# Artificial Intelligence-Based Optimization of Box Culvert Cross-Section Design Under Hydraulic and Structural Constraints

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## ABSTRACT

**Reinforced concrete box culverts are critical infrastructure for flood management and cross-drainage. However, their conventional design relies on iterative sequential processes that oversimplify the coupling of hydraulic and structural constraints, resulting in overly conservative, costly structures. This study proposes a novel Artificial Intelligence (AI)-based optimization framework that tightly couples hydraulic routing equations with rigorous structural mechanics to minimize total construction. The framework evaluates the performance of two advanced metaheuristic algorithms: Grey Wolf Optimizer (GWO) and the Genetic Algorithm (GA). A comprehensive parametric case study was conducted to assess variations in design discharge and soil cover depth. The results demonstrate that the GWO algorithm successfully navigates the highly constrained non-convex design space, achieving a 24.0% reduction in total cost compared to the conventional deterministic design and outperforming the GA (19.4% reduction). Furthermore, the AI framework autonomously identified critical physical trade-offs, dynamically adapting the culvert aspect ratio to meet strict headwater thresholds during extreme flood events and optimizing member thicknesses across varying live and dead load dominance phases. This automated, performance-based framework provides civil engineers with a robust tool to design cost-efficient, climate-resilient hydraulic structures.**

***Keywords-box culvert design; metaheuristic optimization; Grey Wolf Optimizer (GWO); hydraulic engineering; structural constraints; flood control infrastructure***

## I. INTRODUCTION

Reinforced concrete box culverts are critical components of modern transportation and hydraulic infrastructure, serving as essential cross-drainage structures beneath roadways and railway embankments. Their primary function is to safely convey peak flood discharges and maintain stable water levels, acting as hydraulic balancers that mitigate localized flooding and prevent embankment overtopping [1, 2]. Given the increasing frequency of extreme hydrological events and the rapid expansion of global infrastructure, the demand for culverts that are both hydraulically efficient and structurally resilient has intensified [3]. However, the design of these structures is inherently complex, requiring the simultaneous satisfaction of stringent hydraulic conditions such as flow capacity, headwater limits, and velocity constraints, and rigorous structural requirements, including load-bearing capacity under varying dead loads, live traffic loads, and soil-water pressures [4, 5].

Despite these multi-disciplinary demands, the conventional design of box culverts remains predominantly reliant on iterative, trial-and-error procedures and deterministic Finite Element Methods (FEM) [5, 6]. Traditional approaches typically separate hydraulic sizing from structural analysis, leading to conservative assumptions, over-dimensioned cross-sections, and excessive material consumption. For instance, designers often rely on rigid safety factors for earth pressure and surcharge loading without dynamically exploring the trade-offs between structural geometry and hydraulic performance

[7]. Although recent studies have utilized numerical solvers, such as the Sequential Unconstrained Minimization Technique (SUMT) and FEM software packages (e.g., STAAD.Pro and ANSYS), to optimize structural member thicknesses parametrically, these methods often struggle with high-dimensional, nonlinear search spaces and rarely account for coupled hydraulic constraints [1, 8]. Consequently, there is an urgent need to transition from traditional manual iterations to automated, performance-based optimization frameworks that minimize construction costs without compromising safety or flood routing capabilities.

The advent of Artificial Intelligence (AI) and metaheuristic optimization algorithms offers a transformative solution to these engineering challenges. Metaheuristics such as the Genetic Algorithm (GA) and the Grey Wolf Optimizer (GWO) have demonstrated exceptional capacity to navigate complex, nondifferentiable, and multi-objective design spaces across various civil engineering domains [9, 10]. Unlike gradient-based solvers, these algorithms can globally search the design space to simultaneously optimize multiple geometric variables (e.g., span, height, slab thickness, and haunch dimensions) while strictly enforcing hydraulic constraints (e.g., Manning's kinematic flow) and structural serviceability limits [10]. Recent studies in 2024 and 2025 have increasingly adopted these metaheuristic algorithms for structural optimization due to their robustness. For instance, GA has been successfully implemented to minimize the cost and carbon footprint of retaining walls and concrete frames, proving its efficiency over conventional methods [11]. Similarly, the GWO and its variants have demonstrated exceptional search capabilities in constrained structural problems, successfully optimizing reinforced concrete retaining walls [12] and recently advancing complex seismic design frameworks [13]. However, a critical review of recent literature reveals a significant research gap: while AI predictive models (such as artificial neural networks) have been employed to predict structural deflection [2] and metaheuristics have been widely used in water distribution networks, the direct application of AI-driven optimization algorithms for the coupled hydraulic and structural cross-section design of box culverts remains largely unexplored. Furthermore, existing literature lacks multi-objective frameworks capable of quantitatively assessing the trade-off between total construction and hydraulic conveyance efficiency.

