

Automated 3D Piping Routing Synthesis Considering Seismic Resilience: Part I— Mathematical Formulation and Layout Optimization Framework¹

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ABSTRACT

Automated piping routing methods face dual challenges in high-dimensional space planning and structural safety verification. Traditional workflows treat seismic qualification as a retrospective step, leading to inefficient design loops and costly backtracking. This study (Part I) presents a hybrid optimization framework that integrates deterministic A pathfinding with a Multi-Objective Genetic Algorithm (MOGA) to automate seismic-aware 3D piping routing synthesis. To bypass the prohibitive computational cost of full-scale Finite Element Method (FEM) simulations during iterative optimization, a lightweight linear-response spectrum modal analysis is used as a surrogate physical indicator to rank candidate layouts. A stochastic midway point strategy is introduced during initial population generation to ensure topological diversity and bypass local minima. The framework was validated using a 32 x 60 x 20 m congested design space derived from the Onagawa Nuclear Power Plant blueprints with carbon-steel piping (STPT410). The optimization loop evaluated 10,000 unique candidates and converged in 46 minutes and 19 seconds, reducing the aggregate evaluation*

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index by 93.2%. The results successfully characterized the non-linear trade-offs between material length, bend frequency, and dynamic seismic stress. Notably, the framework systematically identified configurations in which expanding pipe length and adding bends to lower structural stiffness successfully shifted the system's natural frequencies away from the resonance peak, thereby reducing peak seismic stress by up to 86.1%. This framework substantiates a transition from reactive verification to proactive, physics-informed layout synthesis.

1. Introduction

In the design and construction of large-scale industrial facilities, such as nuclear power plants, chemical refineries, and shipbuilding facilities, the layout planning of piping systems—commonly termed "piping routing"—remains the most time-consuming and complex engineering process during the detailed design phase. This single process conventionally accounts for over 50 percent of the total engineering person-hours and occasionally requires up to 200 person-months of labor. Piping routing requires comprehensive spatial planning to connect distributed equipment nodes while satisfying numerous geometric and mechanical constraints. As established in industrial design guidelines, these considerations include minimizing total pipe length to reduce material expenditure, limiting the number of directional changes to mitigate fluid pressure drop and fabrication complexity, and ensuring strict obstacle avoidance within congested structural environments [1]. Given that a modern industrial facility can contain tens of thousands of individual piping runs, the conventional design workflow has traditionally depended on the heuristics, spatial reasoning, and accumulated experience of human specialists.

The industrial plant engineering sector is currently confronted with a dual challenge. First, a significant demographic shift is underway as highly skilled piping engineers retire, creating a critical shortage of experienced personnel and complicating the transfer of

specialized design knowledge. Second, regulatory requirements, particularly for safety-critical installations such as nuclear power generation facilities, have become increasingly stringent over the past few decades[2]. In multiple jurisdictions, codes and design standards are revised periodically, requiring engineering workflows to adapt to tighter seismic and structural safety margins. This combination of a diminishing specialized workforce and escalating design complexity has resulted in a substantial increase in both labor expenditures and project lead times.

To improve design efficiency, research on automated piping design has been conducted for over 50 years; however, software packages that use these automation technologies remain limited in practical industrial applications. Comprehensive literature surveys, such as that by Blokland et al. [3], indicate that most previous academic studies and commercial software programs focus exclusively on geometric routing optimization. In contrast, structural analysis is treated as a separate, subsequent verification step. While conventional CAD packages are highly effective at maintaining geometric clearance and identifying the shortest available paths within a 3D model, they remain decoupled from structural mechanics. Consequently, the current industrial workflow still relies on an iterative, sequential approach. Engineers first determine a temporary piping layout based on geometric parameters, and only after the layout is geometrically finalized do they perform structural verification using the Finite-Element Method (FEM). If this dynamic analysis reveals that seismic stresses exceed allowable limits, a time-consuming redesign process, termed "backtracking," must be implemented between routing synthesis and structural evaluation, forming a primary bottleneck in plant engineering. Currently, no

integrated framework simultaneously achieves both automated routing and automated seismic evaluation.

In line with the scope of this special issue, which showcases artificial intelligence and machine learning applications in the assessment and design of pressure vessels and piping systems, this study focuses on developing an AI-powered engineering methodology that directly integrates spatial constraints and mechanical requirements into the design synthesis phase. Early research in automated piping layout design dates to the algorithmic approach of Ikeya [4], followed by Van der Tak et al. [5] in the shipbuilding sector. Initial computational frameworks predominantly relied on deterministic pathfinding algorithms, including Dijkstra's [6], Lee's [7], Hart's A* algorithm [8], and Lozano-Pérez's polyhedral obstacle avoidance [9], to determine grid-based or collision-free paths. While these deterministic methods are highly efficient for local obstacle avoidance, they generally lack the topological flexibility needed to optimize global structural behavior. To overcome this limitation, metaheuristic optimization approaches, particularly Genetic Algorithms (GAs) initiated by Holland [10], were introduced to explore highly non-linear design domains. In plant engineering applications, Szykman and Cagan [11] and Kim and Corne [12] established multi-objective optimization methodologies, laying the technical foundation for balancing spatial efficiency with structural and economic design criteria.

Previously, the authors' research group addressed this challenge by developing optimization methods tailored to flow-induced structural dynamics. Specifically, Fujishima et al. [13] developed a multi-objective optimization framework to suppress piping vibration induced by turbulent flow and evaluated it using the Likelihood of Failure (LOF) index. Their

work demonstrated that coupling evolutionary algorithms with structural evaluation enables the synthesis of layout topologies that inherently mitigate resonance. However, that approach operated under a significant topological constraint: the support spans were deterministically governed by the routing space and obstacle boundaries, causing both the support locations and the resulting pipe geometries to converge to a single unique configuration. Consequently, the broader and more complex engineering challenge of evaluating flexible, multi-bend piping routes to minimize seismic-induced inertial stress—while simultaneously executing automated support distribution within a congested 3D environment—remains an open problem in the field.

The primary obstacle to integrating seismic criteria directly into an automated loop is the prohibitive computational overhead associated with structural dynamic analysis. Although high-fidelity FEM simulations are mandatory for final verification, their execution times are excessively long to be executed thousands of times within the iterative operators of a genetic algorithm. To address this computational bottleneck, Part I of this study introduces a surrogate-model strategy for early-stage design exploration, substituting absolute analytical precision with a lightweight linear-response spectrum modal analysis as a rapid physical indicator of seismic performance. As established in nuclear engineering codes such as JEAC 4601 [2], the response spectrum method extracts the fundamental eigenvalues and eigenvectors necessary to evaluate dynamic compliance. The underlying premise of this approach is that for initial layout synthesis, the absolute value of stress is secondary to the relative performance rankings across the population. By capturing the essential physical trends and dynamic characteristics, this surrogate indicator allows the

optimization algorithm to systematically steer the generation process away from structurally vulnerable configurations and toward code-compliant routing corridors.

To deploy this physics-informed evaluation within a global search loop, the proposed framework couples the deterministic pathfinding of the A* algorithm with a multi-objective genetic algorithm (MOGA), establishing a hierarchical optimization architecture similar to the structural routing configurations found in the literature [14]. While hybrid A*-GA frameworks conventionally focus on geometric efficiency, a distinct technical modification implemented in this study is the integration of a stochastic midway-point strategy during initial population generation. This diversification mechanism is dictated by the specific structural characteristic that piping configurations with identical aggregate lengths can exhibit substantially different dynamic seismic responses depending on their geometric trajectories and automated support distributions. By stochastically allocating intermediate coordinate nodes within the permissible design volume and using the A* algorithm to connect segments, the framework synthesizes a highly diverse initial seed pool. This computational mechanism effectively prevents the evolutionary process from prematurely converging on geometric local minima, such as simple shortest-path corridors. It facilitates the automated synthesis of alternative non-linear layout configurations characterized by functional multi-bend detours.

