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Research on Multi-Objective Optimization Design and Digital Modeling Method of Archimedes Worm Drive

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Abstract: The paper focuses on investigating the impact of integrated multi-objective optimization design, and digital modeling on compactness and mechanical performance of Archimedes worm drive. Worm gear design requires balancing compactness with mechanical performance, as reducing volume and center distance often conflicts with maintaining load capacity and transmission efficiency. Conventional methods treat design parameters such as gear ratio, face width, and pitch circle diameters independently, replying on manual CAD adjustments that neglect their coupled effects on stress, lubrication, and assembly accuracy. To address this, a mathematical model with geometric and operational constraints is formulated and solved using a genetic algorithm. The optimized results are linked to a prototype system built in Solid Works through the API and VBA, enabling automatic geometry generation and updates. Case study demonstrates that this approach reduces design time, produces more compact gear assemblies, and maintains reliable mechanical performance.

Keywords: Multi-objective optimization, Parametric modeling, Worm drive, Genetic algorithm

1. Introduction

Gear transmission systems are fundamental in mechanical engineering, providing reliable motion and power transfer across various industrial applications [1]. Among these systems, worm gear drives stand out due to their high reduction ratios, smooth operational characteristics, and inherent self-locking capabilities [2]. However, the traditional design process for worm drives often proves to be labor-intensive and heavily reliant on iterative calculations and empirical charts. This can create significant challenges in optimizing designs, as the scope for innovation is often constrained by established methodologies [3].

The evolution from conventional two-dimensional design techniques to advanced three-dimensional parametric modeling has brought about a transformative shift in mechanical design processes. This transition enhances accuracy, re-usability, and design speed, making it easier for engineers to meet the demands of contemporary manufacturing environments. Parametric modeling empowers designers to swiftly modify key design variables, including gear ratio, face width, and pitch circle diameters. These modifications are immediately reflected in the 3D CAD model, ensuring that design iterations can be performed more efficiently and effectively [4]. Such flexibility is critical in a fast-paced industrial landscape where rapid prototyping and agile responses to market changes are essential.

In recent years, nature-inspired optimization algorithms, particularly genetic algorithms (GAs) have emerged as powerful tools for solving complex mechanical design challenges [5],[6]. GAs excel in exploring vast solution spaces without requiring gradient information, making them well-suited for multi-objective and nonlinear problems with multiple constraints[7].Previous research has demonstrated the effectiveness of optimization techniques in gear design. For instance, Gologlu et al. minimized the volume of a two-stage helical gear train by optimizing parameters such as normal module, number of teeth, and face width while adhering to bending strength and contact stress constraints[8]. Similarly, Chong et al. applied genetic algorithms to reduce the geometric volume of two-stage and planetary gear trains, achieving notable reductions in size with minimal deviation from target gear ratios[9]. Sanchez et al. further advanced this field by optimizing cylindrical parallel gear trains for weight reduction using variables like gear width, tooth count, and normal module[10]. Additionally, Fang Feng, Hui Pan, and Guojun Hu explored parametric design of spur gears using Pro/E[11], while Weihua Kuang developed a parametric part family system based on UG and Excel[12]. Despite these advancements, existing research has not fully addressed the integration of optimization, digital modeling, and prototype validation specifically for worm drives.

The methodology for this research includes four major components:first, to develop a robust mathematical model that facilitates the optimization of worm drives; second, to implement GA-based optimization techniques aimed at minimizing the volume and center distance of the worm drive while adhering to performance constraints; and third, to build the parametric modeling within SolidWorks and later we use VBA and API scripting. In addition, we will assemble a prototype system to validate our approach through real-world case studies. This integrated framework not only enhances design efficiency but also provides a pathway for innovation in worm drive applications.

Thus, the main area of focus of the paper is the optimization design to minimize volume, center distance as a main objectives, and other design variables, digital modeling methods and in addition, assemble a prototype system to validate our approach.

2. Methodology

The proposed methodology integrates genetic algorithm (GA)-based multi-objective optimization with parametric CAD modeling to develop an efficient and automated design framework for worm gear drives. The process consists of four key phases: (1) Mathematical modeling and problem formulation, (2) Genetic algorithm-based multi-objective optimization (MATLAB implementation), (3) Parametric modelling (Solidworks), and (4) Prototype system. The overall technical road-map figure 1 below visually depicts the sequential progression from mathematical modeling to GA optimization, CAD automation, and physical validation. This dual-platform methodology (MATLAB + Solid Works) ensures a closed-loop design process, enhancing design efficiency and reducing material waste.

