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Genetic Algorithm-Based Inverse Design of Slotted Disc Springs Through Load–Displacement Matching

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ABSTRACT

The load–displacement characteristic is a primary design requirement for a slotted disc spring, but the geometry that produces a prescribed nonlinear response is often unknown. This study couples Schremmer's analytical formulation with a Genetic Algorithm (GA) that minimizes the least mean square (LMS) curve error. The outer diameter was fixed at 152.40 mm to preserve the benchmark installation, while the tongue width and 12-slot topology were retained to isolate the continuous inverse problem. A one-factor-at-a-time analysis ranked the normalized sensitivities as transition diameter (approximately 8.35), thickness (1.69), inner diameter (1.47), slot length (0.76), and cone height (0.67); the indices for slot count, tongue width, and slot width were below 0.05. Because slot length is dependent, transition diameter, inner diameter, thickness, and cone height were optimized. The GA achieved LMS = 0.017, compared with 43.677 for the earlier inverse method. The four optimized dimensions differed from their targets by approximately 0.78%, 4.00%, 1.06%, and 1.18%, respectively. This result verifies computational recovery within the shared analytical benchmark only; no finite element or experimental validation was performed. The method is therefore a preliminary screening tool, and finite element verification, manufacturability assessment, and prototype testing are required before engineering implementation.

1. Introduction

Disc springs are widely used in mechanical systems because of their compact size, high load-carrying capacity, and ability to provide large forces within a relatively small installation space [1–4]. They are commonly found in clamping devices, vibration isolation systems, automotive assemblies, and industrial machinery where controlled stiffness and displacement characteristics are required. The load–displacement behaviour of a conventional disc spring is strongly influenced by its geometric dimensions, material properties, and contact conditions. As a result, considerable research has been

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devoted to the prediction and design of disc spring characteristics for specific engineering applications [2–4]. Classical disc-spring design relations and current calculation and technical requirements are summarized in [19–21].

To improve flexibility and extend the working displacement range, slotted disc springs have been developed by introducing radial slots into a conventional disc spring. The presence of slots creates tongue-like segments that deform during loading, resulting in a nonlinear load–displacement response that differs significantly from that of a conventional disc spring [5–7]. The load characteristics of a slotted disc spring depend on several geometric parameters, including the outer diameter, transition diameter, inner diameter, thickness, cone height, slot dimensions, and number of slots. Consequently, the design of a slotted disc spring often involves a complex relationship between geometry and structural response.

One of the earliest analytical investigations of slotted disc springs was reported by Schremmer [18], who developed a load–displacement formulation by considering both the conical ring deformation and the bending behaviour of the tongue segments. The analytical model provides an efficient method for estimating the nonlinear response of a slotted disc spring and remains one of the most widely referenced formulations in subsequent studies. Building upon this foundation, several researchers have proposed analytical and energy-based approaches to improve the prediction of load–displacement behaviour and to account for additional geometric and mechanical effects [6–10].

In practical engineering design, the required load–displacement curve is often known in advance based on functional requirements, while the corresponding spring geometry remains unknown. Under such circumstances, the design problem becomes an inverse problem. Instead of predicting the load–displacement response from a known geometry, the objective is to determine the geometry that produces a prescribed load–displacement characteristic. Subsequently, Fawazi et al. [11] developed an inverse algorithm capable of estimating the geometric dimensions of a slotted disc spring from a target nonlinear load–displacement response. The study demonstrated the feasibility of inverse geometric design using analytical load–displacement formulations.

Although the inverse algorithm proposed by Fawazi et al. [11] provides a practical design tool, the solution process remains dependent on the analytical search procedure employed in the formulation. For highly nonlinear design spaces, optimization techniques may offer additional flexibility in identifying suitable geometries while simultaneously minimizing the error between the predicted and target responses. Among the available optimization methods, Genetic Algorithms (GAs) have been widely applied to engineering design problems because of their ability to search complex, nonlinear, and multimodal design spaces without requiring gradient information [12–16]. The GA operates through the evolutionary processes of selection, crossover, mutation, and elitism, allowing promising solutions to evolve over successive generations. Previous studies have successfully applied genetic algorithms in structural optimization, topology optimization, and parameter identification problems [14–16]. Genetic algorithms and related evolutionary methods have also been employed in finite element model updating, demonstrating their capability to identify unknown parameters from measured structural responses [17]. Because a GA is stochastic, its outcome may also depend on population initialization and control parameters; repeated runs are normally required to distinguish a robust optimum from a favourable realization [25,26].

