th] particle at instant t

v_i^{t+1}: Velocity of i[th] particle at instant t+1

ω: Inertial coefficient

C_1, C_2: Cognitive Coefficient (personal learning factor) and Social Coefficient (global learning factor):

r_1, r_2: Random coefficients selected between [0.1]

$x_{best,i}^t$: Personal best point of i[th] particle

$x_{best,g}^t$: Global best position

x_i^t: Position of i[th] particle at instant t

Table 3. Pseudo Code

```
Pseudo Code
Initialize a population, positions of each particle, #of iteration
Add Gaussian noise for variables
Assign random values to particles
Evaluate the objective value of each particle
Determine initial pbest and gbest
 while termination criteria are not satisfied do
        for each particle do
        Update the velocity for the particle
               Update the new location for the particle
               Determine the objective value for the particle in its new location
               Update pbest and pbest if required
end for
Save optimal λ at each iteration
 End while
 Calculate mean, standard deviation and 95% confidence interval
 Write λoptimum, standard deviation and 95% confidence interval
End
```

Confidence interval is obtained as follows;

$$CI=1.96*\sigma/\sqrt{N}$$

Where; σ and N represents standard deviation and number of iterations respectively. Here, the coefficient 1.96 is a constant for 95% confidence level. On the other hand, random noise at the variables is calculated as follows.

Var_new=Var_original+ GaussianNoise(0, Var_original * 0.01)

Where, a number with mean of zero and standard deviation equals to Var_original*0.01 that fits the Gaussian distribution is added to the original variable.

The objective function selected during the optimization process must be expressed in terms of geometric dimensions and cylinder speed. The first component of the objective function, angular acceleration and the change in the moment arm, depend on the cylinder speed (vc), the λ ratio, and the angle (β), as shown in Equations 11 and 12. Similarly, the moment arm depends on the angle (β). The objective and constraints of the optimization process is as seen in Table 4. Since the geometry of the mechanism is idealized, the geometric constraints should be taken into account. The diameter of an actual pin used in a crane can be about 120 to 180 mm. For this aim, a constraint is defined as seen in Table 4.

Table 4. Objectives and restrictions

	Objectives
#1	Minimum angular acceleration
#2	Maximum β at θ=-15/+83 interval
#3	Minimum variation at β at θ=-15/+83 interval
	Constraint
#1	$\lambda-cos(\Psi+\theta)\neq 0$ (Numerical constraint)
#2	$\lvert\lambda.sin\,\beta\rvert\leq 1$ (Numerical constraint)
#3	$\lambda_{min}>0,15$ (Manufacturability constraint)

The objective function targeted in optimization has a structure that combines different objectives. When considering a crane boom, it becomes clear that several elements must be combined. These elements are described below. First, considering the crane boom's own mass and the mass it lifts, it becomes clear that angular acceleration must also be minimized. Second, to minimize cylinder forces and linkage forces, the moment arm must be maximum at every angular position. Third, to ensure proper control of the crane, the change in the moment arm depending on the angular position must also be minimized. In order to obtain the requirements, following type objective function has been defined.

$$F=w1.F1+w2.F2+w3.F3 \qquad (13)$$

Where, F1, F2 and F3 represents, maximization of the moment arm, minimization of the change in the moment arm and minimization of the angular acceleration respectively. Various requirements are expected from cranes in various applications. For example, when lifting a delicate load, angular acceleration may be the most important factor. In another application, however, maximizing the moment arm may be the most important factor. Taking all these factors into account, the operating modes and weights in Table 5 were determined by clustering the different requirements for each component of the objective function and assigning a weight to each component of the objective function. The above mentioned factors have been weighted and the overall objective function is then defined as Eq.(13) under specified constraints. A code has been developed by using MS-Excel VBA for solving the above-mentioned problem by using PSO and the results are visualized by using Minitab.