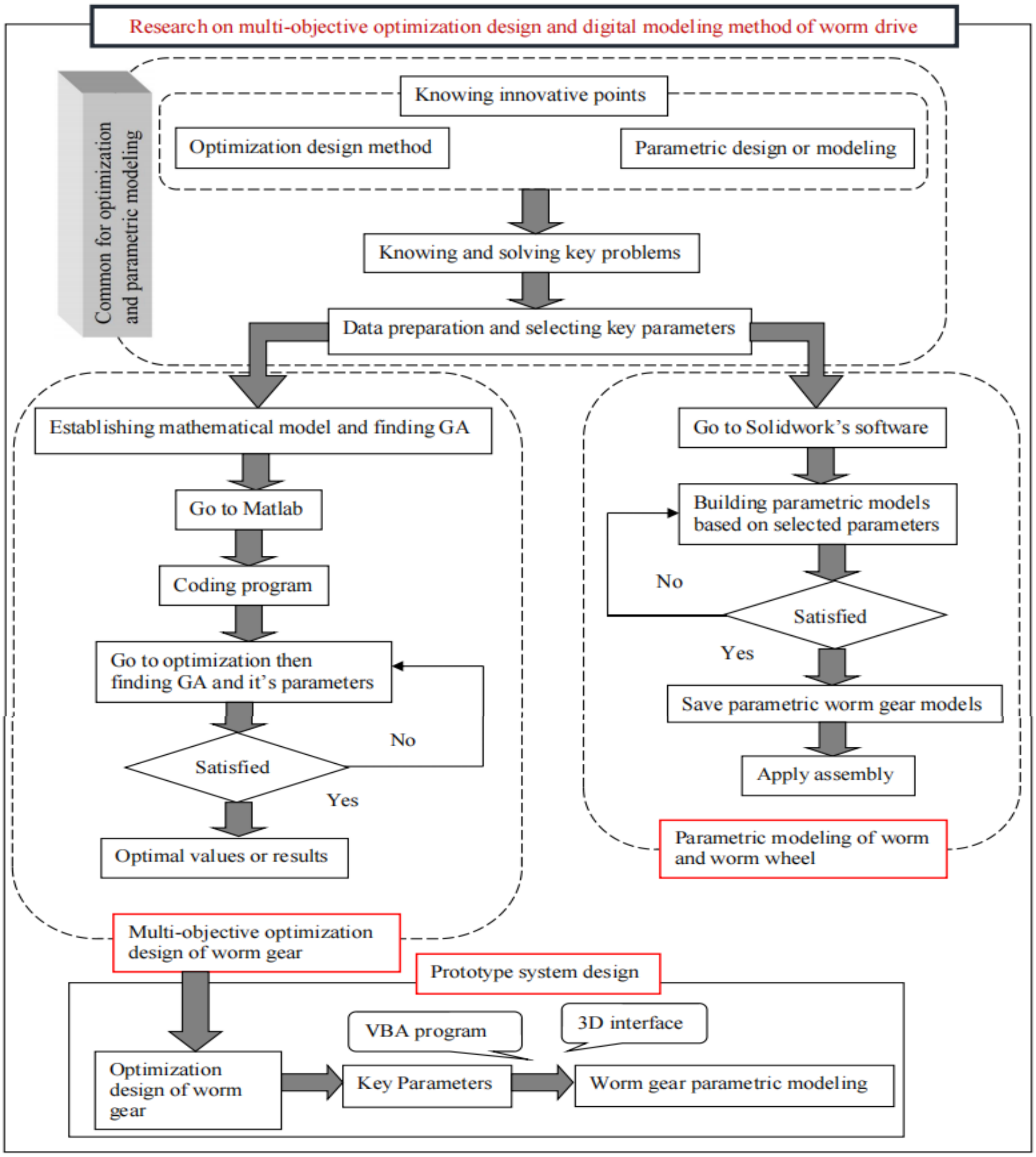


Figure 1: Overall technical road map of thesis research

3. The main components and results

3.1 Mathematical Modeling

Mathematical modeling is pivotal for deriving precise numerical values while enhancing the efficiency of mechanical components. By aligning these models with MOO objectives, the base for effective mechanical part optimization is established.

In formulating the worm drive design problem, several key design variables are identified, including the gear ratio *(i)*, face width (*b*), worm pitch circle diameter (d_w), and worm wheel pitch circle diameter (d_g). The principal design aim in this context is compactness, with a central objective to minimize the total volume of the worm and worm wheel assembly while adhering to critical constraints, such as the center distance [8]. This structured approach ensures that the design not only fulfills functional requirements but also enhances the efficiency and effectiveness of the mechanical components involved.

Table 1: Specifications of worm and worm wheel assembly

Parameters	Worm		Worm wheel
Pitch circle diameter (mm)	240		1560.19
Number of starts or teeth	1		65
Center distance (mm)		901	
Face width (mm)	160		160
Axial pitch (mm)	75.41		-
Speed (rpm)	48		0.7385
Pressure angle (deg)	20		20
Lead angle(deg)	5.71		-

3.1.1 Design Variables

Four geometric parameters govern the optimization:

$$F(h) = \begin{bmatrix} a \\ b \\ d_w \\ d_g \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{bmatrix} \tag{1}$$

Constrained boundaries:

$$\begin{cases} 40 \le h_1 \le 70 \\ 100 \le h_2 \le 200 \\ 150 \le h_3 \le 280 \\ 1000 \le h_4 \le 1500 \end{cases} \tag{2}$$

3.1.2 Objective function

The primary goal is to minimize the combined volume of the worm and worm wheel assembly. Due to the flywheel-like rather than solid structure of the worm wheel, separate equations for volumes of the rim, arms, and core sections are essential. These equations leverage established design references to compute the volumetric elements accurately [13]. The cumulative formula accounting for the worm and worm wheel volumes defines the objective function as follows:

$$min(V_{worm} + V_{wheel}) \tag{3}$$

Worm Volume:

$$V_{worm} = \frac{\pi h_3^2 L_w}{4} \tag{4}$$

Where worm length (L_w)is empirically determined as: $L_w = 2.5\pi\frac{h_3}{h_1} + h_2$.

Worm wheel volume:

$$V_{wheel} = V_{rim} + V_{arms} + V_{hub} \tag{5}$$

With empirical relationships derived from machine design principles:

Rim Volume: $V_{rim} = \pi h_2 \left(\frac{h_4}{2}\right)^2$,

Arm volume(6 arms): $V_{arms} = 6 * \left[\frac{\pi}{4}(0.2h_4)^2 h_2\right]$, and

Hub volume: $V_{hub} = \pi h_2 \left(\frac{0.3h_4}{2}\right)^2$.