The objective of Part I is to establish the theoretical and computational foundations of this automated synthesis framework and to evaluate its algorithmic effectiveness through a series of complex routing configurations. The primary focus centers on characterizing the non-linear trade-offs between geometric efficiency and seismic structural compliance,

illustrating how physics-informed indicators can guide early-stage engineering decisions. The physical validity of the computationally synthesized layouts, along with their correlation with structural reality, is subsequently addressed in Part II of this investigation, which presents scale-model shaking table experiments governed by structural similarity laws. Ultimately, this two-part study provides a scalable and computationally efficient design-support framework that transitions the piping layout workflow from a sequential, verification-based cycle into an integrated synthesis environment, thereby minimizing structural backtracking and substantially reducing design lead times for critical industrial installations.

The core idea of this multi-objective framework was first introduced in our initial conference paper [15]. This paper (Part I) further refines and updates the mathematical models, constraint-repair mechanics, and the interaction between global and local layout optimization to create a complete engineering design platform.

2. Literature Review on Automated Piping Design

The chronological development of automated piping layout design spans more than half a century, beginning with the foundational work of Ikeya [4] in 1971 and subsequent marine routing studies by Van der Tak et al. [5] in 1976. Following these pioneering efforts, routing methodologies evolved through deterministic pathfinding algorithms—such as those by Dijkstra [6], Lee [7], Hart et al. [8], and Lozano-Pérez et al. [9]—as well as metaheuristic optimization frameworks inspired by Holland [10]. In the mid-1990s, these computational tools were actively introduced to the industrial plant sector,

notably through the pathfinding formulations of Szykman et al. [11] and the layout synthesis approaches of Kim and Corne [12]. The application matrix was later expanded to structural wiring domains via Conru [16] in 1994, generic spatial routing models via Zhu et al. [17] in 1991, and aerospace engine components via Van der Velden et al. [18] in 2007. To systematically identify the technical requirements and delineate existing research gaps, this section categorizes the historical literature by underlying algorithmic architectures.

2.1. Grid-Based Deterministic Pathfinding Algorithms

Deterministic algorithms have historically served as the baseline for automated routing, primarily by executing shortest-path exploration in discretized 3D grid environments.

A* Search Framework

Within grid-mapped design domains, optimization is achieved by customizing node-wise and segment-wise cost functions. The earliest implementation was established by Zhu et al. [17] in 1991 and expanded in 1992 [19], focusing on the concurrent optimization of pipe length, bend frequency, obstacle interference, and pipe rack alignment. In the aerospace sector, Van der Velden et al. [18] adapted single-objective A* search to automate routing layouts around aircraft engine casings. In marine engineering applications, Wu et al. [20] in 2009 integrated material length, elbow counts, collision avoidance, and maintenance accessibility into an A* optimization loop. This was followed by Lee et al. [21] in 2019 and Ha et al. [22], who incorporated design space availability and structural feasibility indicators into grid-based generation. Additionally, algorithmic efficiency was

enhanced by using the Jump Point Search (JPS) modification [23] to reduce computational search time.

Dijkstra Methodologies

In contrast to node-prioritized A* heuristics, Dijkstra's algorithm structures optimization by assigning cost values directly to the path edges. Schmidt-Traub et al. in 1998 [24] and 1999 [25] first deployed this edge-cost strategy to enhance plant layout efficiency, incorporating pipe length, elbow frequency, interference clearance, and maintenance access. Ikehira et al.[26] subsequently used Dijkstra's framework to transition automated routing from rigid template combinations toward unconstrained, graph-based spatial synthesis, focusing on valve positioning co-optimized with material expenditures. In 2011, Ando and Kimura [27] integrated T-junction branch logic into discrete equipment components, thereby transforming complex branching problems into multi-stage, single-pipeline subproblems. Further dynamic refinements by Kimura et al. included suppressing localized hydraulic trapping by eliminating of vertical U-shaped geometries [28]. Recently, Ajiwaskita et al. [29] implemented Dijkstra-based routing within marine engine rooms, evaluating path length, bend distribution, and pipeline intersections.

2.2. Evolutionary Computation and Stochastic Metaheuristics

To address highly non-linear, multi-objective design spaces where local node-additive costs are insufficient, evolutionary computation frameworks became a prominent methodology.

Pure Genetic Algorithms:

The earliest integration of GAs in piping synthesis was conducted by Savic and Walters [30] in 1995 to optimize material procurement costs and fluid pressure drops within water distribution networks. In plant design, Ito and Fukuda [31] in 1998 developed a spatial GA that evaluated length and obstacle avoidance; it was updated in 1999 [32] to include bend counts, and in 2002 [33] to introduce strict wall-clearance boundaries. In 2005, Ikehira et al. [34] structured GA routing using pre-configured layout templates, which subsequently evolved to incorporate heuristic enhancements, valve operability indices [26], and multi-terminal branching architectures [35].

Research Group Precedents and Gaps:

Within this evolutionary context, our research group previously developed a multi-objective layout optimization framework targeted at suppressing flow-induced structural dynamics. Fujishima et al. [13] implemented a modal analysis loop within a GA to minimize the Likelihood of Failure (LOF) index induced by fluid turbulence. While the LOF metric successfully characterized internal dynamic excitation, that optimization framework operated under a severe topological constraint: the support spans were deterministically fixed according to predefined layout archetypes and boundary structures. Consequently, both the support distribution and the generated routing geometries converged to a rigid, non-flexible configuration. The generalized coupling of flexible, multi-bend 3D geometries with automated support placement under seismic acceleration remains unaddressed.

2.3. Hybrid Architectures and Advanced Computational Swarms

To bypass the slow convergence rates and lethal genotypes typical of pure metaheuristics in dense obstacle fields, researchers developed hybridized and localized optimization variants.

Swarm and Colony Operators:

Ant Colony Optimization (ACO) was applied by Qu et al. [36][37] for aircraft engine routing, co-optimizing length, bend distribution, clearance envelopes, and—critically—structural natural frequencies. Particle Swarm Optimization (PSO) was extensively employed by Liu et al. [38]–[41] to manage parallel, multi-pipeline layouts and to optimize both the location and the total frequency of structural branches.

Hybrid Frameworks:

Structural integration typically leverages deterministic pathfinding for local feasibility and metaheuristics for global strategy. Sui and Wentie [42] combined Dijkstra routing with an evolutionary refinement layer to optimize marine branching runs. Gunawan et al. [43] used Dijkstra's algorithm for layout generation while running a GA to optimize the sequential order of multiple independent pipelines. Similarly, Dong and Bian [14] verified a coordinated architecture coupling A* path generation with GA-based layout manipulation. Complementary hybridizations include A*-PSO variants by Amara [44] and coordinated GA-ACO operators by Jiang et al. [45].

Machine Learning Advancements:

Recent developments have introduced reinforcement learning to accelerate real-

time layout generation. In the marine engineering sector, Shin et al. [46] executed automated machinery space routing by training neural networks on expert human design histories. Kim et al. [47] optimized this learning framework using curriculum learning protocols, thereby significantly reducing the execution time required to synthesize feasible 3D layouts.

3. Formulations of Objective Functions

The proposed optimization framework evaluates the candidate piping layouts by simultaneously quantifying geometric efficiency, constructability constraints, and structural safety requirements. To evaluate these competing engineering parameters without introducing subjective assumptions, this study presents a multidimensional formulation in which each objective function is nondimensionalized using a specific baseline value, thereby eliminating reliance on arbitrary weighting factors. The optimization routine systematically minimizes a scalar overarching total evaluation index, F , defined as the algebraic sum of the following components:

- Evaluation index of seismic resistance, f_S , representing the normalized maximum analyzed stress.
- Evaluation index of piping length, f_L , characterizing material and spatial efficiency.
- Evaluation index of the bend number, f_B , to minimize dynamic pressure drops and fabrication costs.
- Penalty function of obstacle interference, P_O , to strictly enforce boundary clearance conditions.

This section mathematically defines these constituent functions to establish the deterministic framework used by the Multi-Objective Genetic Algorithm (MOGA).