To address these critical limitations, this study proposes a novel AI-based optimization framework for the detailed cross-section design of reinforced concrete box culverts. The primary objective is to formulate a comprehensive mathematical model that minimizes total material and construction costs while rigorously satisfying standard hydraulic and structural constraints. The specific research questions guiding this study are:

1. How can metaheuristic algorithms (specifically comparing GA and GWO) be effectively coupled with hydraulic governing equations and structural mechanics to automate culvert design?
2. What is the quantitative economic advantage (cost reduction) of the AI-optimized design compared to conventional engineering standards?
3. How do varying hydrological parameters (e.g., peak discharge) and structural constraints (e.g., fill depth) influence the optimal cross-sectional geometry?

By answering these questions, this paper explicitly bridges the identified research gap. Unlike previous studies that optimize structural or hydraulic aspects independently, the primary novelty of this study lies in the direct, simultaneous coupling of hydraulic routing equations and rigorous structural mechanics within a single metaheuristic optimization framework. Specifically, it makes the following novel contributions: First, it eliminates the inefficiencies of sequential trial-and-error designs by using an automated, tightly coupled hydraulic-structural objective function. Second, it provides a comparative convergence and sensitivity analysis of GA and GWO in solving discrete reinforced concrete design problems. Finally, the proposed framework yields actionable, optimized design charts that provide engineers with cost-efficient, climate-resilient, and ready-to-implement culvert configurations under varying environmental scenarios.

## II. METHODOLOGY

The proposed method integrates hydraulic routing, structural mechanics, and economic modeling into a unified computational framework. Two distinct metaheuristic algorithms, GA and GWO, are employed to navigate the complex, non-convex design space of reinforced concrete. The overarching goal is to identify a cross-sectional geometry that minimizes construction while strictly adhering to physical, hydraulic, and structural constraints.

### A. Problem Formulation

The detailed design of the box culvert is mathematically formulated as a constrained, nonlinear optimization problem.

### B. Design Variables

The search space is defined by a continuous and discrete design vector $X$ that encompasses both the geometric dimensions and the internal reinforcement detailing of the culvert:

$$X = [B, H, t_s, t_w, A_{st,s}, A_{st,w}]^T \quad (1)$$

where $B$ and $H$ are the internal clear span and clear height of the culvert (m), $t_s$ and $t_w$ are the thicknesses of the top/bottom slabs and side walls (m), and $A_{st,s}$ and $A_{st,w}$ are the areas of main steel reinforcement for the slabs and walls

### C. Objective Function

The primary objective is to minimize the total direct cost $C_{total}$ per linear meter of the culvert. This cost model accounts for concrete volume, steel reinforcement weight, and required earth excavation.

$$\text{Minimize } f(X) = C_c V_c(X) + C_s W_s(X) + C_e V_e(X) \quad (2)$$

where $C_c$ , $C_s$ and $C_e$ represent the unit prices of concrete (m$^3$), steel (kg) and earth excavation (m$^3$), respectively. The calculated material quantities are derived directly from the candidate design vector $X$.

### D. Design Constraints

To ensure engineering safety and functionality, the objective function is subjected to a rigorous set of inequality constraints, $g_i(X) \leq 0$, categorized into two domains:

Hydraulic constraints

1. Headwater limit: $HW(X) \leq HW_{max}$ (prevents upstream flooding and embankment overtopping).
2. Velocity constraints: $v_{min} \leq v(X) \leq v_{max}$ (typically bounded between 0.9 m/s to prevent sediment accumulation and 3.0 m/s to prevent outlet scour).