3.1.3 Constraints

Constraints are the conditions that must be met in the optimum design and includes restrictions on design variables. These constraints defines boundaries of the feasible and infeasible design space domain. The constraints considered for the optimum design of worm and worm wheel is as follows:

a) Center distance: To have compact design of gear pairs, center distance between worm and worm wheel should be less. This constraint tells that center distance of optimized gear pair should be less than that of actual gear pair and the equation is formulated as[13]:

$$\frac{\frac{h_1 h_2}{2\sqrt{\frac{65h_3}{h_4}+1}} + h_3}{2} - 901 \leq 0 \tag{6}$$

3.2 Multi-Objective Optimization Approach

Multi-objective optimization (MOO) is a crucial approach in engineering that addresses complex problems involving multiple conflicting objectives that must be optimized simultaneously. Unlike single-objective optimization, which focuses on finding a single optimal solution, MOO aims to generate a set of Pareto-optimal solutions. These solutions reflect the trade-offs between competing objectives, enabling decision-makers to select the most suitable option based on specific application requirements. The figure 2 below shows that multi-objectives optimization process and optimization process typically involves two main stages: the Optimization stage, where a set of Pareto-optimal solutions is identified, and the Decision-making stage, where the most appropriate solution is chosen from this set.

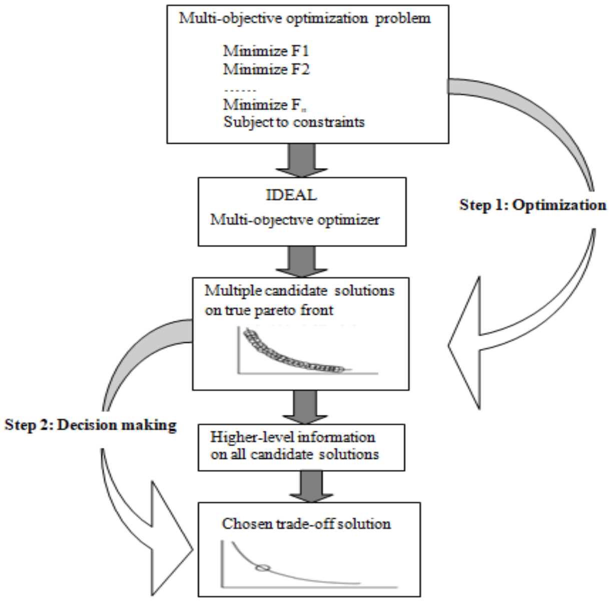


Figure 2: Multi-objective optimization process

3.2.1 Genetic Algorithm (GA) for Worm Gear Optimization

Genetic Algorithms (GA's), which are inspired by the principles of natural selection and genetic inheritance, are particularly effective for solving complex mechanical design challenges, including the optimization of worm gears. Implemented in MATLAB, the GA utilizes thegamultiobjsolver to find Pareto-optimal solutions through iterative selection, crossover, and mutation operations [14],[15].

The implementation of the GA optimization process begins with the formulation of a multi-objective fitness function that captures the geometric characteristics of the worm gear. Specifically, this involves defining the fitness functions as:

$$f(1) = 14.310929\left((h_3^2 * h_4) / h_1 \right) + 455.5309 * h_2 * h_4 + 0.0832\left(\left((256 * h_4^2) + (h_1^2 * h_2^2)\right) / (h_1 * h_4) \right)^2 + 104034.7 \tag{7}$$

$$f(2) = \left({\left(h_3 + (h_1 * h_2)\right)} \Big/ {\left(2 * sqrt\left(\left(65 * {h_3}/{h_4}\right) + 1\right)\right)} \right) \Big/ 2 - 901 \quad (8)$$

where *h1*, *h2*, *h3*, and *h4* represent various design variables that define the geometry of the worm gear. The design variable bounds are established as lower bounds of [40, 100, 150, 1000] and upper bounds of [70, 200, 280, 1500]. Additionally, nonlinear constraints are defined to ensure that structural and operational limits are respected.The optimization process is executed in MATLAB using the optimization toolbox (optimtool) until convergence is achieved, ensuring an effective search for optimal design parameters. The selected values of various parameters for the genetic algorithm are summarized as follows:

Table 2: Selected values of different parameters for generic algorithm

Parameters	Selected values
Population size	50
Initial range	[0;1]
Crossover fraction	0.8
Generations	100
Constraint tolerance	100-3

3.2.2 Results and Discussion

The proposed GA-based optimization significantly reduced the volume and center distance of the worm gear. Table 3 from the original research shows a 66.53% reduction in volume and42.17% reduction in center distance. Additional reductions were observed in gear ratio (38.3%), face width (37.48%), 37.13% in thepitch circle diameter of the worm, and 35.89% in the pitch circle diameter of the worm wheel. The final model assembly demonstrated smooth meshing and compliance with all strength. The GA-optimized worm gear design achieved substantial improvements compared to the conventional design (Table 3):

Table 3: Comparison between conventional design and optimized design

Parameters	Actual	Generic algorithm
Gear ratio	65	40.1
Face width(mm)	160	100.04
Pitch circle diameter ofworm(mm)	240	150.88
Pitch circle diameter of worm wheel(mm)	1560.19	1000.28
Volume(mm^3)	17.72*10^7	5.76*10^7
Center distance(mm)	901	521
Strength of worm	-	92

The Pareto Front (Figure 3) illustrates the trade-off between the two objectives: minimizing volume and minimizing center distance.

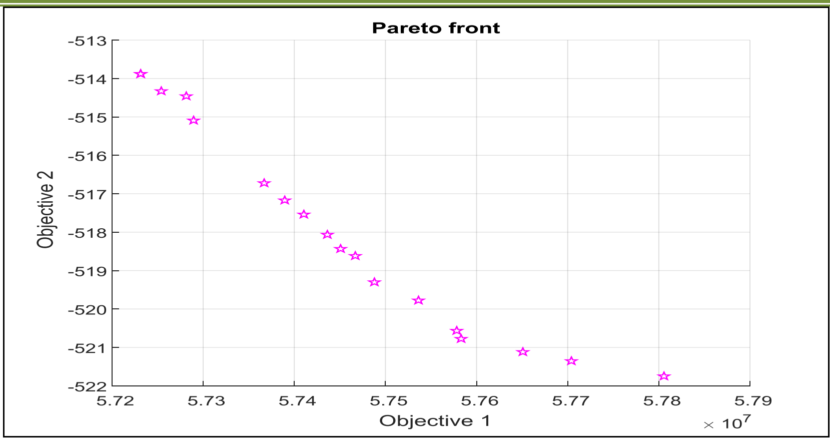


Figure 3: A true Pareto front in generic algorithm

The rank histogram (Figure 4) confirms the dominance of non-dominated solutions in the final population.