3.1. Evaluation Index of Piping Length (f_L)

The evaluation index for piping length, f_L , is formulated to quantify the spatial and material efficiency of a candidate routing solution. Minimizing the total piping layout length is a foundational economic metric heavily used across historical automated routing workflows, spanning early deterministic search algorithms [17], [20], [21] to stochastic evolutionary metaheuristics [32], [33], as it directly impacts procurement expenditures, required insulation volume, and the overall physical footprint within the facility. Furthermore, in high-seismicity regions, restricting the aggregate routing length minimizes the total mass of the piping system, thereby reducing the seismic inertial loads on the structural supports. From a hydraulic perspective, minimizing the length is equally vital for suppressing the total pressure drop induced by internal fluid-wall friction.

Figure 1 schematically illustrates the geometric relationship used in this routing evaluation, defining the spatial correlation between a synthesized multi-bend path and the ideal theoretical boundaries. To eliminate scale dependencies across varying layout environments, the objective function f_L is normalized by comparing the total piping length against the absolute theoretical shortest path, expressed as follows:

$$f_L = \frac{l - l_{\min}}{l_{\min}} \quad (1)$$

where l is the cumulative length of the synthesized piping layout computed as the sum of the discrete straight segments:

$$l = \sum_{i=0}^n l_i \quad (2)$$

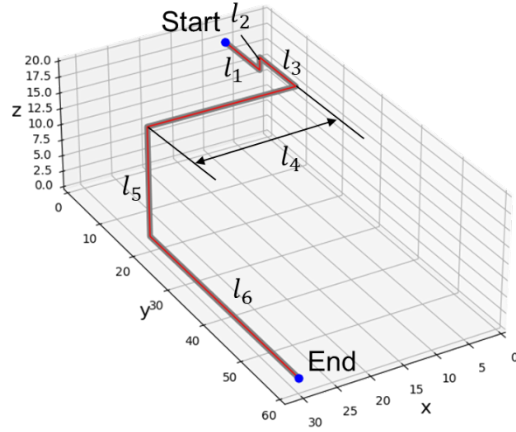


Figure 1: Schematic representation of the piping length calculation, illustrating the relation between the synthesized path length l and the baseline minimum orthogonal distance l_{min} .

Here, l_i represents the length of the i -th straight segment extracted from the sequence of coordinate points defining the path. As characterized by the orthogonal trajectory boundaries depicted in Figure 1, the baseline parameter l_{min} represents the minimum orthogonal distance between the specified start and end terminals, determined via the 3D Manhattan distance metric to reflect orthogonal routing constraints:

$$l_{min} = |x_s - x_e| + |y_s - y_e| + |z_s - z_e| \quad (3)$$

The subscripts s and e denote the coordinates of the start and end points, respectively. When a synthesized layout executes the absolute shortest orthogonal trajectory without any topological detours, the value of f_L becomes zero, establishing a lower bound for the length optimization loop.

3.2. Automated Support Placement Logic

In the proposed framework, structural supports are automatically populated onto the synthesized routing trajectory to establish the boundary conditions necessary for subsequent spectral modal analysis. The dynamic structural compliance of a piping system under seismic acceleration depends strongly on the total number and precise spatial distribution of these support nodes. While conventional routing literature predominantly isolates path exploration from structural boundary synthesis or bounds calculations to fixed, inflexible support intervals, as implemented in our research group's baseline framework [13], this study implements a segment-wise, dynamic automated placement routine. Based on the primary piping parameters, including the outer diameter, wall thickness, and material density, the algorithm scans the localized geometric features of the synthesized path. It assigns support properties according to two explicit deterministic rules:

- **Terminal Boundary Anchors:** The start and the end points of the main pipeline are unconditionally treated as complete structural anchors. These nodes model the rigid boundary connections to major terminal components, such as vessels, pumps, or tanks.
- **Straight-Segment Midpoint Splitting:** The length of the i -th individual straight pipe segment, l_i , is extracted from the coordinate sequence. This length is continuously benchmarked against the maximum allowable support span, l_{span} , derived from the frequency span method:

$$l_{span} = \frac{\pi}{2f_0} \sqrt{\frac{EIg}{w}} \quad (4)$$

where f_0 is the reference target frequency (configured to 10 Hz to bound typical single-digit seismic motion components), E is Young's modulus, I is the sectional second

moment, g is the acceleration of gravity, and w is the weight per unit length. Based on this reference framework, if a straight segment length satisfies $l_i > l_{span}$, a single support node is automatically generated at the exact geometric midpoint of that segment. Conversely, if $l_i \leq l_{span}$, the straight segment is kept unsupported.

To execute the global structural calculations, these generated support nodes and terminal points are integrated into the overall stiffness matrix. As boundary conditions for complete fixation, the terminal anchors are modeled with an absolute axial/shear rigidity of 9.0×10^{14} N/m and a bending rigidity of 9.0×10^{14} N·m. The automated intermediate support points are integrated with an identical translational stiffness of 9.0×10^{14} N/m combined with a specified rotational bending rigidity of 9.0×10^8 N·m. This modular constraint automation ensures that structural metrics can be derived iteratively across generations without requiring manual finite-element remodeling.

3.3. Evaluation Index of Bend Number (f_B)

Beyond the total layout length, the complexity of pipeline fabrication and spatial installation is a primary cost driver in plant engineering projects. Each additional directional change or elbow requires progressive component sourcing, manual welding, non-destructive testing (NDT), and introduces localized stress concentration points. For these reasons, minimizing bend frequency has been treated as a critical, standard objective function in numerous seminal piping optimization models [17][24][33]. Mechanically, within the proposed framework, a high frequency of bends combined with automated support placement (governed by the reference support span l_{span}) can augment global seismic resistance by stiffening the structure. However, from a fluid-dynamics perspective, excessive

directional changes must be strictly limited because every elbow introduces severe localized head losses, thereby penalizing hydraulic efficiency.

To balance this trade-off between seismic stiffness and hydraulic-fabrication efficiency, the evaluation index f_B for the bend number is formulated as a normalized dimensionless ratio that penalizes unnecessary deviations from the ideal orthogonal path. The objective function is defined as follows:

$$f_B = \frac{n_b - n_{b,min}}{n_{b,min}} \quad (5)$$

where n_b is the total number of 90-degree elbows present in the computationally synthesized piping layout, and $n_{b,min}$ represents the theoretical minimum number of bends required to successfully connect the start and end terminals through the obstacle field along the shortest path. By implementing this dimensionless formulation, when the evolutionary optimization algorithm synthesizes a layout topology that achieves the absolute minimum required directional changes, the value of f_B converges to zero.

3.4. Evaluation Index of Seismic Resistance (f_S)

The evaluation index of seismic resistance, f_S , is formulated to bridge the gap in the literature, where dynamic structural behaviors is either omitted or limited to simplified frequency indicators [36]. This study establishes an explicit framework for stress evaluation based on the "Technical Code for Seismic Design of Nuclear Power Plants" (JEAC 4601) [2]. In contrast to static gravitational evaluations, seismic inertial loads are inherently dynamic and frequency-dependent. To evaluate these dynamic characteristics within an iterative

optimization loop, this study uses linear response spectrum modal analysis. The overall computational procedure for the seismic stress evaluation is systematically illustrated in Figure 2.

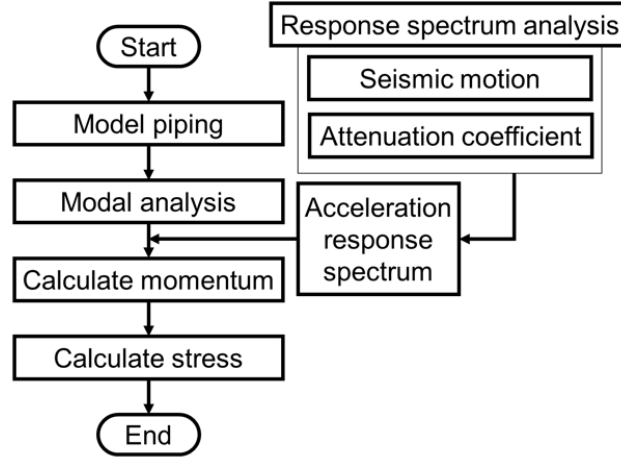


Figure 2: Schematic flowchart of the overarching MOGA-A* hybrid layout optimization framework, delineating the iterative loop between deterministic segment-wise path generation and multi-objective evolutionary selection.