Despite the extensive application of genetic algorithms in engineering optimization, limited work has been reported on the inverse geometric design of slotted disc springs using a GA-based approach. In particular, there remains a need to evaluate whether a conventional genetic algorithm can accurately recover the geometric dimensions of a slotted disc spring from a prescribed nonlinear load–displacement response. Such an approach could provide an alternative design methodology that complements the inverse algorithm developed by Fawazi et al. [11].

Therefore, the objective of this study is to develop a Genetic Algorithm-based inverse design framework for identifying the geometric dimensions of a slotted disc spring from a target load–displacement curve. The analytical load–displacement model proposed by Schremmer [18] is integrated with a conventional genetic algorithm to search for the optimum values of transition diameter, inner diameter, thickness, and cone height. The optimization process minimizes the difference between the predicted and target load–displacement responses using the Least Mean Square (LMS) error as the objective function. The performance of the proposed approach is evaluated through comparison with the target design and the inverse-design method reported by Fawazi et al. [11]. The study aims to assess the capability of the conventional genetic algorithm as a practical tool for inverse geometric design of slotted disc springs with prescribed nonlinear load–displacement characteristics.

2. Methodology

2.1 Geometry of the Slotted Disc Spring

The geometry of the slotted disc spring considered in this study is shown in Fig. 1. The spring consists of a conical annular disc containing uniformly distributed radial slots. The geometric configuration is defined by the outer diameter D_e, transition diameter D_t, inner diameter D_i, thickness t, cone height h, slot length L, tongue width W_1, slot width W_2, and number of slots Z.

The objective of the present study is to identify the geometric parameters of a slotted disc spring from a prescribed nonlinear load–displacement response. The outer diameter was fixed at OD = 152.40 mm to preserve the installation envelope and geometric scale of the Schremmer benchmark [18]. In practical design, OD is commonly imposed by the available radial space; allowing it to vary in this benchmark could reduce curve error through a change in overall package size rather than through recovery of the internal geometry. The fixed OD is therefore a study-specific boundary condition and not a general restriction of the proposed framework [20,21].

The tongue width W1 = 8.89 mm and the number of slots Z = 12 were fixed to retain the reference tongue topology. The slot count is a discrete variable that changes the number of load-carrying segments, while W1 is coupled with circumferential spacing and manufacturability. Optimizing both quantities would require a mixed discrete–continuous formulation together with explicit minimum-ligament and slot-spacing constraints. Within the ranges screened in this study, their normalized sensitivity indices were below 0.05. Fixing them therefore reduced the search dimension with negligible effect on the benchmark response, although they should be released in future application-specific studies when changes in packaging or topology are permitted.

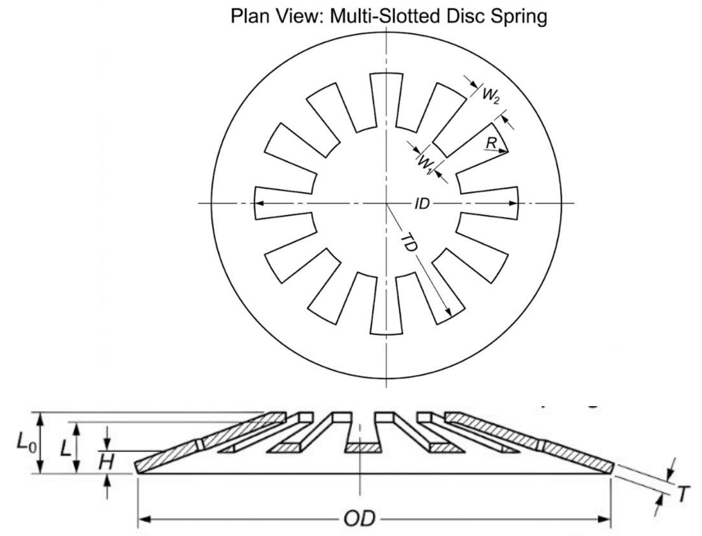

Fig 1 Geometrical parameters of the slotted disc spring.

Table 1
Fixed geometric parameters used in the study.

Parameter	Description	Value
OD=D_e	Outer diameter	152.40 mm
W_1	Tongue width	8.89 mm
Z	Number of slots	12

Table 2
Optimization variables and search ranges.

Variable	Lower Bound	Upper Bound
TD=D_t	128.0 mm	136.0 mm
ID=D_i	72.0 mm	80.0 mm
T	1.90 mm	2.15 mm
H	2.60 mm	3.10 mm

The search ranges were selected to cover the neighbourhood of the target geometry while ensuring physically meaningful spring configurations. These ranges were also sufficiently large to evaluate the capability of the Genetic Algorithm to recover the target dimensions. The resulting solution is conditional on these bounds; geometries outside them, including alternative outer diameters and slot topologies, were not explored.