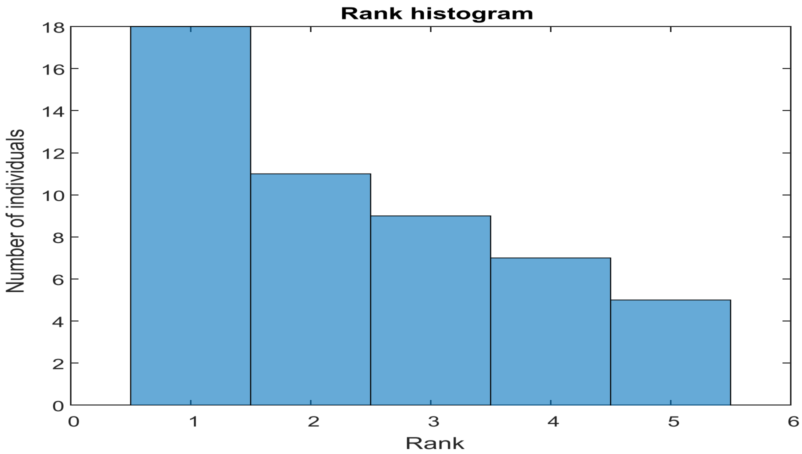


Figure 4: Rank histogram in generic algorithm

This methodology successfully applied a multi-objective GA to optimize worm gear parameters. The approach allowed simultaneous reduction in gear size, material volume, and center distance while maintaining design feasibility under nonlinear constraints. Compared to conventional methods, the GA achieved significant material savings and compactness, confirming its suitability for complex mechanical optimization problems [16]-[18].

3.3 Parametric Modeling of Worm Drive

Parametric modeling is a powerful technique in mechanical design, enabling the creation of adaptable and reusable models by defining key geometric parameters. This study employs SolidWorks to develop digital models of worm and worm wheel assemblies using standardized parameters, ensuring consistency and ease of modification. Feature-based modeling further simplifies the process by breaking down complex geometries into manageable components, reducing ambiguity and enhancing design clarity.

3.3.1 Computer-Aided Design (CAD) and Parametric Modeling Approach

Computer-Aided Design (CAD) has revolutionized mechanical engineering by enabling precise design, simulation, and optimization of mechanical components [19]. Modern CAD systems facilitate the creation of detailed digital models through interactive modeling techniques, mathematical analysis, and process simulation. By integrating CAD into product development, engineers can enhance design accuracy, reduce development time, and minimize production costs. Parametric modeling, a key feature of CAD, allows for the automation of design modifications by defining geometric relationships and constraints. This approach ensures that changes in one parameter automatically update the entire model, improving efficiency and reducing errors in complex assemblies such as worm drives.

3.3.2 Solid Works Platform Overview

Solid Works, introduced in 1995 as the first Windows-native 3D CAD software, has become a widely adopted tool in mechanical design due to its intuitive interface, extensive third-party integration, and cost-effectiveness, particularly for small and medium-sized enterprises [20]. The software includes specialized features such as a built-in gear library and plugin support, which streamline the modeling of in volute profiles-essential for accurate worm and worm wheel design. Solid Works parametric and feature-based modeling capabilities allow engineers to create highly customizable and easily modifiable designs, making it an ideal platform for developing worm drive assemblies.

3.3.3 Worm Modeling

The worm is modeled using a combination of revolve, helix/spiral, and sweep operations. The process begins with sketching the worm's axial profile on the front plane, which is then revolved to form the cylindrical shaft. A helical path is generated along the shaft to define the tooth trajectory, followed by the creation of a trapezoidal tooth profile (Archimeden type). The tooth profile is swept along the helix to produce the worm's threaded structure. Additional features such as chamfers and fillets are applied to refine the model, and material properties are assigned to simulate real-world behavior.

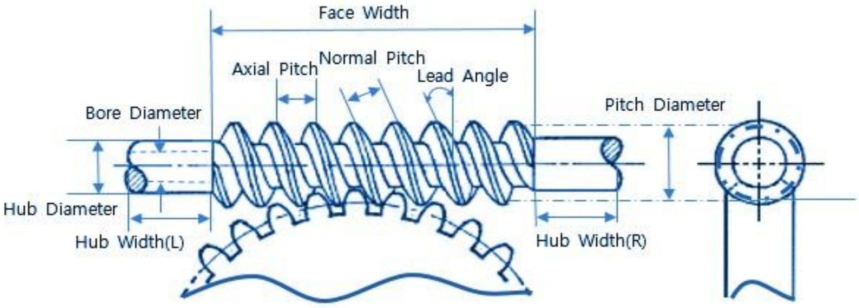


Figure 5: 2D structure diagram of worm

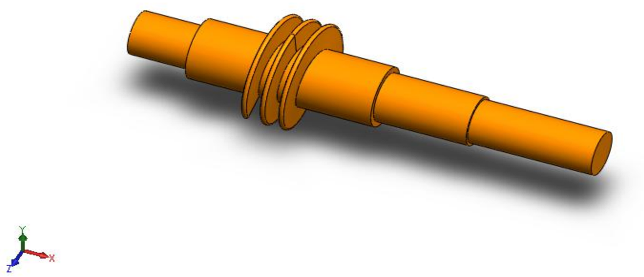


Figure 6: Final parametric worm model

3.3.4 Worm Wheel Modeling

The worm wheel is constructed using an involute profile algorithm, ensuring accurate tooth geometry for smooth meshing with the worm. The modeling process involves extruding the wheel's core structure, followed by the creation of hub features. The involute tooth profile is generated and cut into the wheel, with fillets added to reduce stress concentrations. The parametric approach allows for quick adjustments to tooth dimensions, pitch, and other critical parameters, ensuring compatibility with the worm. The worm wheel was built using an involute profile construction algorithm (Figure 7).