The dynamic response is derived by solving the generalized eigenvalue problem for the multi-mass piping model:

$$([K] - \omega_i^2 [M])\{u\}_i = 0 \quad (6)$$

where $[K]$ represents the global stiffness matrix configured by the layout topology and automated support locations, $[M]$ is the overall mass matrix accounting for the weight of the pipe, internal fluid, and insulation, ω_i is the i -th natural angular frequency, and $\{u\}_i$ denotes the corresponding eigenmode vector. To evaluate the peak response under realistic extreme loading conditions, the acceleration response spectrum observed during the Great East Japan Earthquake is introduced as the seismic input baseline, as plotted in Figure 3.

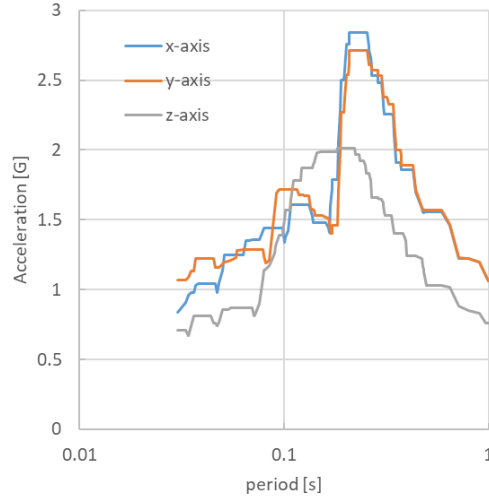


Figure 3: Design floor response spectrum used as the dynamic seismic input baseline, derived from the acceleration time history observed during the Great East Japan Earthquake, outlining the spectral acceleration peak regions critical to the piping structural resonance evaluation.

The dimensional displacement vector for each mode, X_i , is calculated by scaling the eigenmode vector with the modal participation factor, β_i , and the spectral acceleration, a_i :

$$X_i = u_i \cdot \left(\frac{a_i}{\omega_i^2} \right) \cdot \beta_i \quad (7)$$

The modal moment vector for each mode, M_i , is subsequently obtained by multiplying the displacement by the stiffness matrix:

$$M_i = [K] \cdot X_i \quad (8)$$

To synthesize the peak dynamic response, the modal moment vectors are superimposed using the Square Root of the Sum of the Squares (SRSS) method. This SRSS combination is executed independently for the two horizontal seismic components (x and y directions) and the single vertical component (z direction) to yield the directional moment

vectors, M_x , M_y , and M_z . The total resultant seismic moment vector, M , at each spatial coordinate is then determined via a secondary SRSS combination across all three coordinate axes:

$$M = \sqrt{M_x^2 + M_y^2 + M_z^2} \quad (9)$$

Finally, the total generated stress, S_j , at any specific coordinate point j is derived by superimposing the static stress induced by internal operating pressure and the dynamic bending stress induced by the seismic moment:

$$S_j = \frac{B_1(PD)}{2t} + \frac{B_2M_j}{Z} \quad (10)$$

where P is the internal operating pressure, D is the outer piping diameter, t is the nominal wall thickness, Z is the sectional modulus, and B_1 and B_2 represent the standardized code stress coefficients for straight sections and elbows. The objective function f_s is defined by extracting the absolute maximum stress value across all evaluated node coordinates and normalizing it against the allowable design stress, P_{al} , to establish a dimensionless optimization metric:

$$f_s = \frac{\max(S_j)}{P_{al}} \quad (11)$$

Under this mathematical formulation, the optimization routine is subjected to the absolute constraint that the maximum generated stress must remain strictly below the code-defined allowable limit ($f_s < 1.0$).

3.5. Penalty Function of Obstacle Interference (P_o)

To ensure geometric feasibility in densely congested plant environments, a discrete penalty function, P_o , is introduced to enforce collision-avoidance boundaries. Navigating

around pre-existing industrial equipment, structural steel structures, and adjacent piping systems has remained a primary geometric constraint throughout the evolution of automated routing algorithms. Within this framework, any synthesized layout that encroaches upon a prohibited or occupied volume is immediately classified as an invalid topological solution.

To evaluate these spatial interferences deterministically, both the multi-bend piping segments and the plant obstacles are modeled using Oriented Bounding Boxes (OBBs), as schematically illustrated in Figure 4. Spatial collision between these geometric volumes is verified by applying the Separating Axis Theorem (SAT), which checks for overlap in orthogonal projections along all potential separating axes. If the SAT routine identifies an intersection between any piping segment OBB and an obstacle OBB, a step-barrier penalty is applied. The penalty function P_O is formulated in a clean mathematical case structure as follows:

$$P_O = \begin{cases} 10 & \text{if interference exists} \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

where the constant penalty value of 10 is strategically selected to establish a high-cost mathematical barrier within the multi-dimensional fitness landscape. Because the cumulative sum of the normalized objective functions (f_S, f_L, f_B) typically falls within a numerical range of 2.0 to 4.0, assigning a major value of 10 ensures that any candidate solution exhibiting geometric interference is relegated to an inferior fitness tier. This mathematical scaling prevents non-viable offspring from proliferating into subsequent generations during the evolutionary selection phase, guaranteeing that the Pareto-optimal search is restricted exclusively to collision-free design spaces.

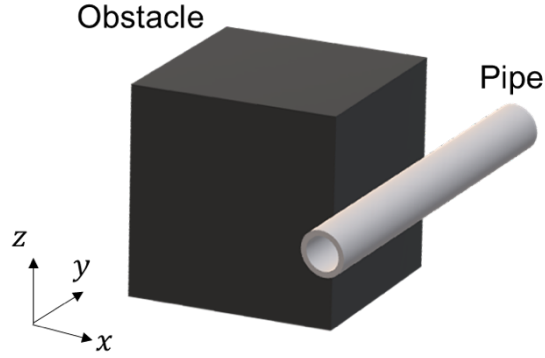


Figure 4: Geometric collision detection mechanism using Oriented Bounding Boxes (OBBs), illustrating the spatial interference evaluation between a synthesized piping segment and a plant obstacle volume.

3.6. Overarching Evaluation Index and Nondimensionalization Strategy

To synthesize balanced Pareto-optimal layouts without introducing engineering subjectivity, the individual mathematical objectives must be integrated into a unified evaluation framework. Traditional multi-objective layout optimizations developed in the literature [17], [37], [48] predominantly rely on the conventional weighted-sum method, in which separate objectives are aggregated via linear combinations weighted by arbitrary factors. However, the assignment of these scalar weights is inherently dependent on human intuition or iterative trial and error, introducing optimization biases that overprioritize certain parameters at the direct expense of others.

To eliminate this methodological bias, the framework established in this study employs a comprehensive nondimensionalization strategy. As mathematically detailed in Sections 3.2 through 3.4, each constitutional evaluation index—namely the seismic resistance index f_S , the piping length index f_L , and the bend number index f_B —is individually normalized within its respective subfunction by its corresponding theoretical minimum or code-defined allowable ceiling parameter. Because this localized normalization

process converts every competing engineering goal into a dimensionless metric operating on an equivalent numerical scale, the overarching total evaluation index, F , is formulated as a direct algebraic sum combined with the geometric obstruction penalty:

$$F = f_S + f_L + f_B + P_O \quad (13)$$

By using this equitable dimensionless formulation, any localized structural or spatial enhancement translates into a strictly proportional numerical progression within the evolutionary selection loop. For example, a fractional reduction in dynamic seismic stress corresponds to an equivalent fractional improvement in material routing length. Consequently, the multi-objective genetic algorithm can perform an unconstrained global search across the multi-dimensional fitness landscape, successfully mapping the balanced Pareto-optimal front without requiring manual weight tuning or incurring scaling distortions.

4. Proposed Hybrid Optimization Algorithm

The automated synthesis of optimized 3D piping routes in highly constrained industrial plant environments requires a computational strategy that balances global topological exploration with localized geometric precision. To satisfy these competing operational requirements, this study implements a hierarchical hybrid framework that couples a Multi-Objective Genetic Algorithm (MOGA) with the deterministic A* pathfinding algorithm. While the integration of metaheuristics and pathfinding baselines has been conceptually explored in other routing domains, the framework developed herein builds a physics-informed architecture in which every stochastically generated layout is rigorously validated for geometric clearance and structural seismic compliance.