2.2 Analytical Load–Displacement Model

The load-displacement response of the slotted disc spring was predicted using the analytical formulation proposed by Schremmer [18]. The model considers the deformation of the conical ring portion together with the bending deformation of the tongue segments created by the radial slots. The total spring deflection is expressed as

$$f = f_1 + f_2 \tag{1}$$

where
f = total spring deflection,
f_1 = deflection of the conical ring section,
f_2 = additional deflection caused by tongue bending.
The first component of deformation is associated with the conical ring section of the spring. The corresponding load is given by

$$P = \frac{Et^4}{MD_e^2} K_1 \left(\frac{f_1}{t}\right) \left[\left(\frac{h}{t} - \frac{f_1}{t}\right)\left(\frac{h}{t} - \frac{f_1}{2t}\right) + 1\right] \tag{2}$$

P = applied load, E = Young's modulus, t = spring thickness, D_e = outer diameter, h = cone height M = material constant, K_1 = geometric coefficient, f_1 = conical ring deflection, The geometric coefficient is

$$K_1 = \frac{2\pi\alpha^2 \ln\ \alpha}{3(\alpha - 1)^2} \tag{4}$$

where

$$\alpha = \frac{D_e}{D_t} \tag{5}$$

And D_t is the transition diameter. The material constant is

$$M = 1 - \nu^2 \tag{6}$$

Where ν is Poisson's ratio. The additional deflection caused by the tongue segments is expressed as

$$f_2 = \frac{C(D_t - D_i)^3 MP}{2Et^3 W_2 Z} \tag{7}$$

Where D_i = inner diameter, W_2 = slot width, Z = number of slots, C = slot correction coefficient, The correction coefficient C is obtained from the ratio

$$\frac{W_1}{W_2} \tag{8}$$

using the empirical relationship reported by Schremmer [18].The total spring deflection is therefore obtained as

$$f = \left(\frac{1 - \frac{D_i}{D_e}}{1 - \frac{D_t}{D_e}} \right) f_1 + f_2 \tag{9}$$

This equation is used to generate the complete nonlinear load-displacement response of the slotted disc spring. The slot length is related to the geometric dimensions by

$$L = h \left(\frac{1 - \frac{D_i}{D_e}}{1 - \frac{D_t}{D_e}} \right) \tag{10}$$

where L denotes the slot length.

2.3 Sensitivity Analysis

Prior to optimization, a local one-factor-at-a-time (OFAT) sensitivity analysis was conducted to quantify how each geometric parameter changed the load–displacement response and to support the selection of GA variables. OFAT provides a transparent screening measure, but it does not identify interactions among simultaneously varying parameters; a variance-based global analysis would be required for that purpose [24].

For the present benchmark, the sensitivity ranking was evaluated for transition diameter, inner diameter, thickness, cone height, slot length, tongue width, slot width, and number of slots. The analysis was used as a quantitative local ranking rather than as a universal material or geometry-independent statement.

The sensitivity analysis was carried out using a one-factor-at-a-time (OFAT) approach. In this procedure, a single geometric parameter was varied within a predefined range while all remaining parameters were maintained at their target values. For each variation, the analytical model described in Section 2.2 was used to generate the corresponding load-displacement curve. The predicted response was then compared with the target load-displacement curve and the Root Mean Square Error (RMSE) was calculated. The RMSE is defined as

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(P_{\mathrm{pred},i} - P_{\mathrm{target},i} \right)^2} \tag{11}$$

where
$P_{\mathrm{pred},i}$ = predicted load at the i^{th} displacement point,
$P_{\mathrm{target},i}$ = target load at the i^{th} displacement point,
n = total number of displacement points.

A lower RMSE indicates a closer agreement between the predicted and target load-displacement curves. Since the geometric parameters possess different units and magnitudes, a normalized sensitivity index was adopted to provide a fair comparison among all parameters. The sensitivity index for parameter X is defined as

$$SI_X = \frac{(RMSE_{\max} - RMSE_{\min})/\bar{P}_{\mathrm{target}}}{(X_{\max} - X_{\min})/X_{\mathrm{target}}} \tag{12}$$

where
SI_X = sensitivity index of parameter X,
$RMSE_{\max}$ = maximum RMSE obtained during parameter variation,
$RMSE_{\min}$ = minimum RMSE obtained during parameter variation,
$\bar{P}_{\text{target}}$ = average target load,
$X_{\max}$ = maximum value of parameter X,
$X_{\min}$ = minimum value of parameter X,
X_{target} = target value of parameter X.