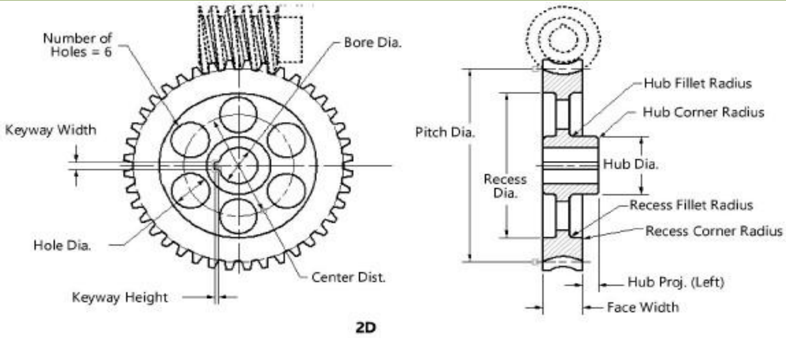


Figure 7: 2D worm wheel structure

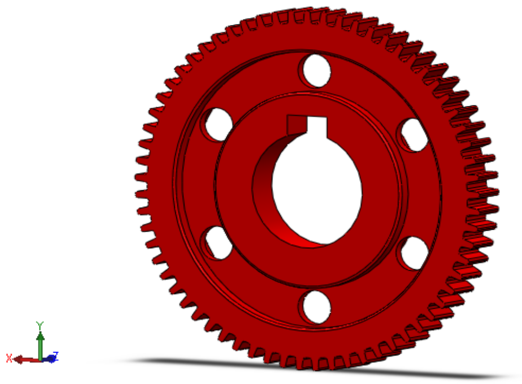


Figure 8: Final parametric worm wheel model

3.3.5 Worm Drive Assembly and Simulation

The final stage involves assembling the worm and worm wheel in Solid Works with a specified center distance of 901 mm. Assembly constraints are applied to validate proper meshing and alignment, while the inherent self-locking characteristic of worm drives is incorporated into the design. Motion simulation is conducted to analyze performance under operational conditions, with parameters including a motor speed of 48 rpm, right-hand rotation, and a frame rate of 25 fps. This simulation ensures that the assembly functions as intended, providing insights into load distribution, contact stresses, and kinematic behavior. The parametric and feature-based modeling approach ensures that the design remains flexible, allowing for rapid modifications and optimizations. The resulting digital model serves as a foundation for further analysis, prototyping, and manufacturing, demonstrating the effectiveness of CAD in modern mechanical engineering applications.

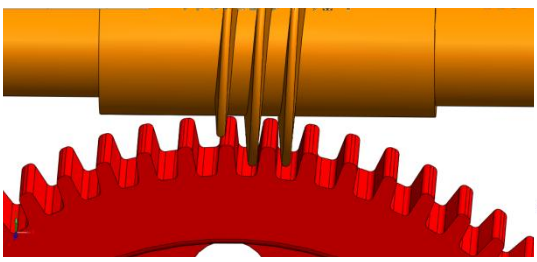


Figure 9: Meshed worm drive teeth

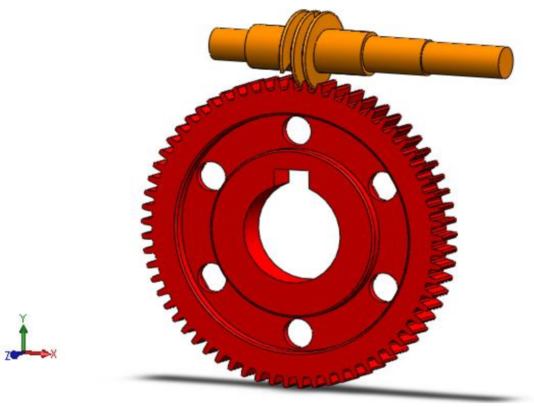


Figure 10: Final parametric worm drive model

3.4 Design and Implementation of Prototype System

3.4.1 System Design

The prototype system integrates multi-objective optimization results from MATLAB with a three-dimensional parametric modeling system developed in Solid Works using Visual Basic for Applications (VBA) and the Solid Works API. This knowledge-based approach allows flexible geometric modifications and reuse of design processes via macros, enabling efficient modeling of worm gear assemblies [21]-[23].Figure 11 below shows the system architecture and it consists of four key components. (1) Solid Works API: The Solid Works API automates part creation, assembly, and property analysis through VBA or other programming languages [24]-[26]. (2) Visual Basic Language(VB): Visual Basic was selected for its ease in creating custom macros and GUI elements in Solid Works [27]. (3) Macros: The macros automate repetitive modeling operations and integrate optimization results into CAD models [28], (4) System function interface: while the system function interface links optimization outputs to 3D modeling operations, facilitating direct modeling without manual data re-entry.