Table 5. Selected weighting factors for different working modes

Mode	w1	w2	w3
Economy	0.3	0.4	0.3
Safety	0.2	0.4	0.4
Performance	0.6	0.2	0.2

$$F = w1 * \min(\mathrm{abs}(\ddot{\theta})) - w2 * \max(\beta) + w3 * \min(\mathrm{abs}(d\beta/dy)) \quad (14)$$

3 Results and Discussions

In Figure 2-4, the optimum lambda values obtained for different cylinder velocities (vc) and geometry parameter (ψ) values for economy, safety and performance modes are presented, respectively. As seen in the figures, the lambda value approaches 1 at values close to the 35- and 65-degrees values of ψ. In addition, it is understood that the optimum lambda value decreases with the increase in cylinder velocity. This situation is similar for all operating modes. On the other hand, as seen in Figure 2-4, it is understood that a minimum region is formed for the optimum lambda value at the middle values of the ψ variable in different operating modes. The position of this region also changes depending on the cylinder velocity (vc). In Figure 5-7, statistical evaluations of the data presented in Figure 2-4 are presented in the form of main effects plot. As can be seen in these figures, the optimum lambda values for different operating modes are highly dependent on the geometry parameter (ψ) value. It can also be evaluated that the optimum values of lambda are slightly dependent on the cylinder velocity.

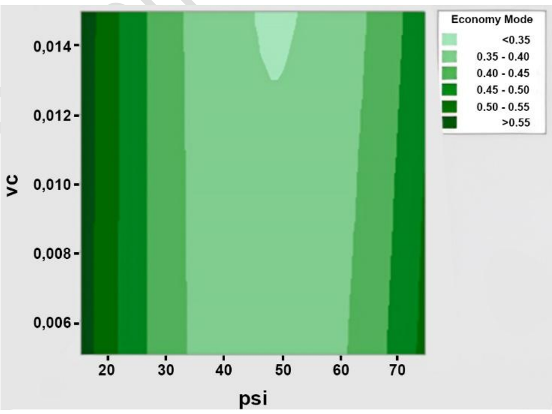

Figure 2. Optimum lambda values for different cylinder velocity (vc) and geometry parameter (ψ) for economy mode

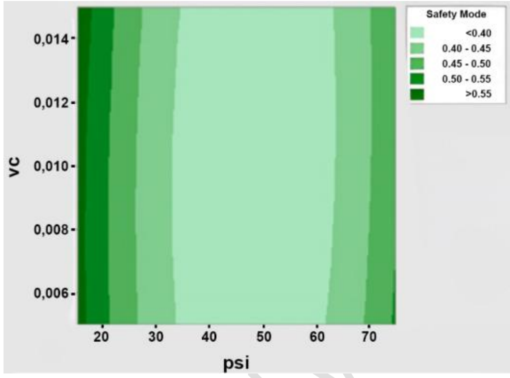

Figure 3. Optimum lambda values for different cylinder velocity (vc) and geometry parameter (ψ) for safety mode

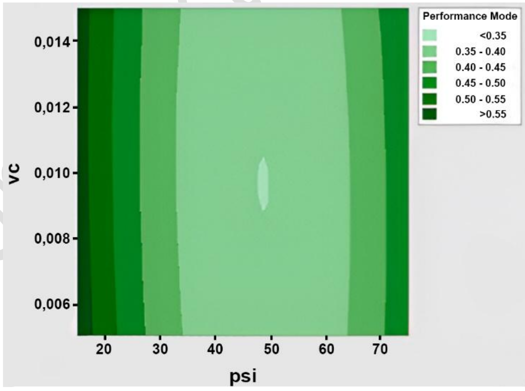

Figure 4. Optimum lambda values for different cylinder velocity (vc) and geometry parameter (ψ) for performance mode

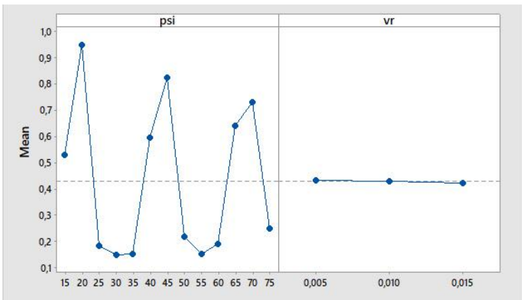

Figure 5. Main effect of cylinder velocity (vc) and geometry parameter (ψ) for economy mode