Equation (12) normalizes the response variation with respect to the relative change in each geometric parameter. A larger index indicates that a smaller relative change in the parameter produces a larger change in the complete load–displacement curve. The index should be interpreted within the stated perturbation range and benchmark geometry.

The resulting normalized sensitivity indices, read from the computed values plotted in Fig. 3, were approximately 8.35 for the transition diameter, 1.69 for thickness, 1.47 for the inner diameter, 0.76 for slot length, and 0.67 for cone height. The indices for the number of slots, tongue width, and slot width were each below 0.05 within the evaluated ranges. The outer diameter was not screened because it was imposed by the benchmark installation envelope. Slot length is a dependent quantity calculated using Equation (10); therefore, the four independent continuous variables retained for the GA were transition diameter, inner diameter, thickness, and cone height. This choice preserves the dominant independent effects while reducing the search space.

2.4 Genetic Algorithm-Based Inverse Design

The objective of the inverse design process is to determine the geometric parameters of a slotted disc spring that produce a load–displacement response matching a prescribed target curve. Unlike the conventional forward design approach, where the geometry is known and the corresponding load–displacement response is calculated, the inverse design problem starts with a target load–displacement curve and seeks the geometry that reproduces the desired behaviour.

In the present study, the target load-displacement curve was obtained from the reference design reported by Schremmer [18]. The analytical model described in Section 2.2 was used to predict the load-displacement response corresponding to each candidate geometry generated during the optimization process.

The independent variables selected for optimization were the transition diameter, inner diameter, thickness, and cone height. This selection follows the local ranking in Section 2.3. Although slot length also showed a measurable effect, it is derived from the other dimensions through Equation (10) and was not treated as an independent variable.

The design vector is defined as

$$\mathbf{x} = [D_t \quad D_i \quad t \quad h] \tag{13}$$

where
D_t = transition diameter,
D_i = inner diameter,
t = thickness,
h = cone height.
Each candidate solution generated by the Genetic Algorithm represents a unique combination of

these four design variables. For every candidate geometry, the analytical model was used to generate a complete load displacement curve over the prescribed displacement range.

Because the displacement coordinates of the predicted and target curves may not coincide exactly, interpolation was performed before evaluating the objective function. The predicted load values were interpolated onto the displacement coordinates of the target curve to ensure point-by-point comparison. The quality of each candidate solution was evaluated using the Least Mean Square (LMS) error. The LMS objective function is expressed as

$$LMS = \frac{1}{n}\sum_{i=1}^{n} \left(P_{\text{pred},i} - P_{\text{target},i}\right)^2 \tag{14}$$

where

$LMS =$ least mean square error,
$P_{\text{pred},i} =$ predicted load at the i^{th} displacement point,
$P_{\text{target},i} =$ target load at the i^{th} displacement point,
$n =$ total number of displacement points.
A lower LMS value indicates better agreement between the predicted and target load-displacement curves. Consequently, the optimization problem can be formulated as

$$\min(LMS) \tag{15}$$

subject to

$$128.0 \leq D_t \leq 136.0 \tag{16}$$
$$72.0 \leq D_i \leq 80.0 \tag{17}$$
$$1.90 \leq t \leq 2.15 \tag{18}$$
$$2.60 \leq h \leq 3.10 \tag{19}$$

These bounds define the feasible design space explored by the Genetic Algorithm. They were selected around the reference dimensions to test parameter recovery under physically meaningful geometries. Accordingly, the reported optimum is a bound- and topology-dependent result rather than proof of a unique global geometry over all possible slotted-disc designs.

The Genetic Algorithm was selected because of its ability to search complex nonlinear design spaces without requiring gradient information. Unlike gradient-based optimization techniques, the Genetic Algorithm can effectively handle multiple local minima and is therefore suitable for inverse design problems involving nonlinear load-displacement behaviour.

Each optimization cycle begins with the generation of an initial population of candidate geometries. The load–displacement response of each candidate is then calculated using the analytical model, and the corresponding LMS value is evaluated. Individuals with lower LMS values are considered more fit and therefore have a higher probability of contributing to the next generation.