Structural constraints (per AASHTO/ACI Standards)

3. Flexural capacity:$M_u(X) \leq \phi M_n(X)$ (factored ultimate moment must not exceed the nominal moment capacity of the concrete section).
4. Shear capacity: $V_u(X) \leq \phi V_c(X)$ (concrete section must safely resist factored shear without requiring shear reinforcement links).
5. Geometric proportions: Strict boundary limits on minimum member thicknesses $t_{min}$ and aspect ratios $B/H$.
6. Reinforcement limits: $\rho_{min} \leq \rho(X) \leq \rho_{max}$ (ensures ductile failure modes and controls temperature/shrinkage cracking).

### E. Governing Hydraulic Equations

Hydraulic performance is dynamically evaluated for each candidate solution. Depending on the culvert geometry and tailwater conditions, flow is governed by either inlet control or outlet control [4]. The algorithm computes the required headwater HW for both flow regimes and conservatively selects the higher value: $HW = max(HW_{inlet}, HW_{outlet})$

#### 1) Outlet Control

Under outlet control, the culvert barrel restricts flow. The required headwater is calculated using the conservation of energy (Manning's friction loss equation):

$$HW_{outlet} = TW + \left(1 + K_e + \frac{29n^2L}{R^{1.33}}\right)\frac{v^2}{2g} - S_oL \qquad (3)$$

where $TW$ is tailwater depth, $K_e$ is the entrance loss coefficient, $n$ is Manning's roughness coefficient, $L$ is the culvert length, $R$ is the hydraulic radius $A/P$, $v$ is the average barrel velocity $Q/A$, and $S_o$ is the longitudinal bed slope.

#### 2) Inlet Control

Under inlet control, the entrance geometry restricts flow. The required headwater is computed using standard FHWA non-dimensional empirical regression equations. For an unsubmerged condition:

$$\frac{HW_{inlet}}{H} = \frac{H_c}{H} + K\left(\frac{Q}{BH^{1.5}}\right)^M - 0.5S_o \qquad (4)$$

where $H_c$ is the critical depth, $Q$ is the design peak discharge, and $K$ and $M$ are standard regression constants based on the specific inlet edge configuration

### F. AI-Based Optimization Models

Due to the highly nonconvex nature of the constraint space, standard gradient descent algorithms are ineffective. Therefore, two advanced metaheuristic algorithms were implemented and compared.

#### 1) Constraint Handling via Static Penalty

To enforce strict compliance with engineering limits, a static penalty method is incorporated into the objective function to calculate a design's overall fitness. The penalized fitness function $F_p(X)$ is defined as:

$$F_p(X) = f(X) + \sum_{i=1}^{N_c} R_i \cdot max(0, g_i(X))^2 \qquad (5)$$

where $N_c$ is the number of constraints, and $R_i$ is a severe penalty multiplier (e.g., 106). Any design that violates a hydraulic or structural limit is heavily penalized, rapidly pushing the AI population toward the feasible, safe design region.

#### 2) Grey Wolf Optimizer (GWO)

GWO is a swarm intelligence algorithm inspired by the social hierarchy and hunting mechanics of grey wolves [10]. The population is stratified into alpha ($\alpha$, best solution), beta ($\beta$, second best), delta ($\delta$, third best), and omega ($\omega$, remaining solutions). The position of each candidate design is iteratively updated based on the location of the top three leaders:

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|, \quad \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|, \quad \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \qquad (6)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \qquad (7)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \qquad (8)$$

The coefficient vectors $v = Q/A$ linearly decrease over the course of the iterations, allowing GWO to smoothly transition from broad global exploration (searching varying span/height ratios) to fine local exploitation (optimizing slab thickness to the millimeter).

#### 3) Genetic Algorithm (GA)

To serve as an evolutionary baseline, a real-coded GA is deployed using standard operators:

- Tournament Selection: Probabilistically selects highly fit structural designs to serve as parents.
- Simulated Binary Crossover (SBX): Blends variables between two parent designs to share beneficial geometric traits.
- Polynomial mutation: Applied randomly to prevent premature convergence by perturbing individual dimensions (e.g., slightly altering wall thickness).

