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Parçacık Sürü Optimizasyonu ile Mafsallı Bomlu Vinçlerin Kaldırma Mekanizmasının Optimizasyonu

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ÖZ

Mobil vinçler, ağır yükleri kaldırmak ve taşımak için tasarlanmış özel makinelerdir. Tekerlekli veya paletli bir şasiye sahip olabilirler ve inşaat, ağır sanayi, enerji ve denizcilik gibi sektörlerde yaygın olarak kullanılmaktadırlar. Bu vinçler, uzatılabilir kollar ve kaldırma ekipmanları kullanarak hidrolik sistemler ve mekanik kuvvetler aracılığıyla yükleri yüksek veya dar alanlardan kaldırır. Verimli bir çalışma, ağırlık ve kapasitenin optimize edilmesine bağlıdır; aşırı yükler veya dinamik kuvvetler güvenlik risklerine veya mekanik arızalara yol açabilir. Bu araştırma, parçacık sürü optimizasyon yöntemi kullanarak bir mafsallı bomlu vincin kaldırma mekanizmasının boyutlarını optimize etmeye, moment kolunu maksimize etmeye ve ivmeyi minimize etmeye odaklanmaktadır. Bu çalışmada, silindir hızının optimum λ değerinin belirlenmesinde ihmal edilebilir bir etkiye sahip olduğu, optimum lambda değeri için birincil belirleyici faktörün ise (ψ) açısı olduğu gösterilmiştir.

Design Optimization of Knuckle Joint Crane Lifting Mechanism by Using Particle Swarm Optimization

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ABSTRACT

Mobile cranes are specialized machines designed for lifting and moving heavy loads. They feature either a wheeled or tracked chassis and are widely used in industries such as construction, heavy manufacturing, energy, and maritime operations. These cranes utilize hydraulic systems and mechanical forces to lift objects from elevated or confined spaces by employing extended arms and lifting attachments. Efficient operation depends on optimizing weight and capacity, as excessive loads or dynamic forces can lead to safety risks or mechanical failures. This research focuses on optimizing the dimensions of a knuckle joint boom crane's lifting mechanism to maximize the moment arm and minimize acceleration, by employing the particle swarm optimization (PSO) method. It is shown in this study that cylinder velocity has a negligible impact on the determination of the optimal λ value while the primary determining factor for the optimum value of lambda is the (ψ) angle.