Table 3
Genetic Algorithm parameters used in the present study

Parameter	Value
Population size	80
Number of generations	150
Tournament size	3
Crossover probability	0.85
Mutation probability	0.20
Mutation scale	0.04
Elite count	4

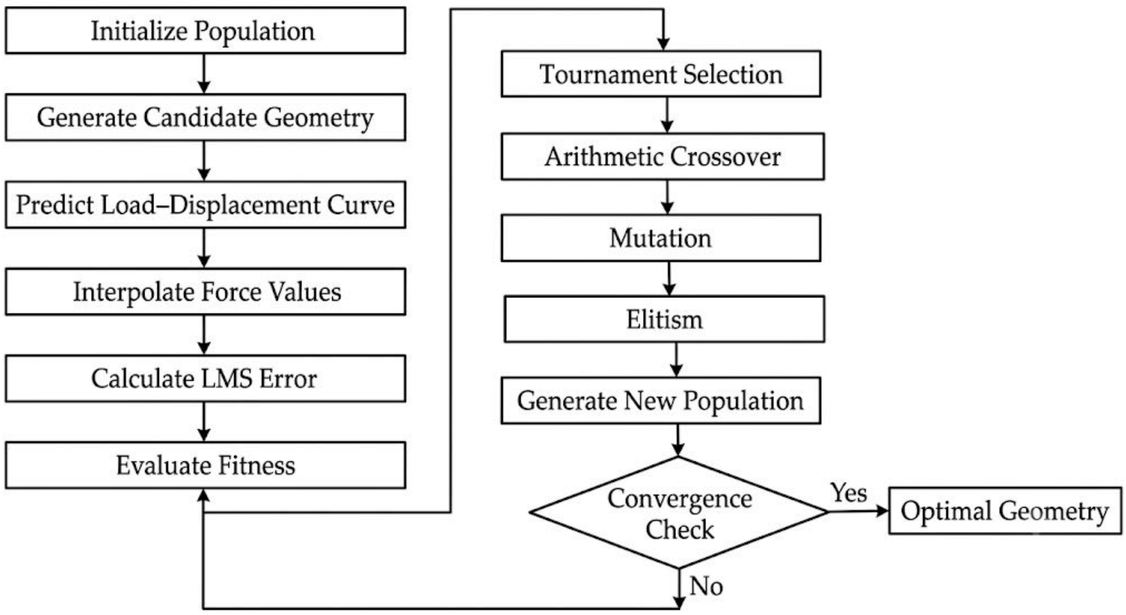

Fig. 2 Flowchart of the Genetic Algorithm-based inverse design procedure

The optimization process continues until the maximum number of generations is reached. The individual with the lowest LMS value in the final generation is selected as the optimum solution and represents the recovered geometry of the slotted disc spring. The recovered geometry is subsequently evaluated using additional performance metrics and compared with the inverse geometric design approach proposed by Fawazi et al. [11], as discussed in the following subsection.

2.5 Computational Verification and Scope of Validation

The numerical implementation was verified internally by reproducing the target curve from the Schremmer reference geometry, interpolating every candidate response to the same displacement coordinates, and comparing the recovered dimensions and curve error with the target and the inverse method in [11]. This protocol evaluates whether the optimizer can recover a prescribed response under a common analytical model.

The target and candidate curves were generated using the same simplified analytical formulation. Consequently, the comparison is a synthetic inverse-recovery benchmark and not an independent validation against a finite element model or physical test. Published disc-spring studies show that finite element and experimental checks are needed to quantify effects such as three-dimensional stress, contact, friction, and manufacturing variation [22,23]. The claims of the present study are therefore limited to computational curve matching within the stated model, ranges, and fixed topology.

3. Results and Discussion

3.1 Sensitivity Analysis of Geometric Parameters

The sensitivity analysis quantified the local influence of each geometric parameter using Equation (12), and Fig. 3 presents the ranking. The transition diameter was dominant, with a normalized index of approximately 8.35. Thickness and inner diameter followed at approximately 1.69 and 1.47, respectively; slot length and cone height produced moderate indices of approximately 0.76 and 0.67. The indices of the number of slots, tongue width, and slot width were each below 0.05 over the evaluated ranges. Thus, the transition-diameter index was about 4.9 times the thickness index and about 5.7 times the inner-diameter index.