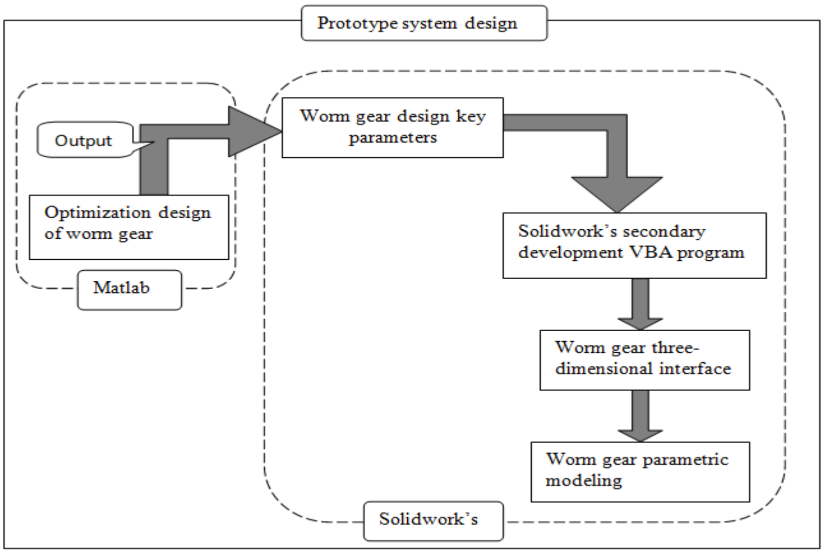
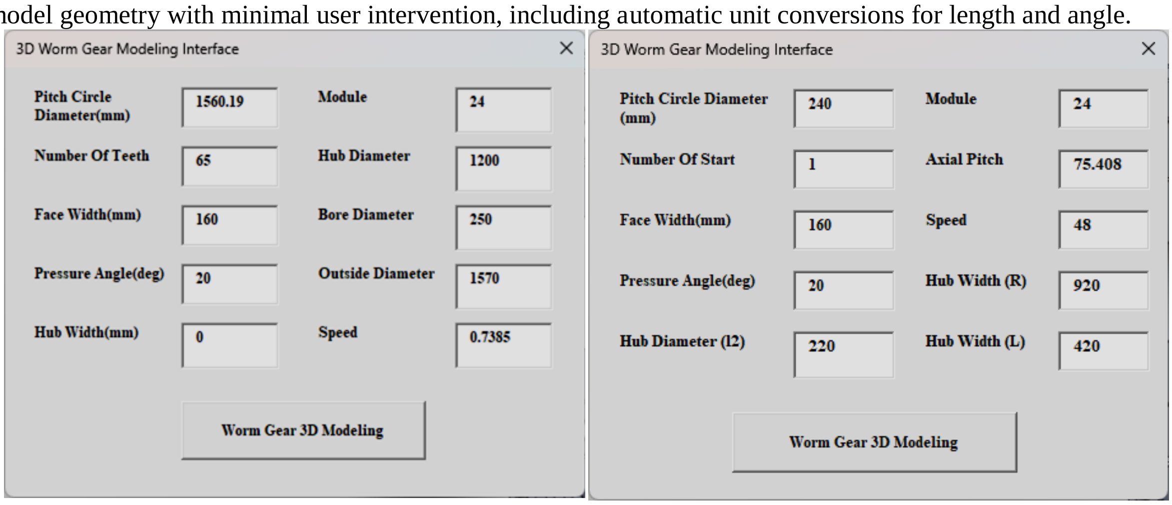


Figure 11: System architecture

3.4.2 System Development

A custom GUI in Solid Works provides user-friendly parameter input fields and control buttons for worm gear generation. The interface collects inputs such as module, teeth number, and pressure angle, passing them to the computational module for design calculation [29]. The calculation module automates dimensional computations traditionally done manually, ensuring optimized parameters are transformed into Solid Works model geometry with minimal user intervention, including automatic unit conversions for length and angle.



(a) Interface for worm wheel(b) Interface for worm

Figure 12: GUI for Worm Gear

3.4.3 Case Verification and Results

A case study was conducted with the following parameters: Module: 24, Number of starts: 1, Teeth: 65, Pressure angle: 20°, and others. Using the proposed system, the entire modeling process in Solid Works 2016 was completed in seconds, compared to hours with manual methods [3]. The generated CAD models matched literature-reported designs with negligible dimensional deviations [22],[26].

During the process, it's crucial to consider that most of the API default values are in meters. For instances, if the value in the program is 1.7, it will become 1700.0 in the Solid Works function with millimeters as the default unit. Hence, it needs to be divided by 1000.0 to obtain 1.7. Similarly, when dealing with angles in the API with radians as the default value, it needs to be multiplied by 180/π.

There are three main objects in the API: Connection, Command, and Recordset that program developers can create.

Set Paart = swApp.ActiveDoc
Boolstatus = Part.Extension.SelectByID2("Front Plane","PLANE",0,0,0,False,0,Nothing,0)

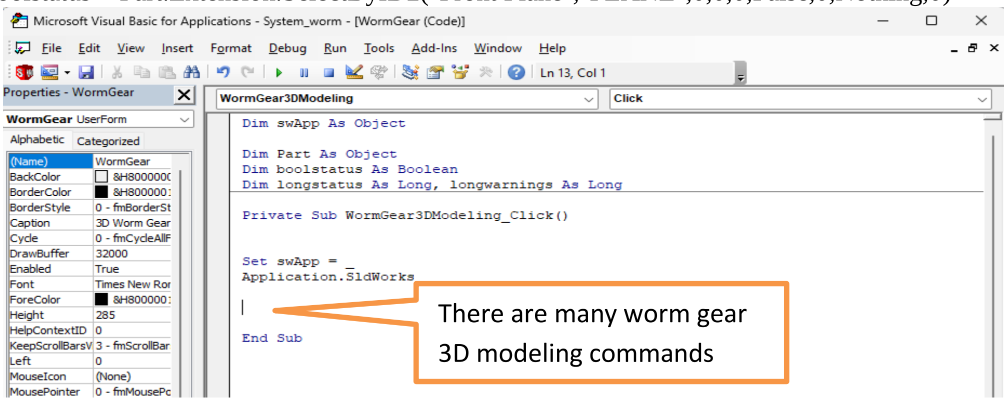


Figure 13: Usable macro as source code

As mentioned earlier, We aim to demonstrate some programs with illustrations on the gear forming process. Many commands have not been introduced yet. For instance, a program larger than 65 teeth involves a matching large gear modeling process. However, the design idea remains the same, so it will not be repeated here.