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1. Introduction

The dimensional optimization of mobile crane lifting mechanisms is crucial for performance, safety, and cost-efficiency. The main goal of optimizing crane mechanism dimensions is to enhance the lifting capacity. This process is critical for properly sizing the mechanism's components, optimizing material use, and ensuring that performance remains within safe limits. Dimensional optimization is generally achieved by physical and operational parameters. Various numerical analysis and simulation techniques are commonly employed to achieve optimal results. In practical engineering applications, various sources of uncertainty frequently arise due to inconsistencies in material properties, manufacturing processes, and measurement techniques (Fang et al., 2015; Sun et al., 2018; Dawood et al., 2020; Xu et al., 2021). Accordingly, the consideration of uncertainties in engineering design has garnered increasing attention in recent years (Yuan et al., 2019; Li et al., 2020; Chen et al., 2021). For example, Xian et al. (2022) 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 (Tan et al., 2023). If such uncertainties are not properly accounted for, ensuring the reliability and safety of engineering systems becomes increasingly difficult (Zhu et al., 2020; Bagheri et al., 2021; Xue et al., 2022; Plotnikov, 2023). In this context, the Reliability-Based Design Optimization (RBDO) methodology has been widely employed to enhance the safety and robustness of complex mechanical systems (Zhang et al., 2022). RBDO seeks to maintain system reliability within acceptable bounds while optimizing performance-related objective functions (Dui et al., 2023). In recent years, numerous optimization algorithms have been developed, inspired by nature. One of the most commonly used techniques is Particle Swarm Optimization (PSO), which is frequently applied to solve complex engineering design problems involving multiple parameters, nonlinearity, and continuous variables. PSO is an optimization method widely used in machine learning and artificial intelligence domains. This algorithm involves a group of particles (candidate solution points) moving through a predefined space in search of the best solution. Each particle is located within the solution space, and its velocity vectors are updated by remembering both its own best position and the best position found within the swarm. PSO has gained significant attention over the years, inspired by the social behavior of animals, particularly the flocking patterns of birds (Moravec, 2017). The algorithm was first introduced in 1995 (Kennedy et al., 1995). By simulating a simplified social system, the behavior of PSO can be understood as an optimization process. Compared to other optimization algorithms, PSO requires less computational time. However, it is important to note that not all optimization algorithms are suited for every type of problem (Wolpert et al., 1997; Belot, 2020). Despite this, PSO is known for its ability to find global optimum solutions and offers the advantage of greater computational efficiency, making it highly suitable for nonlinear optimization problems (Wu and Wu, 2018). In PSO, particle movement is governed by rules that update both speed and position. The cognitive component involves each particle recalling its best position from the past and moving toward that point, while the social component directs the particle to move based on the best solution found by the entire swarm. The interplay of these two factors enables faster and more precise convergence to the optimal solution. In PSO, the process starts by determining the solution space for each parameter, assigning random initial positions, evaluating the objective function, updating the particles' velocities and positions based on their individual best solutions and the best solution in the swarm, and then repeating the process a set number of times. As a result, PSO has been successfully applied to solve various problems (Naka et al., 2003; Arumugam et al., 2009; Wang and Guan, 2013). proposed an optimal design for hydraulic supports using an analytical approach (Oblak et al., 2000). Prebil et al. showed how the synthesis of a four-bar linkage in a hydraulic support could be achieved through a global optimization algorithm (Prebil et al., 2002; Jianguo et al., 2012). Dan et al. applied a multi-objective mathematical model to optimize the four-bar linkage while ensuring the strength requirements were met, based on kinematic and mechanical analysis (Dan et al., 2009). Ye et al. utilized the least squares method to optimize the four-bar linkage of hydraulic supports (Ye et al., 2009) Additionally, some researchers (Fateh et al., 2011; Dong-yun et al., 2013) applied Particle Swarm Optimization (PSO) for the optimal control of hydraulic excavators. Given the highly standardized nature of crane design procedures, the majority of time and effort is often spent interpreting and implementing existing design standards (Erden, 2002). The design characteristics of cranes can differ significantly depending on their primary operational specifications (Abid et al., 2015). Numerous studies have focused on analyzing stress distributions and tip deflection, employing optimization techniques such as the Marine Predator Algorithm and the Search and Rescue algorithm (Mladenović, et al., 2024). Cross-section optimization was explored using the Lagrange multiplier method (Stephen et al., 2018), while the effects of inertial loads were examined by other researchers (Volianiuk et al., 2021). The finite element method was also employed to analyze the performance of work platforms in studies (Zdravković et al., 2010; Guo et al, 2016). This study is focused on optimizing the geometric dimensions of a three-limb mechanism used for positioning the movable arm in mobile cranes, with the goal of obtaining the minimum acceleration and the maximum moment arm using the PSO technique.

2. Materials and Methods

The Particle Swarm Optimization (PSO) algorithm operates by representing the unknown parameters as particles. Starting with a random initialization, the particles move through a search space to minimize an objective function. The parameters are estimated by minimizing the objective function. Each particle's fitness is assessed based on the objective function, which helps update both the particle's best position and the best position among all particles. In each iteration, particles are directed towards both their previous best position and the best position found by the entire swarm. As a result, particles tend to fly toward the more promising areas of the search space. The velocity of the ith particle, vi, is calculated as follows [2]:

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

It is important to note that the inertia weight was not included in the original version of PSO (Ratnaweera et al 2004). 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

It is reported that the solution of PSO algorithm is highly influenced by weight factors and the acceleration factors. Larger coefficients are beneficial to global search, while smaller coefficients encourage local exploitation. Algorithm parameters are shown in Table 1.