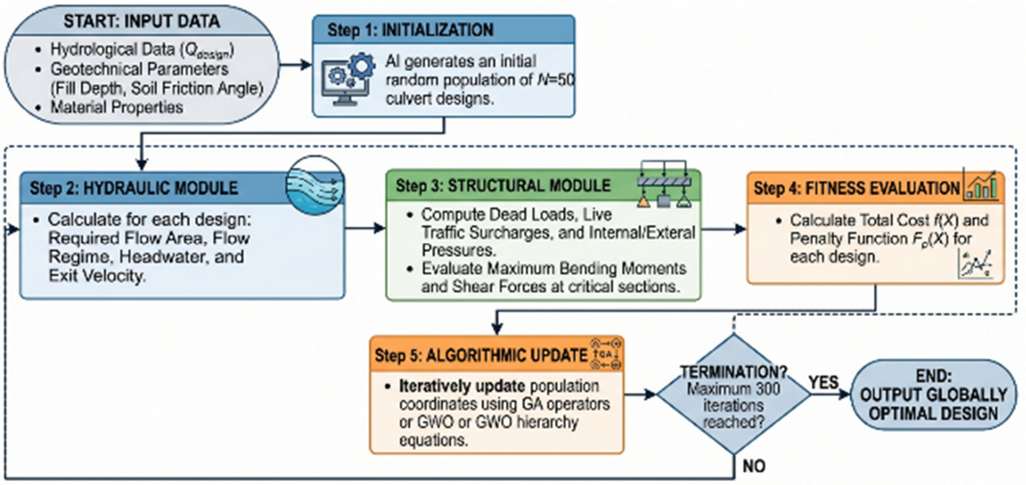

Fig. 1. AI-based hydraulic and structural optimization workflow for box culverts.

#### 4) *Model Workflow*

The proposed optimization framework was implemented through a tightly integrated and automated computational pipeline, as illustrated in Figure 1. The workflow initiates by defining the deterministic input parameters (e.g., design discharge, soil properties). It then generates an initial random population of candidate culvert cross-sections. For each candidate design, the hydraulic module evaluates the required headwater under both inlet and outlet control conditions. Subsequently, the structural module rigorously checks the flexural capacity, shear capacity, and geometric constraints. The overall fitness of each design is computed using the penalized cost function (5). Based on these fitness scores, the selected metaheuristic algorithms (GA or GWO) apply their specific mathematical operators to update the population. This iterative loop continues until the termination criterion is met, yielding the optimal geometric and reinforcement configuration.

## III. RESULTS

The proposed metaheuristic optimization framework was implemented using the defined case study parameters, including a design discharge of $Q = 25.0$ m$^3$/s, culvert length $L = 30$ m, and fill height $H_{fill} = 1.5$ m. Two widely adopted metaheuristic algorithms, GWO and GA, were implemented in Python. Both algorithms were configured with a population size of 50 and a maximum of 300 iterations to balance computational efficiency and solution quality. To account for the inherent stochastic nature of metaheuristic optimization, each algorithm was executed 30 times independently. The final reported solution corresponds to the best-performing design obtained from the median run, thereby ensuring robustness and reducing the influence of outlier solutions.

For performance evaluation, the optimized results were benchmarked against a conventional design obtained through deterministic manual calculations and validated using finite element analysis in STAAD.Pro. This framework enables a systematic assessment of the efficiency, reliability, and practical applicability of the proposed optimization approach.

### A. *Optimal Culvert Dimensions and Cost Reduction*

Table I presents a comparative evaluation of the optimized culvert sections obtained using metaheuristic algorithms against the conventional benchmark, including geometric dimensions, hydraulic performance indicators, and total construction cost.