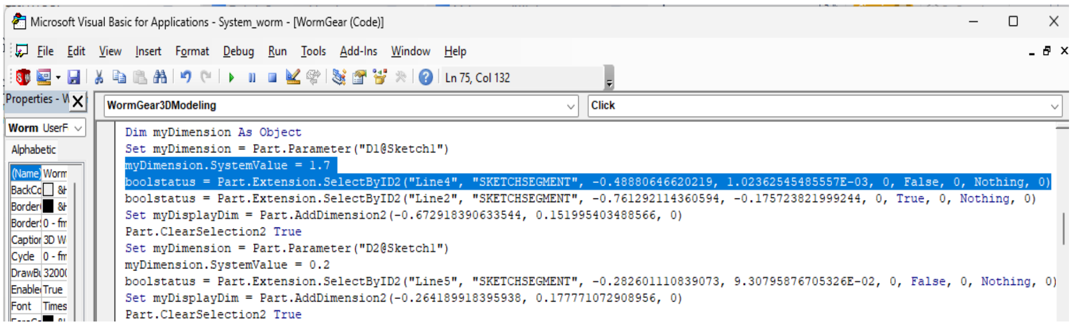


Figure 14: Commands

Once the gear parameters are calculated, the three-dimensional parametric modeling of the gear can be initiated. Before clicking on the **WormGear3DModeling** button of the user form, ensure that Solid Works software is turned on. The system will automatically carry out the three-dimensional modeling of the gear in Solid Works software.Figure 15 and 16 illustrate the input data of the proposed system in the 3D worm gear modeling interface. It also showcases the output model of the proposed system (worm wheel).

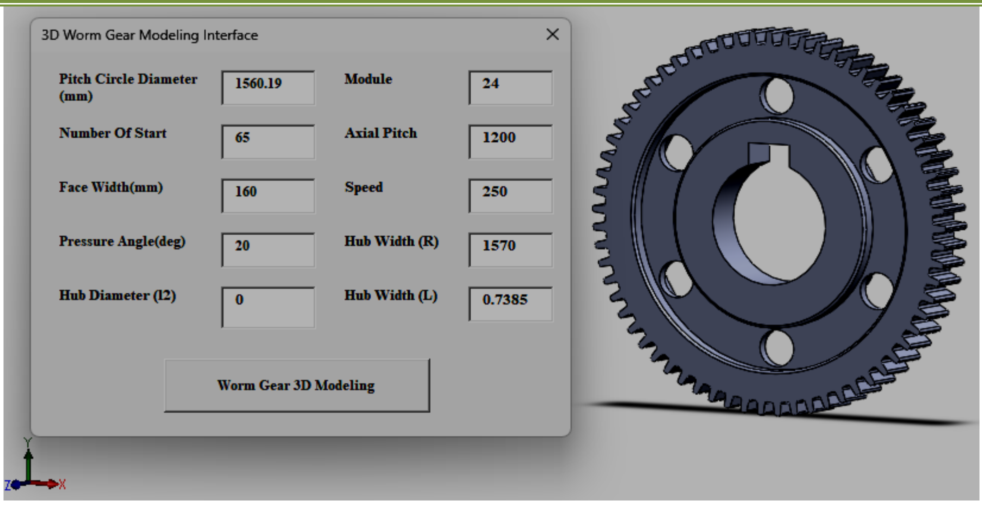


Figure 15: Worm wheel 3D modeling result

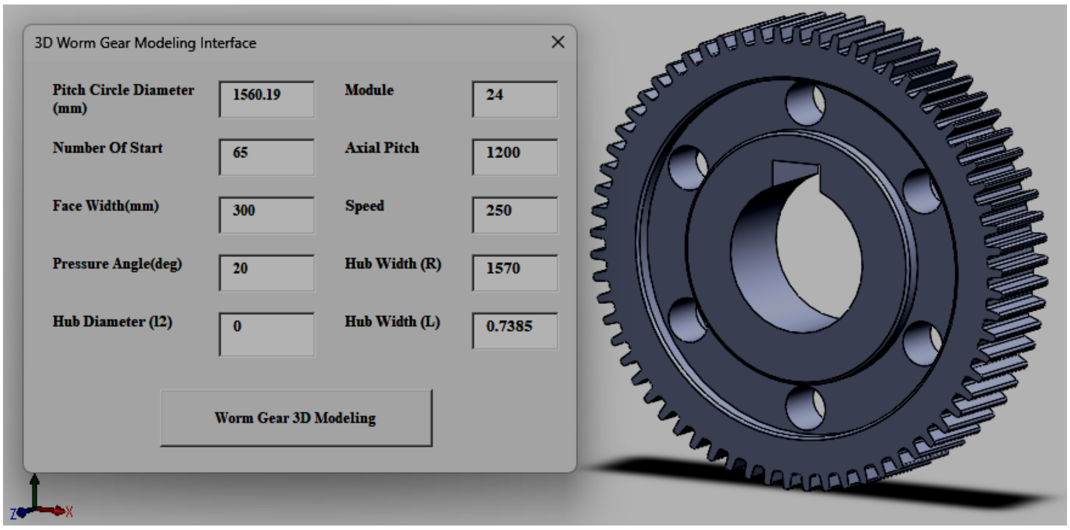


Figure 16: Worm wheel 3D modeling result with different face width

Similarly, Figure 17and 18 present the input data in the 3D worm gear modeling interface, along with the output model (worm) generated by the proposed system.