The comprehensive operational flowchart for this integrated architecture is shown in Figure 5. As visually outlined in the layout synthesis loop, the overarching algorithmic structure does not simply run the genetic operators and pathfinding in isolation; instead, it establishes a continuous data-exchange network where the global MOGA layer dictates strategic topological targets, while the embedded local A* layer dynamically resolves localized spatial feasibility. This hierarchical interaction ensures that the evolutionary search is performed exclusively within a population of fully valid, collision-free candidate geometries. The detailed computational progression of this evolutionary pipeline is governed by five discrete sequential phases, as delineated in the following subsection.

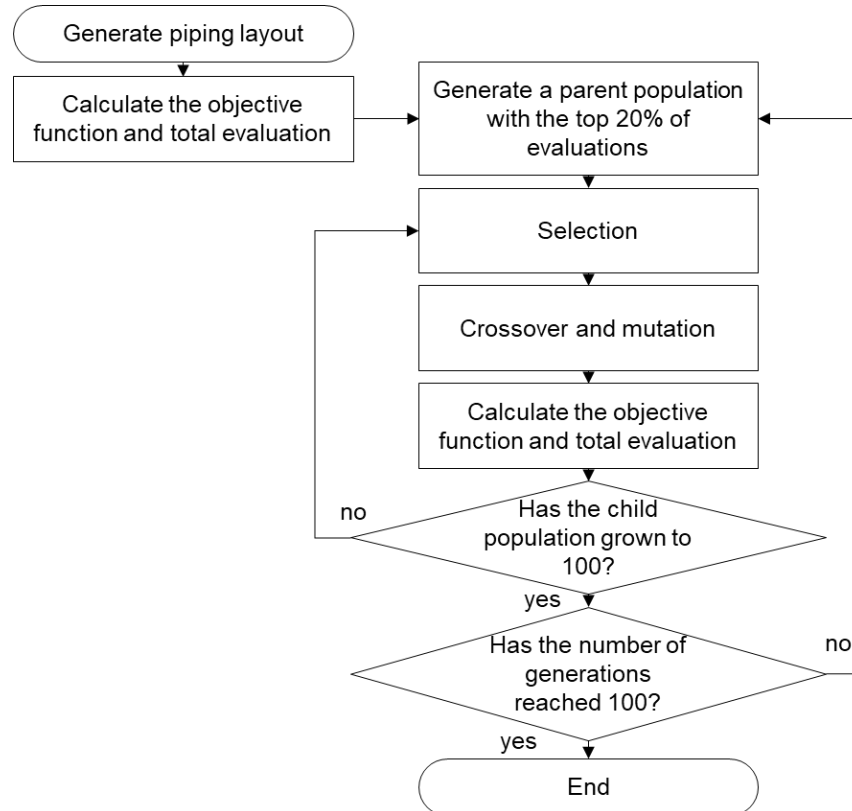


Figure 5: Comprehensive operational flowchart of the integrated MOGA-A* hybrid optimization algorithm, illustrating the evolutionary lifecycle from stochastic midway point initialization to Pareto-optimal selection.

4.1. Generational Workflow of the Evolutionary Pipeline

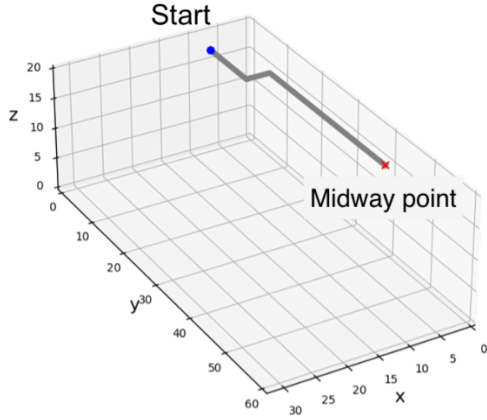
The optimization routine executes a structured, multi-phase generational pipeline to progressively transmute a diverse pool of initial layout candidates into highly refined, code-compliant structural configurations. The computational workflow is partitioned into five discrete phases:

Phase 1: Stochastic Population Initialization:

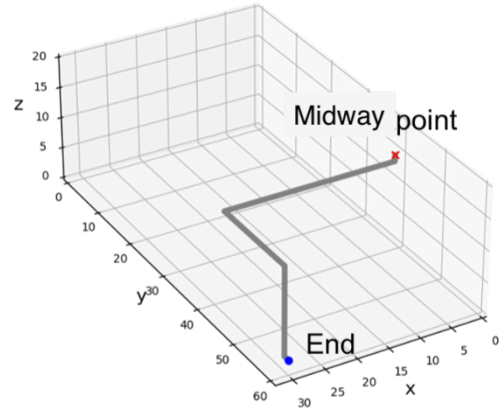
The evolutionary cycle begins with Generation 0, which constructs a population of specialized piping chromosomes. To eliminate conventional human design biases and prevent the search space from prematurely converging on geometric local minima (such as simple straight-line paths), a stochastic midway point strategy is employed. For each genotype, a series of intermediate coordinate target nodes are randomly scattered within the permissible 3D design volume. The local A* algorithm sequentially connects these coordinates, yielding a diverse initial pool of continuous, collision-free paths with alternative multi-bend trajectories.

Figure 6 schematically visualizes this early-stage generation process executing within the discrete grid space. As illustrated by the directional sequence vectors, the local A* pathfinding heuristic acts as a segment-wise connector; it dynamically synthesizes the first path segment from the fixed start terminal to the stochastically allocated connect point (midway point), and subsequently completes the overarching pipeline topology by routing from the connect point to the end destination nozzle. This dual-segment initialization mechanism effectively forces the early population to explore unconventional spatial

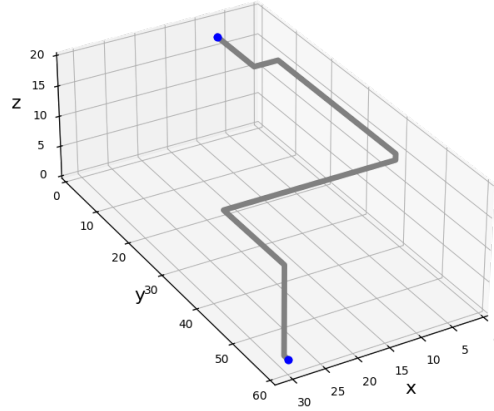
corridors around complex obstacle blocks.



(a) Routing from the start to the midway point



(b) Routing from the midway point to the end



(c) Example of piping layout on 1st generation: combination of (a) and (b)

Figure 6: Comparative routing trajectories during the early evolutionary stage, illustrating the segment-wise path synthesis connecting the start terminal, stochastically allocated midway points, and the end destination node.

Phase 2: Fitness Evaluation and Non-Dominated Sorting:

Each synthesized layout is subjected to the multi-dimensional evaluation routine detailed in Section 3. The total piping length index f_L , the bend frequency index f_B , and the maximum structural seismic stress index f_S are derived concurrently. Based on these metrics, the population is categorized using the Non-dominated Sorting Genetic Algorithm

II (NSGA-II) framework. Individuals are ranked into discrete non-domination fronts based on Pareto dominance, and a crowding-distance metric is calculated to maintain topological diversity across the fitness landscape.

Phase 3: Selection and Evolutionary Refinement:

The evolutionary cycle selects high-performing layout genotypes to function as parents via tournament selection. Genetic operators—consisting of adaptive crossover and targeted mutation—are applied directly to the midway point coordinate sequences to generate next-generation offspring. During this reproductive phase, the deterministic A* algorithm operates as an embedded real-time repair mechanism. It automatically recalculates and recalibrates the local path segments between any newly inherited or modified waypoints, ensuring that the resulting offspring maintain strict geometric validity and obstacle clearance despite drastic structural alterations.

Figure 7 schematically illustrates an architectural example of this genetic restructuring process. As delineated in the chromosome mapping, the crossover operator isolates specific segments from the midway-point arrays of two elite parent configurations and recombines them. This localized structural recombination enables the framework to synthesize a hybrid offspring layout that simultaneously inherits the material-efficiency strengths of Parent 1 and the localized structural resilience profiles of Parent 2.