Table 1. Algorithm parameters

Parameter Name	**Value**
Population Size	30
Number of Iteration	100
Inertial Weight	0.7
c1	1.5
c2	1.5

Table 2. Mechanism design parameters

Parameter Name	Value
θ angle (Deg.)	-15 to +83
ψ angle (Deg.)	+15 to +75
Cylinder velocity (m/s)	0.005 to 0.015
[AB], [AC]=Fixed	
[BC]= Variable	

Figure 1 illustrates the schematic representation of lifting mechanism widely used in knuckle joint boom cranes. The mathematical formulations and numerical solutions were carried out by using parameters presented in Table 2.

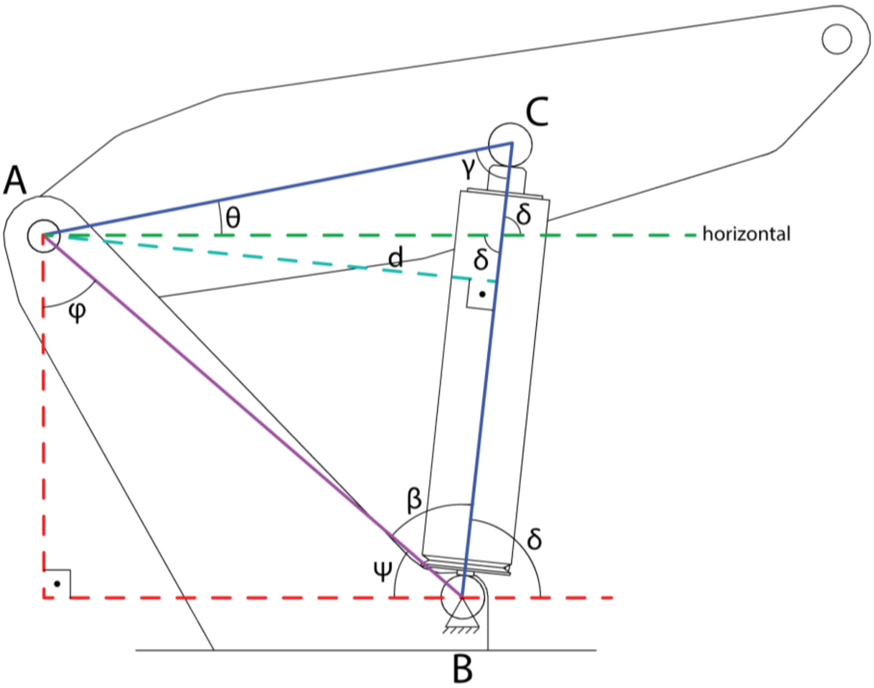

Figure 1. Mechanism design parameters

$$\boldsymbol{\Psi + \theta + \beta + \gamma = 180 = \pi} \quad (1)$$

$$\boldsymbol{\sigma + \theta = \gamma} \quad (2)$$

$$\boldsymbol{\beta + \theta + \gamma = \pi - \Psi = Fixed} \quad (3)$$

$$\boldsymbol{\beta = \pi - \Psi - \gamma - \theta} \quad (4)$$

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

$$\frac{\boldsymbol{|AB|}}{\boldsymbol{\sin\gamma}} = \frac{\boldsymbol{|AC|}}{\boldsymbol{\sin\beta}} \quad (5)$$

$$\boldsymbol{\gamma = \sin^{-1}(\frac{|AB|}{|AC|} . \sin\beta)} \quad (6)$$

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

In triangle ABC, the length of link BC is variable. Therefore, the remaining lengths are AB and AC. In cranes, the basic length AC determines the moment arm, and therefore the lifting capacity. Therefore, when designing cranes with different capacities, AC is the primary determining parameter. However, this length is related to the crane's horizontal capacity. The amount of space the crane will occupy on the chassis and the length of the moment arm at different angular positions (θ) and the angular velocity and acceleration of link AC depend on length AB. Therefore, a new parameter has been used to represent the required length of AB for a given AC length. Introducing a new parameter as λ=[AB]/[AC], Eq (8) can be obtained;