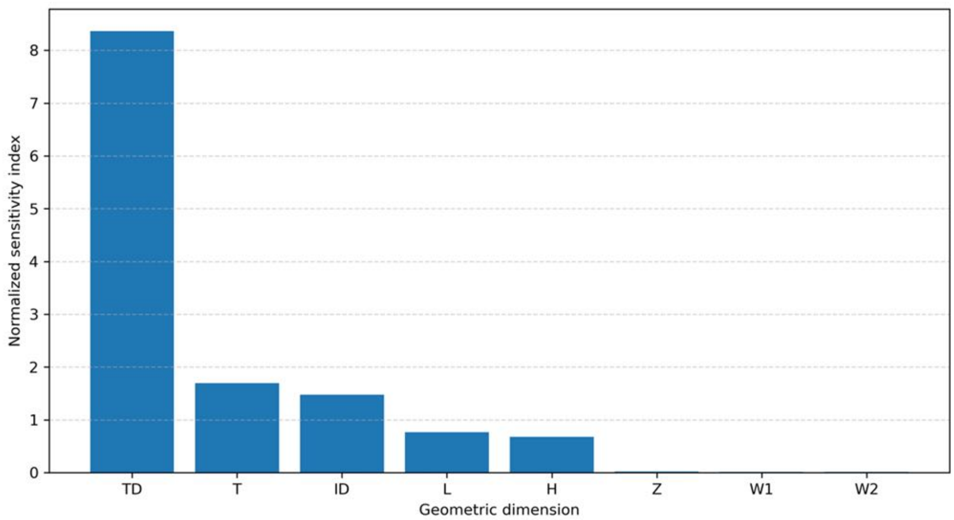

Fig. 3 Sensitivity ranking of geometric parameters based on the normalized sensitivity index

The dominant transition-diameter effect arises from its role in the diameter ratio and geometric coefficient of the conical ring, while thickness has a strong effect because the load term is proportional to the fourth power of t in Equation (2). Cone height affects the nonlinear deformation term but ranked below transition diameter, thickness, inner diameter, and the dependent slot length for this benchmark. Because slot length is calculated from the candidate geometry, transition diameter, inner diameter, thickness, and cone height were retained as the independent continuous GA variables. This ranking is local to the specified target and perturbation ranges and does not quantify parameter interactions.

3.2 Convergence Behaviour of the Genetic Algorithm

The convergence history of the Genetic Algorithm is shown in Fig. 4, which presents the evolution of the best LMS value during the reported optimization run.

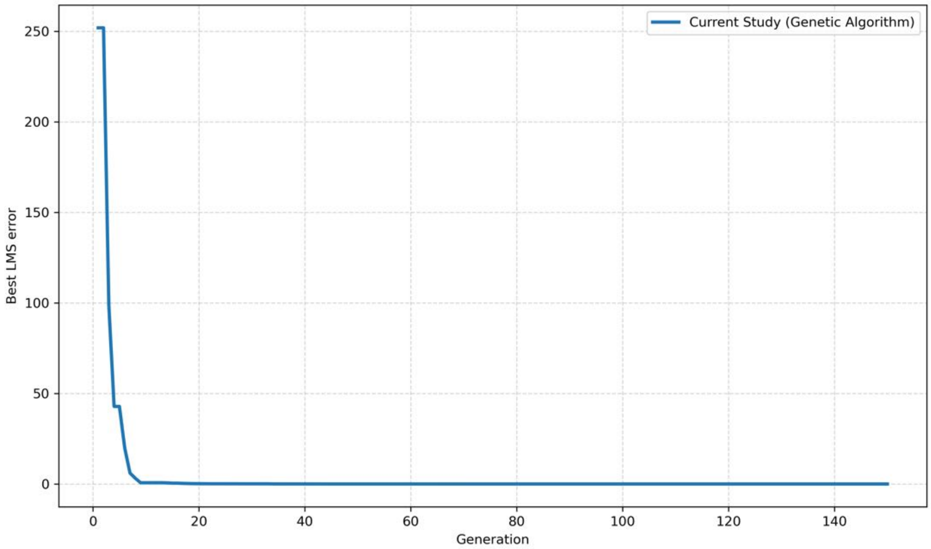

Fig. 4 Evolution of the best LMS value throughout the optimization process

The best LMS value decreased rapidly during the early generations and then approached a stable value, indicating convergence for the reported run. However, this single history does not establish insensitivity to the initial population, random seed, crossover and mutation settings, or premature convergence. Genetic Algorithms are stochastic, and repeated independent runs are normally required to characterize reliability [25,26]. Because repeated-run statistics were not available in the present study, the final LMS value of 0.017 is reported as the best computational result for this configuration rather than as a guaranteed global optimum.

3.3 Load–Displacement Comparison

The load–displacement responses obtained from the target design, the inverse geometric design approach [11], and the present Genetic Algorithm are compared in Fig. 5.

The target load–displacement curve reported by Schremmer [18] serves as the reference response. It can be observed that the curve predicted by the Genetic Algorithm closely follows the target response throughout the entire displacement range.

The inverse geometric design method proposed by Fawazi et al. [11] also produces a load–displacement curve that follows the target trend. However, larger deviations can be observed at higher displacement levels. These deviations contribute to the higher LMS and RMSE values obtained for the inverse geometric design approach.