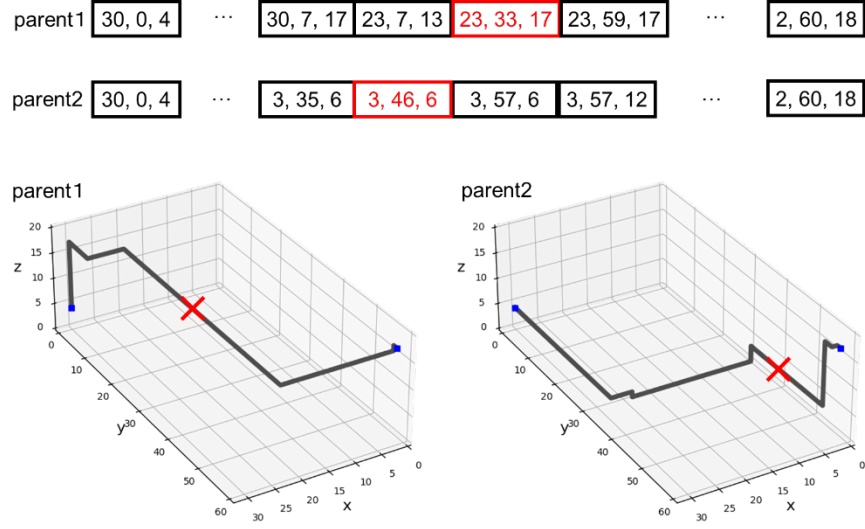


Figure 7: Schematic representation of the genetic crossover mechanism, demonstrating the exchange of midway point sequence segments between selected parent genotypes to yield hybrid offspring.

Phase 4: Iterative Generation Convergence:

The operations configured in Phases 2 and 3 are executed iteratively across hundreds of successive generations. Throughout this computational evolution, the chromosome pool discards structurally deficient, high-stress layout configurations. The population progressively concentrates around the multi-dimensional Pareto-optimal front, where any further reduction in material expenditure (f_L or f_B) directly compromises the dynamic structural safety margin (f_S).

Phase 5: Automated Decision Support:

The optimization terminates upon satisfying a predefined generational limit or convergence stability threshold. The final output presented to the plant engineer is a distribution of distinct Pareto-optimal layout configurations rather than a single scalar

solution. This framework provides a multi-criteria decision-support platform, enabling engineers to select the specific piping geometry that matches the project-specific operational boundaries.

4.2. Hierarchical Architecture: The Global-Local Synergy

To handle the extreme dimensionality characteristic of 3D plant models, the computational architecture is divided into two mutually reinforcing, hierarchical layers. This formal separation of concerns isolates global macro-topology decisions from localized micro-pathfinding operations:

Global Strategic Layer (MOGA):

This upper-level routine governs the macro-topological evolution of the piping paths. It operates as a stochastic search mechanism that evaluates overarching layout strategies, determining complex structural features such as obstacle-bypass directions, support-alignment vectors, and the deliberate synthesis of multi-bend expansion loops to alter the system's natural frequency. The MOGA directly manipulates the length and coordinates of the midway point array, thereby shifting the pipeline's global skeletal profile.

Local Tactical Layer (A*)

This lower-level routine operates as a high-speed, deterministic local path generator. It treats the coordinate nodes provided by MOGA's genetic sequence as localized sequential targets and computes the shortest possible grid-based path segment between them. By delegating the intensive geometric calculations of collision avoidance and spatial

grid navigation exclusively to the A* loop, the framework guarantees that every chromosome returned to the MOGA for fitness evaluation represents a continuous, collision-free route. This hierarchy prevents the genetic algorithm from expending computational cycles on disjointed or structurally invalid geometries.

4.3. Piping Gene and Midway point Strategy

The fundamental data structure driving the optimization loop is a specialized, variable-length piping chromosome $\mathbb{C}$ that encodes the layout trajectory as an ordered sequence of 3D Cartesian coordinate nodes. Traditional grid-based genetic algorithms frequently encode each directional voxel step as a discrete gene, which often results in broken path segments or severe topological disintegration under standard stochastic mutation operators. To eliminate this limitation, this study implements a specialized midway point strategy: $\mathbb{C} = [P_{start}, P_{w,1}, P_{w,2}, \dots, P_{w,k}, P_{end}]$

The start terminal coordinate P_{start} and the end terminal coordinate P_{end} remain spatially fixed, representing the designated physical equipment nozzles. The intermediate coordinate array, consisting of $P_{w,i}$ (where i ranges from 1 to k), represents an evolving set of spatial targets that serve as gravitational steering nodes for the routing trajectory. The MOGA is tasked with concurrently optimizing both the total number of intermediate waypoints, k , and their exact spatial coordinates within the permissible design volume. This variable-length chromosome encoding empowers the framework to autonomously synthesize complex expansion geometries—such as omega-shaped loops or significant multi-bend detours—that increase the flexibility of the piping system and shift its natural frequency away from seismic resonance zones.

4.4. Evolutionary Operators Integrated with A* Search Heuristics

To ensure that the population remains geometrically viable when operating within densely populated obstacle fields, standard genetic operators are augmented with deterministic A* pathfinding heuristics:

Adaptive Crossover:

This operator isolates two successful parent genotypes and exchanges portions of their midpoint sequences at a stochastically determined crossover point. If Parent A exhibits highly efficient routing within the initial design quadrant and Parent B features an optimized terminal connection, the crossover operation generates an offspring chromosome that inherits both structural and material advantages. The embedded A* algorithm immediately re-routes the connection boundary between the newly juxtaposed segments, dynamically adjusting the local voxels to ensure the hybrid path does not collide with adjacent obstructions.

Targeted Mutation

Mutation acts as the primary computational mechanism for introducing structural innovation and maintaining genetic diversity. It executes across three stochastically selected operational modes:

- (1) **Coordinate Shifting:** Jittering the spatial position of an existing waypoint $P_{w,i}$ by a randomized displacement vector to fine-tune local segment alignment, enhance automated support positioning, or mitigate localized stress concentrations.
- (2) **Point Insertion:** Injecting a new intermediate waypoint into the chromosome array to

force a geometric detour. This operation is critical for navigating around newly encountered plant obstacles or deliberately introducing flexibility-enhancing curves into the pipeline.

- (3) Point Removal: Deleting a redundant waypoint from the sequence to straighten the local trajectory. This operator drives the chromosome toward geometric minimization, reducing unnecessary elbows to optimize both f_B and f_L .

Figure 8 schematically illustrates the geometric mechanics of these three stochastic mutation modes acting on the spatial midway point sequences. As indicated by the trajectory alterations, each operator systematically modifies the chromosome's skeletal framework before routing validation. Every mutation applied to a chromosome is immediately validated by the local A* connector. If a mutation places a waypoint within an impassable obstruction or creates an unconnectable segment, the framework executes real-time repair heuristics or discards the offspring, preventing lethal genotypes from degrading the computational efficiency of the generational loop.

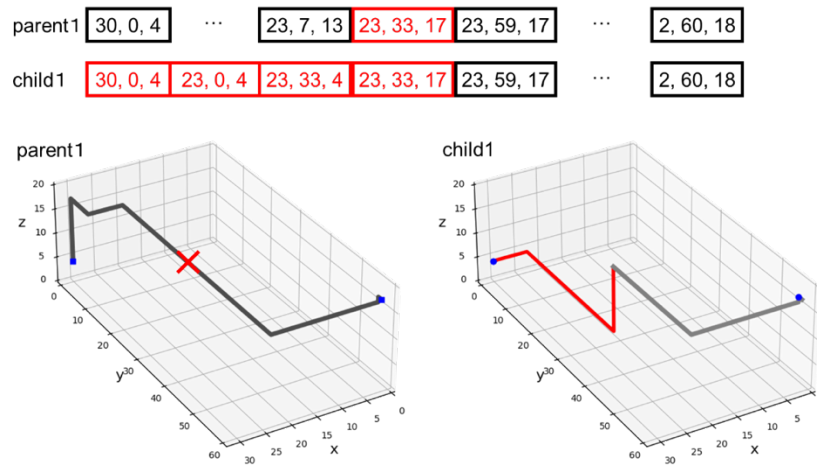


Figure 8: Geometric path transitions induced by the point removal operator, demonstrating the trajectory simplification and bend reduction achieved via redundant waypoint deletion.