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

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

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

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

$$\dot{\boldsymbol{\theta}} = \frac{d\boldsymbol{\theta}}{dt} = \frac{V_r.\sin\boldsymbol{\gamma}}{|AC|} \tag{9}$$

$$\ddot{\boldsymbol{\theta}} = \frac{d^2\boldsymbol{\theta}}{dt^2} = \frac{V_r}{|AC|}.\cos\boldsymbol{\gamma}\ .\boldsymbol{\gamma}' \tag{10}$$

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

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

Where

$$\dot{\boldsymbol{\beta}} = \frac{d\boldsymbol{\beta}}{dt} = \frac{1-\boldsymbol{\lambda}.\cos(\boldsymbol{\theta}-\boldsymbol{\Psi})}{1-2\boldsymbol{\lambda}.\cos(\boldsymbol{\theta}-\boldsymbol{\Psi})+\boldsymbol{\lambda}^2}.\frac{Vr}{|AC|}.\boldsymbol{\lambda}^2.\frac{Vr}{|AC|}.\boldsymbol{\lambda}.\sin\boldsymbol{\beta} \tag{11}$$

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

$$\ddot{\boldsymbol{\theta}} = \frac{\boldsymbol{V_r}}{|\boldsymbol{AC}|} \cdot \cos(\sin^{-1}(\boldsymbol{\lambda} \cdot \sin \boldsymbol{\beta})) \cdot \frac{\boldsymbol{\lambda} \cdot \cos \boldsymbol{\beta}}{\sqrt{1 - \boldsymbol{\lambda}^2 \cdot \sin^2 \boldsymbol{\beta}}} \cdot \dot{\boldsymbol{\beta}} \tag{12}$$

The objective and constraints of the optimization are summarized in Table 3

Table 3. 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	$\boldsymbol{\lambda - cos(\Psi + \theta) \neq 0}$ (Numerical constraint)
#2	$\boldsymbol{\lambda - cos(\Psi + \theta) \neq 0}$ (Numerical constraint)
#3	$\boldsymbol{|\lambda. \sin \beta| \leq 1}$ (Numerical constraint)
#4	$\boldsymbol{\lambda_{min} > 0,15}$ (Manufacturability constraint)

The above-mentioned requirements yield the following type of objective function.

F(ψ, Vr) = w 1 · F 1 + w 2 · F 2 + w 3 · F 3 (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. On the other hand, these factors need to be weighting by using weighting factors and the overall objective function is then defined as Eq. (13) under specified constraints. The weights lifted by a crane and operator's interest are depends on fragility of the lifted material and operational costs. So, these relative weights were chosen in such a way that it covers all aspects of the lifting operations in the view of our experience.

Three weighting factors have been defined and a code has been developed by using MS-Excel VBA for solving the above-mentioned problem by using PSO. The final form of objective function is shown in Eqn (14)

F(ψ, Vr)=0,6*min (abs(angular acceleration))-0,2*max(β)+0,2*min (abs(dβ/dy)) (14)

3.Results and Discussions

The solution to the problem mentioned above was carried out based on the geometric parameters and speed values commonly used in the crane industry. The results obtained are presented in Figure 2. Additionally, the effects of the vr and (ψ) parameters on the lambda value were statistically evaluated and presented in Figure 3. As seen in the figures, depending on the selected (ψ) angle, the lambda value varies between the dimensional limits of 0,15 and 0,9. On the other hand, as shown in the figure, the primary determining factor for the optimum value of lambda is the (ψ) angle. When considering the selected values for the cylinder speed, it has been evaluated that their effect on the optimum value of lambda is negligible. When the same problem was analyzed based on minimizing the change in the moment arm during the lifting operation, it was observed that the lambda value approaches 1. When examining cranes of different capacities available in the market, it is generally seen that the (ψ) angle is chosen between 40°-50° and the lambda value is typically chosen to be approximately 1. In this case, it can be concluded that the solution was based on minimizing the change in the moment arm during the lifting operation for these products.