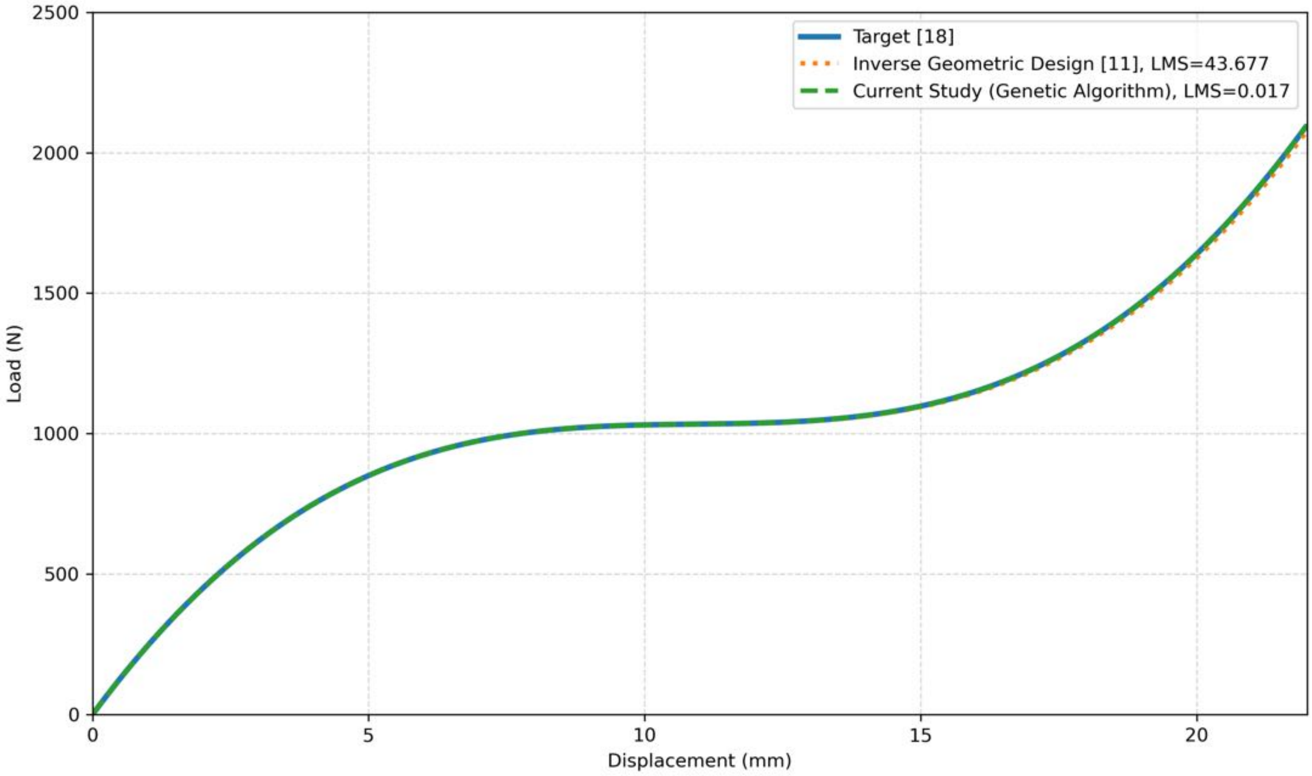

Fig. 5 Load Displacement comparison using [11] and current study

The Genetic Algorithm provides a more accurate representation of the nonlinear response because the optimization process directly minimizes the LMS error over the complete load–displacement curve. Instead of matching only selected response characteristics, the algorithm attempts to minimize the discrepancy at every displacement point considered in the analysis. The close agreement between the target and optimized curves demonstrates accurate curve recovery within the common analytical benchmark. It should not be interpreted as experimental or finite element validation of the physical spring response.

Table 4
Geometries comparison using [11] and current study

Parameter	Target [18]	Current Study GA	Inverse Geometric Design [11]
OD=D_e	152.4	152.4	152.34
TD=D_t	132.08	133.1166946	132.4695652
ID=D_i	76.2	79.24656815	77.19049719
T	2.032	2.010512029	2.025266559
H	2.8448	2.811316905	2.835373183
L	10.668	10.6650533	10.668
W_1	8.89	8.89	8.89
W_2	15.49	14.93323235	15.25646909
Z	12	12	12

For the optimized variables, the absolute relative errors were approximately 0.78% for transition diameter, 4.00% for inner diameter, 1.06% for thickness, and 1.18% for cone height. These results show that a very small curve error does not require every recovered dimension to be equally close to the target.