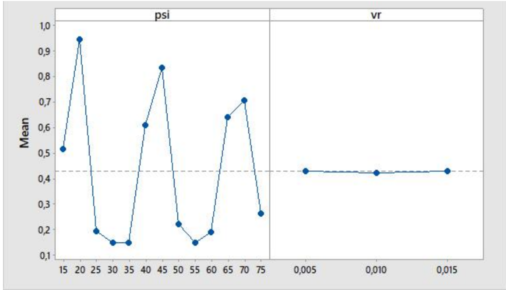

Figure 6. Main effect of cylinder velocity (vc) and geometry parameter (ψ) for safety mode

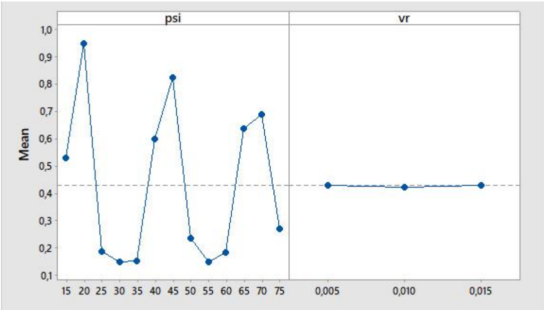

Figure 7. Main effect of cylinder velocity (vc) and geometry parameter (ψ) for performance mode

In general, it is quite difficult to ensure absolute certainty in flow control, especially in hydraulic systems. Experimental observations have revealed that there is approximately a 1% uncertainty in the cylinder movement velocity related to this phenomenon. Similarly, for the geometry parameter (ψ), measurement errors, joint clearances, and assembly errors lead to an assumed uncertainty of about 1%, and calculations have been carried out accordingly. Considering these uncertainties, the evaluations have been made based on a 95% confidence interval. A 95% confidence interval means that there is a 95% probability that the predicted optimal lambda value lies within this range. A narrow confidence interval indicates that the results have low uncertainty and that the optimization is reliable. A wide confidence interval suggests greater variability or uncertainty and may require further improvements to the model. Figures 8-10 present the confidence interval values for different operating modes. As shown in the figures, while cylinder velocity (vc) does not have a significant impact on the confidence interval, it is clear that the most influential parameter is the ψ value. It is observed that in all operating modes, the situation is similar, with the optimal lambda values obtained within a very narrow range, indicating that the optimal lambda values are achieved with high certainty.

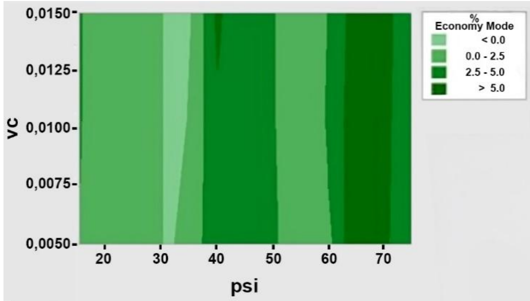

Figure 8. Contour plot of 95% confidence interval values for economy mode

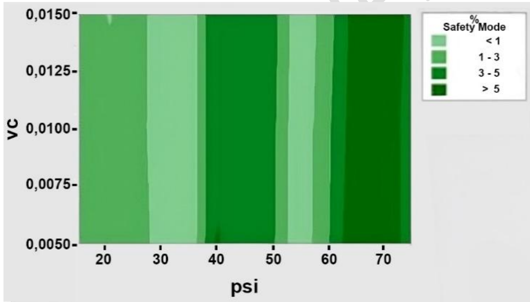

Figure 9. Contour plot of 95% confidence interval values for safety mode

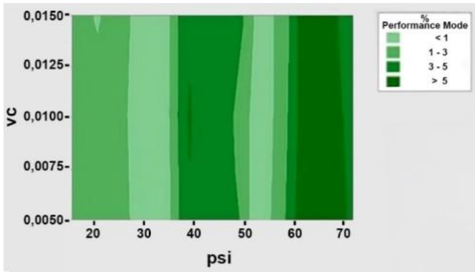

Figure 10. Contour plot of 95% confidence interval values for performance mode

4 Conclusions

The optimization of lambda values for different operating modes in hydraulic systems is primarily influenced by the geometry parameter (ψ) and, to a lesser extent, the cylinder velocity (vc). As observed, the lambda value approaches 1 at both the minimum and maximum ψ values, with a clear decrease in the optimal lambda value as cylinder velocity increases. This behavior is consistent across all operating modes, highlighting the dominant effect of the ψ parameter.