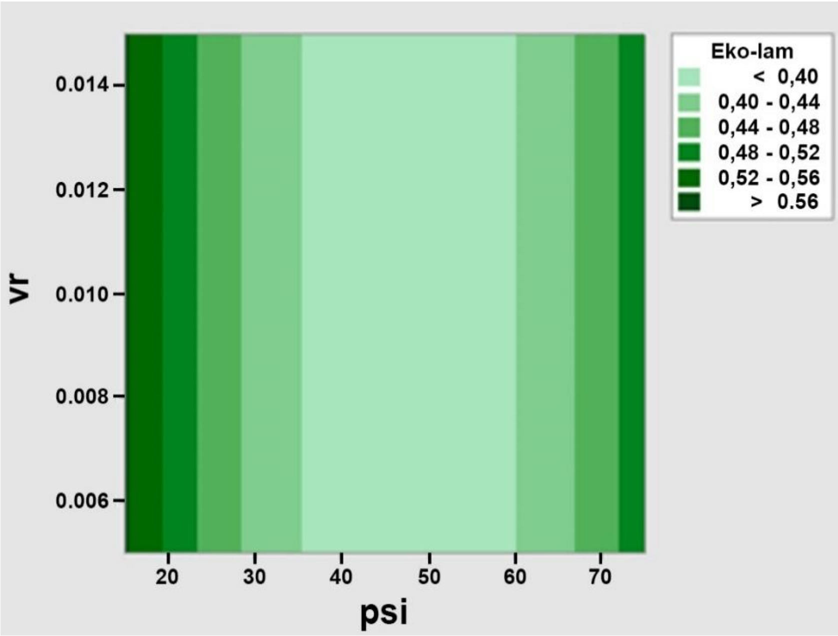

Figure 2. Optimal lambda values for cylinder velocity (vr) and geometry parameter ((ψ))

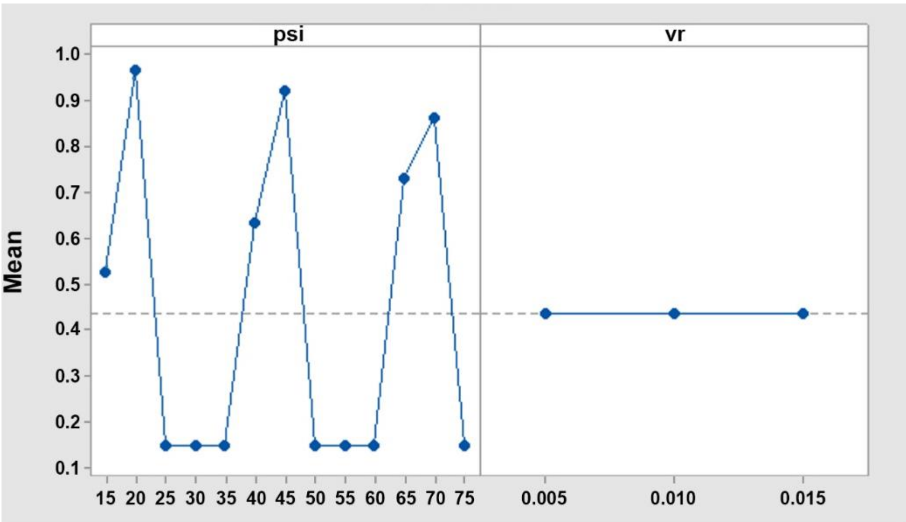

Figure 3. Main effect of cylinder velocity (vr) and geometry parameter ((ψ))

When the Figures 2 and 3 are examined together with the numerical results presented in the appendix, it can be said that the numerical magnitude of the "angular acceleration" term does not have a significant impact on determining the optimum point, due to its relatively small magnitude. However, considering the capacities and reach distances of cranes in the industry (400 ton.m, >60m), it can be said that the crane itself can reach significant dimensions with its own inertia. Therefore, more detailed studies are planned for high-capacity cranes.