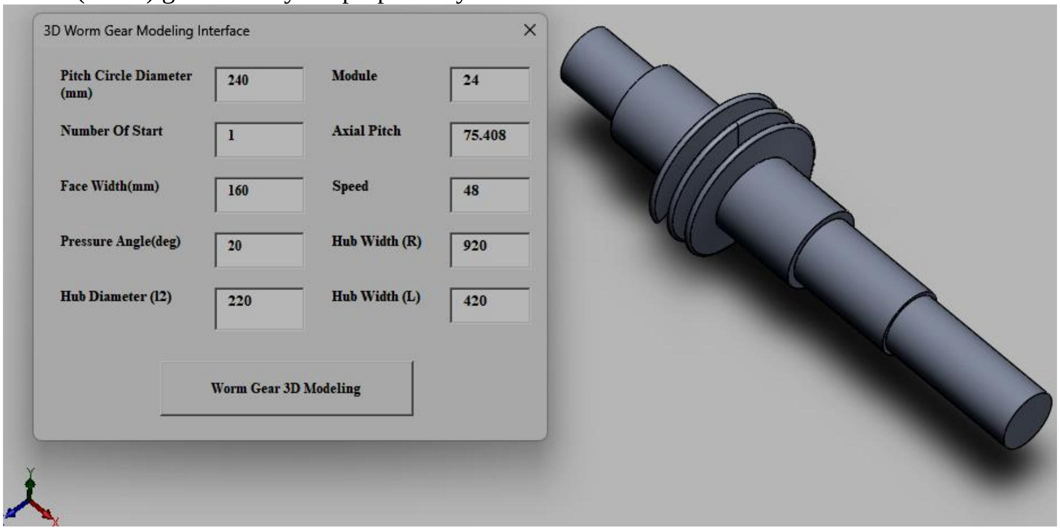


Figure 17: Worm 3D modeling result

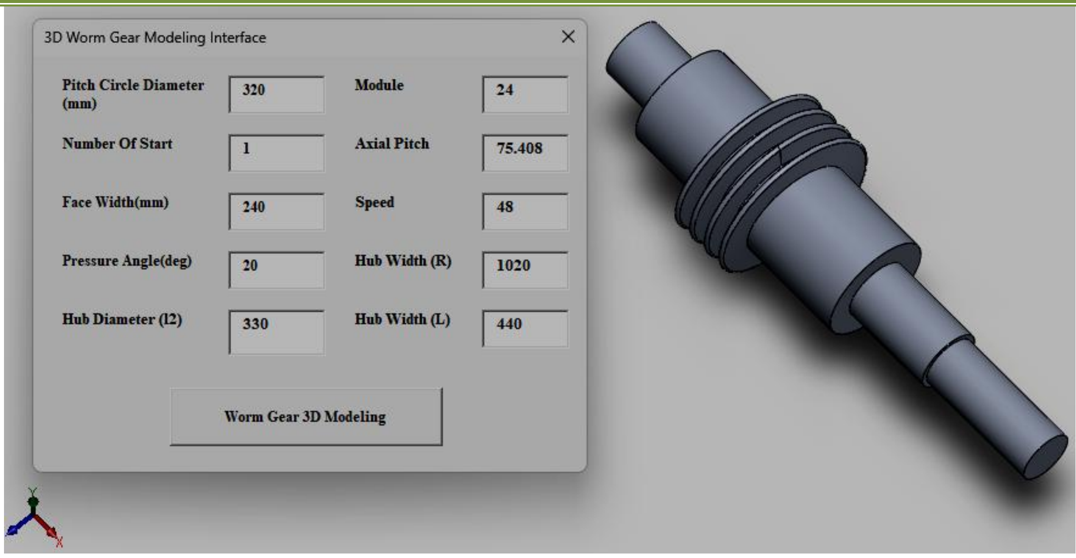


Figure 18: Worm 3D modeling result with some different parameters

The system automatically generates accurate 3D worm and worm wheel models, virtually assembles and simulates the meshing performance, and validates operational characteristics under motion simulation in Solid Works. By embedding VBA macros within the Solid Works API, the system achieves rapid and precise model creation, assembly, and performance evaluation, significantly reducing design time and ensuring consistent accuracy, thus providing a valuable tool for mechanical transmission design automation.

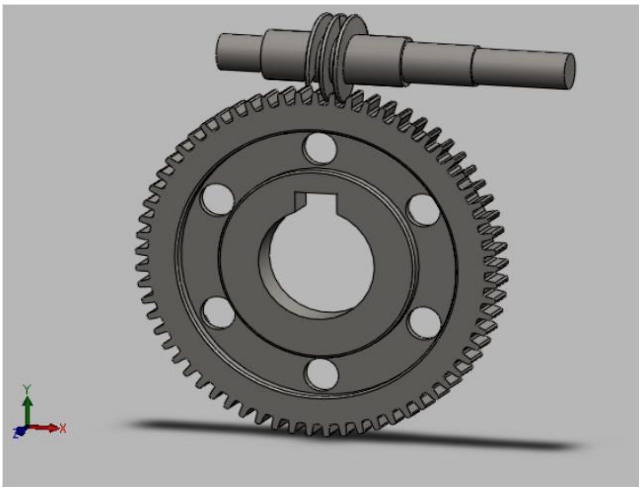


Figure 19: Worm gear meshing effect

4. Conclusion

In conclusion, the findings of this study suggest that optimization and digital modeling play a significant role in the design of worm drive in mechanical manufacturing and successfully integrated genetic algorithm-based optimization with parametric modeling for worm drive systems. As a result, volume and center distance of the worm drive are minimized and the design variables such as gear ratio, face width, pitch circle diameter of the worm, and pitch circle diameter of the worm wheel are reduced when its compared to literature and then building parametric model and prototype system are done as proposed in the methodology.

Therefore, the results of this experiment demonstrate the importance of building optimized worm drive in reducing materials and costs, and implementing prototype system in reducing design cycle time, complexity and increasing the productivity and the lifespan of worm drive. Further research can explore the design of the otherobjectives such as dynamic load testing, fatigue analysis, and real-time optimization, to provide the more comprehensive understanding of the optimization and digital modeling mechanism in industrial environments.

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