TABLE I. COMPARISON OF OPTIMAL DESIGN SOLUTIONS FOR THE CASE STUDY

| Parameter | Unit | Conventional design | GA | GWO |
|---|---|---|---|---|
| Internal span ($B$) | m | 3.50 | 3.20 | 3.00 |
| Internal height ($H$) | m | 3.50 | 2.80 | 3.00 |
| Slab thickness ($t_s$) | m | 0.40 | 0.32 | 0.28 |
| Wall thickness ($t_w$) | m | 0.40 | 0.30 | 0.28 |
| Flow area ($A$) | m$^2$ | 12.25 | 8.96 | 9.00 |
| Flow velocity ($v$) | m/s | 2.04 | 2.79 | 2.77 |
| Required headwater ($HW$) | m | 2.65 | 3.25 | 3.42 |
| Max Allowable ($HW$) | m | 4.00 | 4.00 | 4.00 |
| Total cost | /m | $4,520.00 | $3,640.50 | $3,435.20 |
| Cost reduction | % | — | 19.4% | 24.0% |

The conventional design approach resulted in a relatively conservative cross-section of $3.50 \times 3.50$ m, accompanied by substantial structural thicknesses of 0.40 m. Although this configuration ensures compliance with safety requirements, it results in material overuse and a total construction cost of 4,520 per linear meter.

In contrast, both metaheuristic algorithms GWO and GA successfully identified more efficient design configurations that strictly satisfy all hydraulic and structural constraints. The optimized solutions exhibit reduced cross-sectional dimensions and material usage without compromising performance, demonstrating the effectiveness of AI-driven design exploration. Among the evaluated approaches, GWO demonstrated superior optimization performance. The algorithm converged to an optimal configuration of $3.0 \times 3.0$ m with reduced slab and wall thicknesses of 0.28 m. This geometry adopts a near 1:1 aspect ratio, which is structurally advantageous as it minimizes peak bending moments at critical locations such as mid-span and haunch regions. Importantly, structural checks confirmed that the optimized 0.28 m slab thickness provides sufficient concrete shear capacity ($V_c$) to safely resist the ultimate shear forces without requiring any additional shear reinforcement (stirrups). Consequently, both concrete volume and longitudinal reinforcement demand are significantly reduced.

The GWO-based design achieved a total cost of 3,435/m, corresponding to a 24.0% reduction compared to the conventional design. Furthermore, it outperformed the GA-based solution by approximately 5.6%, highlighting the robustness and efficiency of the GWO algorithm in navigating the complex, constrained design space.

To rigorously validate the structural mechanics module integrated into the AI framework, the optimal cross-section generated by the GWO algorithm ($3.0 \times 3.0$ m span and height, with 0.28 m member thicknesses) was modeled in the commercial finite element software STAAD.Pro. A 2D frame analysis was conducted applying the identical Ultimate Limit State (ULS) load combinations, including structural dead load, lateral earth pressure, and live traffic surcharge. Table II presents the quantitative comparison of the critical internal forces calculated by the AI's analytical module versus the STAAD.Pro FEM outputs.

TABLE II. COMPARISON OF CRITICAL INTERNAL FORCES BETWEEN AI ANALYTICAL MODEL AND STAAD.PRO FEM

| Critical parameter | AI analytical model | STAAD.Pro (FEM) | Difference (%) |
|---|---|---|---|
| Max Bending Moment at corner (kN.m) | 145.2 | 142.8 | 1.68% |
| Max Bending Moment at mid-span (kN.m) | 110.5 | 112.1 | 1.43% |
| Max Shear Force near support (kN) | 185.6 | 181.4 | 2.31% |

This comparison demonstrates excellent agreement between the proposed optimization framework and the standard numerical solver, with discrepancies remaining below 3%. This minor variance is attributed to the difference between 1D centerline frame analysis and 2D stiffness matrix formulations. This quantitative validation confirms that the AI framework not only optimizes costs but also accurately predicts structural demands, thereby guaranteeing engineering safety.

## *B. Convergence Analysis*

The convergence behavior of the employed metaheuristic algorithms is a critical indicator of their efficiency in solving the highly nonlinear, constrained optimization problem associated with reinforced concrete culvert design. As illustrated in Figure 2, GWO exhibits a significantly faster convergence rate than GA. In the early search stages (iterations 1–50), GWO exhibits a steep decline in the objective function, indicating strong global exploration capability. This behavior is attributed to the coordinated movement of the alpha, beta, and delta wolves, which effectively guides the search process and prevents premature convergence.