As can be seen in the results, in some cases, optimal value of λ can go as low as 0.15, indicating that it is highly dependent on the selected ψ angle. Therefore, it was concluded that the optimum values obtained in this study are more suitable for use in telescopic cranes where the load is lifted by using pulleys while the boom is kept still.

4.Conclusions

This study primarily focused on the optimization of the lifting mechanism in a knuckle joint boom crane, with the main objective of maximizing the moment arm and minimizing acceleration through the application of the Particle Swarm Optimization (PSO) method. The analysis underscored the critical influence of the (ψ) angle on determining the optimal lambda (λ) value. It was observed that λ varies within the range of 0.15 to 0.9, depending significantly on changes in ψ, highlighting the interdependency between these two parameters in achieving an optimal lifting configuration. Moreover, the results indicated that cylinder speed has a negligible impact on the determination of the optimal λ value. This finding suggests that within the studied operational range, dynamic effects related to speed do not substantially alter the optimal geometrical parameters, thereby simplifying the control requirements for the system. A key conclusion drawn from the study is the importance of minimizing variation in the moment arm throughout the lifting process. Maintaining a consistent moment arm contributes to improved load stability and more efficient energy usage during crane operation. The optimal configuration for effective and stable lifting was found to generally occur when the ψ angle lies between 40° and 50°, with a corresponding λ value approaching 1. This combination provides a favorable balance between mechanical advantage and control stability, which is essential for safe and efficient crane performance.

The focus of the current study is to obtain the geometric dimensions based on bioinspired approach and manufacturers expectations. However, these solutions covers only the lifting mechanism. It is obvious that optimal geometrical dimensions may vary depending on the weighting factors preferred by scenario.

5.Acknowledgement

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6.Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

7.Authors' Contributions

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

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9. Appendix: Numerical results

ψ	vr	λ_{opt}	Ang. acc. $\ddot{\theta}$
15	0,005	0,525321757	7,49956E-12
15	0,01	0,525321524	2,99982E-11
15	0,015	0,525321298	6,7496E-11
20	0,005	0,964966017	2,19442E-11
20	0,01	0,964966006	8,77769E-11
20	0,015	0,964965995	1,97498E-10
25	0,005	0,15	4,05567E-13
25	0,01	0,15	1,62227E-12
25	0,015	0,15	3,6501E-12
30	0,005	0,15	9,68778E-15
30	0,01	0,15	3,87511E-14
30	0,015	0,15	8,719E-14
35	0,005	0,15	-6,88855E-13
35	0,01	0,15	-2,75542E-12
35	0,015	0,15	-6,1997E-12
40	0,005	0,633319041	1,09584E-11
40	0,01	0,633318873	4,38336E-11
40	0,015	0,633318703	9,86256E-11
45	0,005	0,921751243	1,9037E-11
45	0,01	0,92175122	7,61481E-11
45	0,015	0,92175119	1,71333E-10
50	0,005	0,15	7,65808E-13
50	0,01	0,15	3,06323E-12
50	0,015	0,15	6,89227E-12
55	0,005	0,15	-2,77807E-13
55	0,01	0,15	-1,11123E-12
55	0,015	0,15	-2,50026E-12
60	0,005	0,15	-5,04878E-13
60	0,01	0,15	-2,01951E-12
60	0,015	0,15	-4,5439E-12
65	0,005	0,730173454	1,44998E-11
65	0,01	0,730173332	5,79994E-11
65	0,015	0,730173218	1,30499E-10
70	0,005	0,862318825	1,40982E-11
70	0,01	0,862318781	5,63926E-11
70	0,015	0,862318731	1,26883E-10
75	0,005	0,15	1,04273E-12
75	0,01	0,15	4,17094E-12
75	0,015	0,15	9,38461E-12