It is concluded that the analysis indicates that a minimum region for the optimal lambda value forms at the middle values of ψ, and this region's position is influenced by changes in cylinder velocity. Statistical evaluations confirm that the lambda values are highly sensitive to ψ, while cylinder velocity has a smaller effect on optimization. The uncertainties associated with hydraulic system control, such as variations in cylinder velocity and geometry parameter measurements, were accounted for in the evaluation process. A 95% confidence interval was used to assess the reliability of the results, with the narrow range of the confidence intervals indicating a high degree of certainty in the optimal lambda values across all operating modes. These findings suggest that the optimization model is reliable, although further improvements may be necessary if wider variability or uncertainty is observed in future studies. It is also concluded that precise control of the geometry parameter (ψ) plays a critical role in achieving optimal system performance, with cylinder velocity having a secondary, though still significant, influence on the overall optimization.

5 Acknowledgements

6 Authors contribution statements

All authors contributed to the article and approved the submitted version.

7 Ethics committee approval and conflict of interest statement

“There is no need to obtain permission from the ethics committee for the article prepared”. “There is no conflict of interest with any person/institution in the article prepared”.

8 References

[1] Kennedy J, Eberhart R. "Particle swarm optimization". *Proceedings IEEE International Conference Neural Networks*, IEEE, Perth, WA, Australia, 27 November 1995- 01 December 1995.

[2] Naka S, Genji T, Yura T, Fukuyama Y. "A hybrid particle swarm optimization for distribution state estimation". *IEEE Transactions on Power Systems*, 18, 60-68, 2003.

[3] Ratnaweera A, Halgamuge SK. "Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficient". *IEEE Transactions on Evolutionary Computation*, 8, 240-255, 2004.

[4] Shi Y, Eberhart RC. "A modified particle swarm optimizer". *Proceedings of the IEEE International Conference on Evolutionary Computation,* Anchorage, Alaska, 4-9 May 1998.

[5] Clerc M. "The Swarm and the Queen: Towards the deterministic and adaptive particle swarm optimization". *Proceedings of the Congress on Evolutionary Computation*, IEEE Service Center, Washington, DC, USA, 06-09 July 1999.

[6] Arumugam MS, Rao MVR, Tan AWC. "A novel and effective particle swarm optimization-like algorithm with extrapolation technique". *Applied Soft Computing*, 9, 308-320, 2009.

[7] Fateh MM, Zirkohi MM. "Adaptive impedance control of a hydraulic suspension system using particle swarm optimisation". *Vehicle System Dynamics*, 49, 12, 1951-1965, 2011.

[8] Lu H, Dong Y. "A reliability index computation method based on particle swarm optimization". *International Conference on Advances in Energy*, Environment and Chemical Engineering, AEECE-2015.

[9] Elegbede C. *"*Structural reliability assessment based on particles swarm optimization*". Structural Safety*, 27, 171-186, 2005.

[10] Wu P, Gao L, Zou D, Li S. “An improved particle swarm optimization algorithm for reliability problems“ *ISA Transactions*, 50, 71-81, 2011.

[11] Chengming L, Hui L. “Structural reliability and sensitivity analysis of random variables based on PSO”. Journal of Xi'an University of Architecture & Technology, 38, 614-618, 2006.

[12] Kuo W, Prasad VR. "An annotated overview of system-reliability optimization". *IEEE Transactions on Reliability*, 49, 176–187, 2000.

[13] Gaby G, Prayogo D, Wijaya BH, Wong FT, Tjandra D. "Reliability-based design optimization for structures using particle swarm optimization". *Journal of Physics Conference Series,* 1625, 012016, 2020.

[14] Prayogo D, Cheng MY, Wong FT, Tjandra D, Tran DH. "Optimization model for construction project resource leveling using a novel modified symbiotic organisms search”. *Asian Journal of Civil Engineering*, 19, 625–638, 2018.