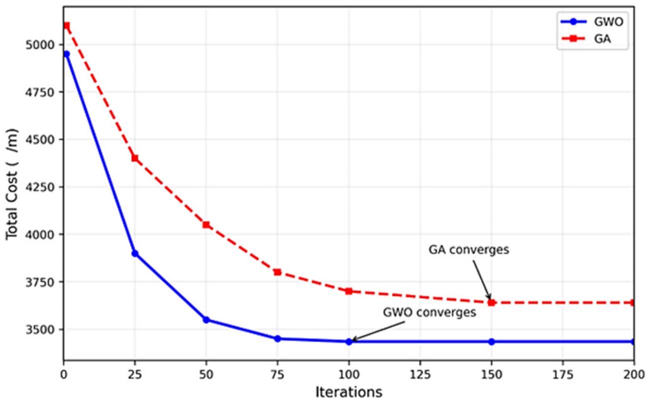

Fig. 2. Convergence curves of GWO and GA for the total cost objective function.

GWO achieves near-optimal convergence at approximately iteration $85-100$, stabilizing at a cost of 3,435 /m. In contrast, GA shows a more gradual, stepwise convergence pattern, characterized by intermittent improvements and periods of stagnation. This reflects the inherent limitations of crossover and mutation operators in efficiently navigating complex, constrained design spaces.

Notably, GA requires more than 140 iterations to converge and ultimately stabilizes at a higher cost of 3,640/m, indicating entrapment in a local optimum. The slower convergence and suboptimal final solution highlight the reduced exploitation efficiency of GA in problems involving discrete structural variables and heavily penalized constraint functions.

## *C. Sensitivity Analysis*

To validate the robustness of the AI framework across varying environmental and infrastructural conditions, a parametric sensitivity analysis was conducted using the GWO algorithm.

### *1) Impact of Design Discharge*

To further evaluate the robustness of the proposed optimization framework under varying hydraulic demands, a sensitivity analysis was conducted by systematically varying the design discharge. Figure 3 illustrates the resulting variations in total cost and optimal geometric proportions.

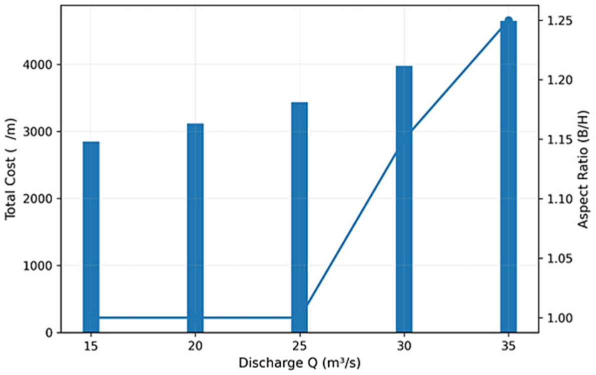

Fig. 3. Sensitivity of total cost and optimal aspect ratio to variations in design discharge.

As shown in Figure 3, the total cost increases nonlinearly with increasing discharge, reflecting the compounded effects of larger structural dimensions and higher hydraulic loading. For lower discharge values $Q \leq 25$ m$^3$/s, the optimizer consistently maintains an aspect ratio of $B/H \approx 1.0$, indicating a structurally efficient configuration that minimizes bending moments.

However, a distinct transition occurs at $Q \approx 30$ m$^3$/s, where the governing design constraint shifts from structural efficiency to hydraulic capacity. Beyond this threshold, the required headwater limit $HW_{\max} = 4.0$ m becomes critical, forcing the optimizer to adopt wider, flatter geometries $B/H > 1.0$ to increase flow capacity without exceeding allowable upstream water levels.

Although this geometric adjustment introduces structural penalties, such as increased bending in the top slab, it represents an optimal trade-off to satisfy hydraulic constraints. This behavior highlights the GWO algorithm's ability to dynamically adapt design variables in response to competing constraints, thereby ensuring both feasibility and cost efficiency across a wide range of operating conditions.

### 2) *Impact of Soil Cover Depth*

To further investigate the influence of geotechnical conditions on structural design, a sensitivity analysis was conducted by varying the soil cover depth while maintaining a constant design discharge. Figure 4 shows the resulting variation in optimal slab thickness.