The smallest relative dimensional error occurred for the transition diameter, followed by thickness and cone height; the inner diameter showed the largest difference. Together with the LMS value of 0.017, this pattern indicates parameter compensation and possible non-uniqueness in the inverse solution. Although differences remain between the optimized and target geometries, the resulting load–displacement response changes only slightly. This supports the existence of multiple near-equivalent geometries within the analytical model and shows why curve agreement alone is insufficient to establish a unique physical design. Compared with the inverse geometric design approach [11], the GA produced a lower curve-matching error for the stated benchmark. The comparison demonstrates improved optimization of the shared analytical objective, but it does not establish superior experimental predictive accuracy. The results demonstrate that the proposed Genetic Algorithm can successfully recover the geometric parameters of a slotted disc spring from a prescribed nonlinear load–displacement response. The sensitivity analysis identified the most influential design variables, allowing the optimization process to focus on the parameters that contribute most significantly to the spring behaviour.

The optimization results show that the recovered geometry produces a load–displacement curve that closely matches the target response reported by Schremmer [18]. The agreement achieved by the present method is generally superior to that obtained using the inverse geometric design approach proposed by Fawazi et al. [11].

One advantage of the proposed framework is that it does not require gradient information or explicit inverse equations. Instead, the analytical model and Genetic Algorithm are coupled through the LMS objective function. This allows the optimization procedure to be applied to nonlinear design problems where analytical inverse solutions are difficult to derive. Within the stated benchmark, the method provides a transparent preliminary approach for inverse geometric identification without requiring analytical inversion or gradients. Its engineering use remains conditional on independent structural and physical verification.

3.4 Limitations and Practical Engineering Use

The present findings are subject to four main limitations. First, Schremmer's analytical model idealizes the spring and does not explicitly resolve three-dimensional stress concentrations, contact and friction at the support surfaces, material plasticity, fatigue, or manufacturing tolerances. Second, the target curve was generated with the same model used to evaluate candidates, so model-form error is not tested. Third, the selected bounds and fixed OD–W1–Z topology exclude alternative package sizes and discrete slot layouts. Fourth, only one convergence history is available; sensitivity to initialization and GA control parameters has not been quantified. The LMS value is therefore a curve-matching measure, not a structural-safety or manufacturability criterion. For practical application, an engineer would (i) define the target loads over a common displacement grid; (ii) impose packaging, geometry, material, and manufacturing bounds; (iii) implement the analytical equations, interpolation, and GA in a numerical environment such as Python or MATLAB; (iv) run multiple random seeds; and (v) verify the selected geometry by finite element analysis and prototype testing. No commercial optimization package is inherently required, but the user needs working knowledge of spring mechanics, curve interpolation, constrained geometry, and stochastic optimization. The reported setting evaluates approximately 80 × 150 = 12,000 candidate curves. Because each candidate uses the analytical model, the evaluation is expected to be much lighter than an FEA-coupled search; however, wall-clock time was not recorded and should not be inferred from the present data.

3.5 Future Work

Future work should validate the recovered design using nonlinear finite element analysis and instrumented axial compression tests. The design space should then be expanded through mixed discrete–continuous optimization of outer diameter, tongue width, slot width, and number of slots with explicit constraints on ligament width, interference, stress, fatigue life, and manufacturability. Repeated-seed studies and alternative population settings should quantify convergence reliability, while global sensitivity analysis should examine parameter interactions [24]. Robust or multiobjective formulations can further address material and dimensional tolerances, friction, mass, peak stress, and service life. For computationally expensive FEA-based searches, surrogate-assisted optimization may be used to reduce the number of high-fidelity evaluations.

4. Conclusions

This study developed a Genetic Algorithm-based inverse design framework for matching a prescribed slotted-disc-spring load–displacement curve. The local sensitivity ranking was transition diameter (approximately 8.35), thickness (1.69), inner diameter (1.47), slot length (0.76), and cone height (0.67), with indices below 0.05 for the screened slot count, tongue width, and slot width. Because slot length is dependent, transition diameter, inner diameter, thickness, and cone height were optimized. For the computational benchmark, the GA reduced the LMS error to 0.017 compared with 43.677 for the earlier inverse method, while the four optimized dimensions differed from their targets by approximately 0.78–4.00%.

The method is best used as a preliminary, software-independent screening procedure: an engineer supplies a target curve and feasible bounds, evaluates approximately 12,000 analytical candidates under the reported settings, repeats the stochastic search, and then subjects the preferred geometry to manufacturing, stress, fatigue, finite element, and experimental checks. The current study does not quantify runtime, repeated-run variability, or real-spring predictive error. Accordingly, the results establish numerical inverse-recovery capability within a simplified analytical model, rather than final design certification. The proposed extensions in Section 3.5 define the route toward a validated engineering tool.

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