4.5. Multi-Objective Pareto Selection and Decision Analysis

The framework deploys the NSGA-II selection mechanism to construct and maintain a well-distributed, non-dominated Pareto front. By concurrently optimizing the three competing engineering subfunctions—the length index f_L , the bend index f_B , and the seismic stress index f_S —the system maps out the comprehensive performance envelope of the design space. This multi-objective output redefines the engineering workflow, shifting it from a traditional search for a single intuitive layout to a quantifiable analysis of structural and economic trade-offs.

The computationally synthesized Pareto-optimal set routinely isolates three distinct classes of engineering configurations:

The Minimum-Length Configuration:

Characterized by minimal material investment and low pressure drops, optimizing spatial footprint and logistics, but operating with reduced structural safety margins near the code-permissible seismic stress ceiling (f_S approaches 1.0).

The Minimum-Stress Configuration

Characterized by maximum seismic resilience and high structural safety margins, achieved via deliberate multi-bend expansion loops that decrease peak dynamic stress, but incur increased procurement, insulation, and welding expenditures.

The Compromise Configuration

A balanced, mid-ground topology that satisfies all standardized regulatory codes while restricting unnecessary material detours, optimizing overall system reliability.

By evaluating these non-dominated solutions, plant engineers can quantify the exact material cost associated with structural safety—specifically, the piping length or the number of extra elbows required to achieve a discrete reduction in peak seismic stress. This high data transparency ensures robust, defensible, and reliable engineering decisions for critical industrial infrastructure.

5. Case Study Settings

This section defines the spatial environment parameters, physical material properties, and the configurations of the multi-objective genetic algorithm (MOGA) used to validate the proposed hybrid routing framework. These boundary parameters are established to replicate the high-congested constraints characteristic of actual industrial infrastructure, providing a deterministic validation benchmark for the multi-objective routing synthesis.

5.1. Design Space and Obstacle Layout

The numerical design environment is modeled as a large-scale, 3D rectangular spatial grid volume. To ensure industrial relevance, the geometric coordinates and internal structural configurations are reconstructed and genericized from publicly available safety analysis reports and official technical design documents of the Onagawa Nuclear Power Plant. This benchmark environment has been simplified for academic evaluation purposes while strictly preserving the representative level of spatial congestion and physical compartmentalization found in real-world energy facilities.

Boundary Dimensions

The search space is defined by the coordinates $(L_x, L_y, L_z) = (32, 60, 20)$ m. This vast volume provides a high degree of routing freedom, allowing the algorithm to explore various corridors ranging from direct paths to complex, multi-bend detours.

Target Terminals:

To simulate a typical connection between major equipment, the starting point (x_s, y_s, z_s) is fixed at $(7, 0, 17)$ m, and the destination point (x_e, y_e, z_e) is located at $(30, 60, 2)$ m.

Obstacles:

Five primary structural obstacles are placed within the space to represent "keep-out" zones. Their center coordinates and overall dimensions (w_x, w_y, w_z) are detailed in Figure 9 and Table 1.

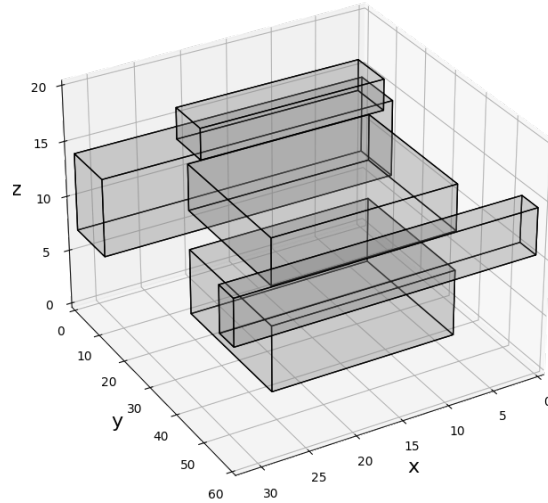


Figure 9: 3D isometric arrangement of the spatial obstacle blocks and keep-out zones within the 32 × 60 × 20 m plant design environment.

Table 1: Center coordinates and width of obstacles (unit: m)

Obstacle	x	y	z	w_x	w_y	w_z
Obstacle 1	14	15.5	17.2	10	4.5	1.4
Obstacle 2	14	30	12.3	10	15	2.1
Obstacle 3	14	30	3.6	10	15	3.0
Obstacle 4	16	56.5	12.3	15	2.5	2.1
Obstacle 5	16	5.5	10.5	16	5.5	3.5

5.2. Material Properties and Design Stress Limits

The evaluated piping model is configured with carbon steel for high-temperature service (STPT410), which is a standard structural material choice in high-pressure energy piping codes. The core mechanical properties and the calculated design seismic stress limit, P_{al} , are summarized in Table 2.

Table 2: Mechanical Properties of STPT410

Property	Symbol	Value
Design Yield Point	S_y	245 MPa
Design Tensile Strength	S_u	404 MPa
Design Stress Intensity	S_m	103 MPa
Allowable Stress	P_{al}	309 MPa ($\min(3S_m, 2S_y)$)

To maintain complete consistency with the structural code requirements defined in JEAC 4601, the allowable stress threshold P_{al} used in the seismic evaluation index f_s (Section 3.1) is mathematically formulated via the following min-max boundary:

$$P_{al} = \min(3S_m, 2S_y) \quad (14)$$

Evaluating this criterion using the material characteristics of STPT410 yields $\min(3S_m, 2S_y) = \min(309, 490) = 309$ MPa. This computed value functions as a strict penalty threshold within the MOGA loop; any candidate route geometry that generates a

localized peak equivalent stress exceeding this boundary ($f_s \geq 1.0$) is immediately treated as a structurally invalid offspring.

5.3. Support Auto-Placement Framework: Frequency Span Execution

To automate the iterative definition of localized finite-element boundary conditions, the segment-wise automated support routing routine applies the frequency-span method detailed in Section 3.4. The spatial discretization and geometric assignment mechanics of this support allocation process are systematically illustrated in Figure 10.

Theoretical Support Span:

Based on the reference target cutoff frequency of $f_0 = 10$ Hz configured to isolate the pipeline from single-digit seismic floor excitation bands, the maximum allowable theoretical support span l_{span} is computed as 9.23 m.

Implementation Logic:

The automated module scans the precise length of each straight pipe section, l_i , within the chromosome trajectory and enforces the following deterministic actions:

1. Case 1 ($l_i > l_{span}$):

A translational rigid support constraint is automatically assigned at the exact geometric midpoint of the individual straight segment. This spatial splitting suppresses high-amplitude low-frequency vibration modes and controls the local seismic inertial stress.

2. Case 2 ($l_i \leq l_{span}$):

The straight section is preserved as a completely unsupported segment, allowing

the localized pipeline topology to retain its inherent structural flexibility, thereby absorbing dynamic displacements.

By applying this dynamic boundary allocation framework, the support node distribution autonomously shifts and adapts as the macro-routing geometry evolves across generations, establishing a highly coupled physics-informed layout synthesis.

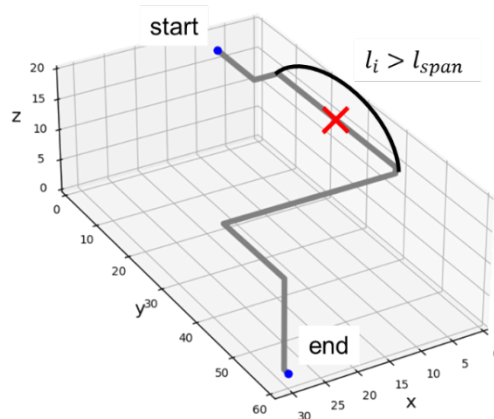


Figure 10: Schematic illustration of the segment-wise support allocation process, demonstrating the midpoint splitting rule executed by the automated frequency span algorithm.

5.4. GA Configuration and Optimization Setup

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is deployed to govern the multi-objective evolutionary search. The operational genetic control parameters are configured based on the engineering metrics compiled in Table 3.