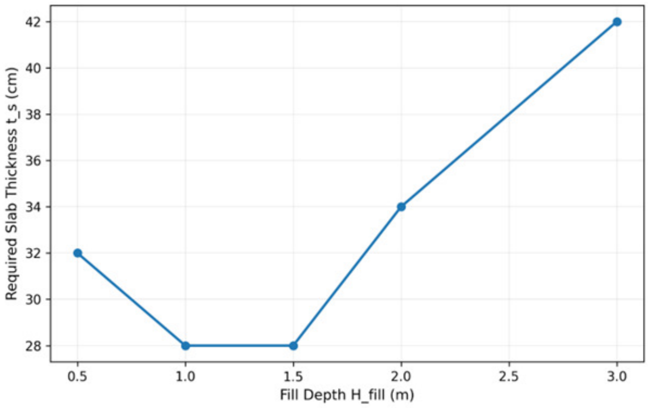

Fig. 4. Influence of soil cover depth on optimal slab thickness.

As illustrated in Figure 4, the relationship between soil cover depth and required slab thickness exhibits a clear nonlinear (parabolic-like) trend, reflecting the transition between different governing load mechanisms.

At shallow cover depths $H_{fill} = 0.5$ m, the slab thickness remains relatively high (32 cm) due to the dominant influence of live vehicular loads, which are insufficiently dispersed through the overlying soil layer. As the fill depth increases to approximately $1.0 - 1.5$ m, the soil effectively redistributes the applied loads, reducing bending demand and allowing the slab thickness to reach its minimum value (28 cm).

Beyond this optimal range, a distinct shift in governing behavior is observed. For $H_{fill} \geq 2.0$ m, the dead load induced by the increasing soil surcharge becomes the dominant factor, resulting in a rapid increase in required slab thickness, reaching 42 cm at $H_{fill} = 3.0$ m. This transition highlights the competing effects of load dispersion and self-weight in culvert design.

Importantly, the proposed AI-based optimization framework successfully captures this critical load transition without manual intervention, demonstrating its ability to adapt to complex, nonlinear structural-geotechnical interactions.

## IV. DISCUSSION

The findings of this study clearly demonstrate the advantages of replacing conventional, sequential culvert design approaches with a coupled, AI-driven optimization framework. By integrating hydraulic routing and structural mechanics into a unified optimization process, the proposed metaheuristic model effectively explores a highly constrained non-convex design space, leading to substantially more economical, performance-compliant solutions.

### A. *Algorithmic Superiority and Convergence*

A key outcome of this study is the superior performance of GWO compared to GA and conventional deterministic design approaches. Traditional workflows, often supported by software such as STAAD.Pro inherently promotes conservative design practices. Engineers typically adopt iterative trial-and-error procedures and apply safety-based dimension rounding, which results in overdesigned sections, as evidenced by the $3.50 \times 3.50$ m benchmark configuration.

Although GA achieved a notable 19.4% cost reduction, its convergence behavior (Figure 2) indicates a tendency toward premature stagnation, ultimately trapping it in a local optimum. This limitation is particularly pronounced in discrete structural optimization problems, where mutation operations may violate strict constraint boundaries, leading to the rejection of otherwise promising candidate solutions [10].

In contrast, GWO demonstrates a more robust search mechanism. Its hierarchical structure, comprising alpha, beta, and delta wolves, enables an adaptive balance between global exploration and local exploitation. As a result, the algorithm converges more rapidly and consistently to a near-global optimum. The optimized design, characterized by reduced slab and wall thicknesses of 0.28 m, achieves a 24.0% cost reduction while fully satisfying both the ULS and Serviceability Limit State (SLS) requirements. This highlights GWO's effectiveness in handling nonlinear, constrained engineering optimization problems.

### B. *Physical Interpretation of Optimal Geometries*

Beyond numerical optimization, the resulting design configurations provide important physical insights into the structural-hydraulic behavior of box culverts. As observed in the sensitivity analysis (Figure 3), for moderate discharges $Q \leq 25$ m$^3$/s, the optimizer consistently selects a $B/H$ aspect ratio of approximately 1.0.

From a structural mechanics perspective, this near-square configuration enhances system efficiency by balancing stiffness distribution within the frame. It reduces differential bending moments between the mid-span and corner haunch regions, thereby minimizing reinforcement demand and material usage.