[15] Coelho LS. "An efficient particle swarm approach for mixed-integer programming in reliability–redundancy optimization applications". *Reliability Engineering and System Safety*, 94, 4, 830-837, 2009.

[16] Liu Z, Zhu C, Zhu P, Chen W. "Reliability-based design optimization of composite battery box based on modified particle swarm optimization algorithm". *Composite Structures*, 204, 239-255, 2018.

[17] Liu Y, Qin G. "A modified particle swarm optimization algorithm for reliability redundancy optimization problem". *Journal of Computers*, 9, 9, September 2014.

[18] Malhotra R, Negi A. "Reliability modeling using particle swarm optimization". *International Journal of System Assurance Engineering and Management, 4, 275–283, 2013.*

[19] Sun G, Zhang H, Fang J, Li G, Li Q. "A new multi-objective discrete robust optimization algorithm for engineering design". *Applied Mathematical Modelling*, 53, 602-621, 2018.

[20] Xu X, Chen X, Liu Z, Yang J, Xu Y, Zhang Y, Gao Y. "Multi-objective reliability-based design optimization for the reducer housing of electric vehicles". *Engineering Optimization*, 1-17, 2021.

[21] Xu X, Chen X, Liu Z, Xu Y, Zhang Y. "Reliability-based design for lightweight vehicle structures with uncertain manufacturing accuracy". *Applied Mathematical Modelling*, 95, 22-37, 2021.

[22] Fang J, Gao Y, Sun G, Xu C, Li Q. "Multiobjective robust design optimization of fatigue life for a truck cab". *Reliability Engineering & System Safety*, 135, 1-8, 2015.

[23] Dawood T, Elwakil E, Novoa HM, Delgado JFG. "Soft computing for modeling pipeline risk index under uncertainty". *Engineering Failure Analysis*, 117, 104949, 2020.

[24] Li W, Gao L, Xiao M. "Multidisciplinary robust design optimization under parameter and model uncertainties". *Engineering Optimization*, 52, 426-445, 2020.

[25] Chen Z, Li T, Xue X, Zhou Y, Jing S. "Fatigue reliability analysis and optimization of vibrator baseplate based on fuzzy comprehensive evaluation method". *Engineering Failure Analysis*, 127, 105357, 2021.

[26] Yuan R, Tang M, Wang H, Li H. "A reliability analysis method of accelerated performance degradation based on Bayesian strategy". *IEEE Access*, 7, 169047-169054, 2019.

[27] Xian J, Su C. "Stochastic optimization of uncertain viscous dampers for energy-dissipation structures under random seismic excitations". *Mechanical Systems and Signal Processing*, 164, 108208, 2022.

[28] Tan Y, Zhan C, Pi Y, Zhang C, Song J, Chen Y, Golmohammadi AM. "A hybrid algorithm based on social engineering and artificial neural network for fault warning detection in hydraulic turbines". *Mathematics*, 11, 2274, 2023.

[29] Xue Y, Deng Y. "Extending set measures to orthopair fuzzy sets". *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 30, 63-91, 2022.

[30] Zhu SP, Keshtegar B, Bagheri M, Hao P, Trung NT. "Novel hybrid robust method for uncertain reliability analysis using finite conjugate map". *Computer Methods in Applied Mechanics and Engineering*, 371, 113309, 2020.

[31] Bagheri M, Zhu SP, Ben Seghier MEA, Keshtegar B, Trung NT. "Hybrid intelligent method for fuzzy reliability analysis of corroded X100 steel pipelines". *Engineering Computations*, 37, 2559-2573, 2021.

[32] Plotnikov L. "Preparation and analysis of experimental findings on the thermal and mechanical characteristics of pulsating gas flows in the intake system of a piston engine for modelling and machine learning". *Mathematics*, 11, 1967, 2023.

[33] Zhang D, Zhang J, Yang M, Wang R, Wu Z. "An enhanced finite step length method for structural reliability analysis and reliability-based design optimization". *Structural and Multidisciplinary Optimization*, 65, 231, 2022.

[34] Dui H, Song J, Zhang YA. "Reliability and service life analysis of airbag systems". *Mathematics*, 11, 434, 2023.