However, as the discharge increases (e.g., $Q = 35$ m$^3$/s), a critical shift in governing constraints is observed. The hydraulic headwater limit $HW_{max}$ becomes the controlling factor. In conventional design workflows, this would typically lead to a uniform increase in both width and height, resulting in substantial cost escalation.

In contrast, the AI-driven framework identifies a more efficient alternative: increasing the culvert width while limiting the height, resulting in a wider and flatter geometry. Although this configuration introduces structural penalties such as increased bending moments in the top slab, it allows for a significant increase in flow area without exceeding the allowable headwater level. This trade-off demonstrates the optimization framework's ability to reconcile competing hydraulic and structural objectives cost-effectively.

### C. Load Transition and Engineering Applicability

The sensitivity analysis with respect to soil cover depth (Figure 4) further highlights the proposed framework's ability to capture complex, nonlinear load interactions. The results reveal a distinct transition between governing load mechanisms as the fill depth increases. At shallow depths $H_{fill} = 0.5$ m, live vehicular loads dominate due to limited load dispersion through the soil layer, necessitating relatively thick slab sections. As the fill depth increases to approximately $1.0 - 1.5$ m, the soil effectively distributes the applied loads, reducing bending demand and enabling thinner slab designs. Beyond this optimal range, a second transition occurs. For $H_{fill} \geq 2.0$ m, the dead load induced by the increasing soil surcharge becomes the governing constraint, resulting in a rapid increase in required slab thickness and overall cost. This behavior is consistent with previous parametric studies (e.g., [5]) and confirms the physical validity of the optimization results.

Importantly, the AI framework automatically captures these transitions, without the need for manual recalibration or separate design checks. This capability significantly enhances its practical applicability, allowing engineers to generate site-specific, optimized culvert designs that simultaneously ensure hydraulic safety and structural reliability while minimizing material consumption and associated environmental impacts.

## V. CONCLUSION

This study presents a novel AI-driven framework for the optimal cross-sectional design of reinforced concrete box culverts by tightly coupling FHWA-based hydraulic routing with structural mechanics within a unified optimization scheme. Unlike conventional sequential design approaches, the proposed method enables simultaneous satisfaction of hydraulic and structural constraints, thereby eliminating inefficiencies associated with iterative trial-and-error procedures. The key findings can be summarized as follows:

- Cost efficiency: The integration of metaheuristic optimization significantly enhances economic performance. GWO achieved a total cost of $3{,}435.20$/m representing a $24.0\%$ from $4{,}520.00$/m. It also outperformed GA, which yielded a $19.4\%$ reduction. Specifically, the GWO algorithm successfully reduced both slab and wall thicknesses from the conventional $0.40$ m down to a highly optimized $0.28$ m, while maintaining full structural safety and hydraulic compliance. This demonstrates the strong potential of AI-based optimization in minimizing material consumption.
- Algorithmic robustness and convergence performance: GWO exhibited faster, more stable convergence than GA, effectively avoiding local optima. Its hierarchical search mechanism enables a more efficient balance between global exploration and local exploitation, making it particularly suitable for solving highly constrained, nonlinear structural design problems.
- Adaptive geometric optimization: The coupled framework successfully captures multi-objective trade-offs between hydraulic performance and structural efficiency. Under standard discharge conditions, the optimizer converges to structurally efficient square sections ($B/H \approx 1.0$). Under high-flow scenarios, it dynamically shifts toward wider geometries ($B/H > 1.0$) to satisfy headwater constraints while minimizing cost penalties. This adaptive behavior highlights the framework's ability to respond intelligently to changing design conditions.
- Load-sensitive structural response: The model accurately reproduces the nonlinear transition between governing load mechanisms. It identifies an optimal fill depth range ($\approx 1.0 - 1.5$ m) where load dispersion minimizes structural demand, while also capturing the shift from live-load dominance at shallow depths to dead-load dominance at greater depths. This demonstrates the framework's ability to incorporate realistic soil-structure interaction effects into the optimization process.

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## CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## ACKNOWLEDGMENT

Not applicable to this work.

## DATA AVAILABILITY

The data, codes, and numerical models that support the findings of this study are available from the corresponding author upon reasonable request.

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