Table 3: GA Configuration Parameters

Parameter	Value
Number of Generations	100
Number of Individuals	100
Crossover Rate	0.85
Mutation Rate	0.05 (5%)
Selection Method	Binary Tournament Selection

The definition of these generational control boundaries was validated through preliminary numerical sensitivity sweeps. For the designated $32 \times 60 \times 20$ m plant coordinate design space, the multi-objective Pareto-optimal front consistently achieves stability and mathematical convergence within 100 generations, establishing an optimal balance between the global exploration of alternative topologies and total computational runtime.

The entire computational pipeline—encompassing deterministic A* pathfinding, automated support allocation, multi-objective genetic operators, and the response-spectrum modal-analysis solver—was implemented in Python 3. All iterative generational simulations were executed seamlessly, without third-party finite-element software dependencies, thereby maximizing data exchange efficiency between the global and local layers.

6. Results and Discussion

This section presents a quantitative and qualitative evaluation of the multi-objective optimization framework implemented in the 3D industrial piping environment. By coupling the A* pathfinding heuristic's deterministic grid-navigation capabilities with the MOGA's global space exploration, the system simultaneously visualizes and resolves the highly coupled trade-offs among structural safety limits, spatial efficiency, and constructability requirements.

6.1. Convergence Characteristics of the Overarching Evaluation Index

The evolutionary optimization loop demonstrated stable mathematical convergence and robust structural adaptation throughout the designated 100-generation

runtime. The overarching total evaluation index, F , which serves as the cumulative metric balancing the normalized length f_L , bending frequency f_B , and the seismic stress index f_S , exhibited a continuous, asymptotic decay profile.

As shown in Figure 11, the total evaluation score F of the elite individual in the initial population (Generation 0) was recorded at 11.82. This elevated score directly reflects the spatial and geometric inefficiency triggered by the stochastic midway point allocation phase, which routinely introduces redundant path detours, excessive pressure drops, and complete structural misalignment relative to the supporting framework. By the final evolutionary cycle (Generation 100), the overarching index F decreased smoothly to 0.8, representing a total optimization reduction of approximately 93.2%. This clean convergence trajectory confirms that the fitness landscape effectively navigated toward high-efficiency topological regions while systematically discarding structurally non-compliant candidates.

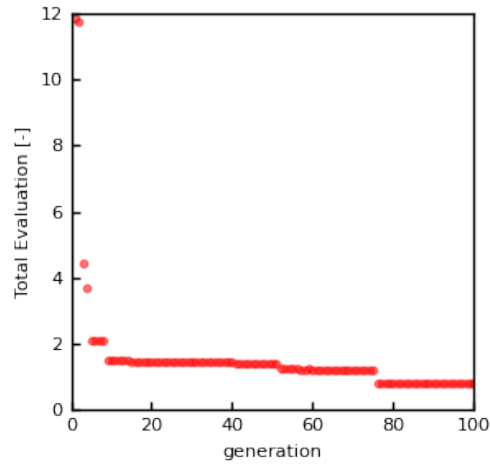
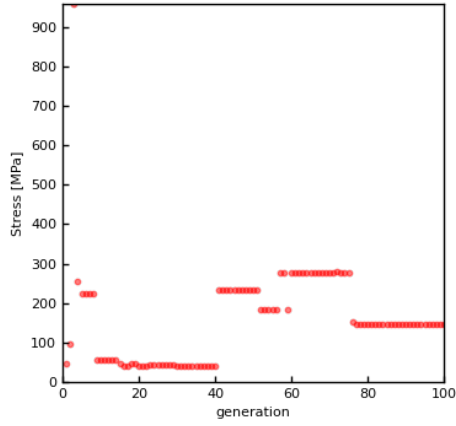


Figure 11: Convergence history of the overarching total evaluation index F across 100 successive generations, illustrating the generational reduction in layout inefficiencies.

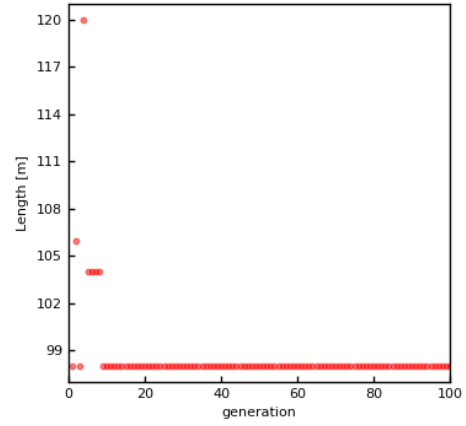
A detailed examination of the evolutionary history reveals that the structural seismic stress values experienced localized numerical fluctuations during the initial 20

generations. This transient behavior corresponds to the MOGA's macro-topological exploration phase, where the algorithm systematically sweeps the alternative routing corridors to determine which coordinate paths to execute around the boundaries of the five rigid structural obstacles. Once these macroscopic corridor selections stabilized, the index fluctuations dampened progressively, indicating that the chromosome pool successfully converged into a localized design space where geometric clearance and structural safety criteria were concurrently satisfied.

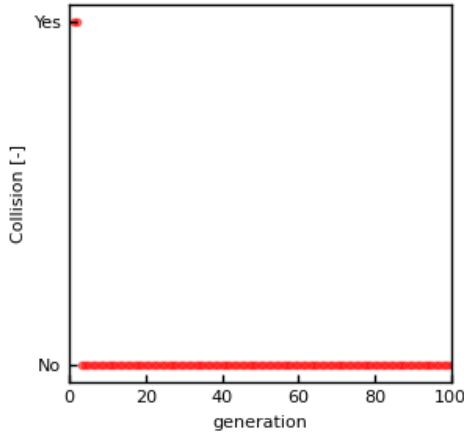
The generational progression of each objective subfunction is compiled in Figure 12. Specifically, the generated dynamic seismic stress plotted in Fig. (a) varies in complete correlation with the structural trajectory modifications (Figs. (b) and (d)) and the successful elimination of spatial obstacle interference (Fig. (c)). These inter-dependent trends confirm that the evolved elite individuals successfully synchronized their automated support node placements with the macro-piping geometry to suppress peak resonant modal responses.



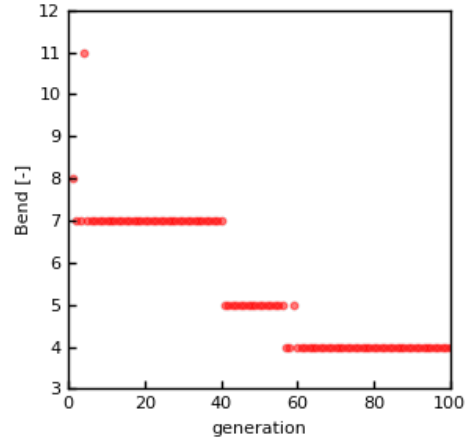
(a) Stress



(b) Length



(c) Collision



(d) bend

Figure 12: Generational history of the individual objective functions and constraints: (a) peak seismic stress index f_S , (b) total piping length l , (c) obstacle collision status P_O , and (d) total bend count n_b .

6.2. Structural Analysis of Intermediate Generations: Geometry vs. Seismic Resilience

The numerical results highlight the highly non-linear trade-offs governing geometric path minimization and structural safety margins, proving that a physically shorter layout trajectory does not inherently yield a seismically compliant design. This characteristic engineering behavior was explicitly observed during the generational transition between the elite individuals of Generation 3 and Generation 4.

As compiled in the structural dataset of Table 4, the elite individual of Generation 4 achieved a significantly lower overarching evaluation index of 3.72 and a drastic reduction in peak seismic stress to 254.42 MPa. In comparison, its Generation 3 predecessor generated an extreme, structurally catastrophic stress response of 957.15 MPa, while failing spatial clearance constraints due to an active obstacle collision. Although the unpenalized structural-geometric baseline score of Generation 3 was recorded at 4.43, the presence of the active obstruction encroachment immediately triggers the step-barrier penalty, relegating it to an inferior fitness tier.

Crucially, this vital enforcement of structural safety between the two consecutive generations was achieved by deliberately increasing the total piping length from 98 m to 120 m and expanding the total bend frequency from 7 to 11.

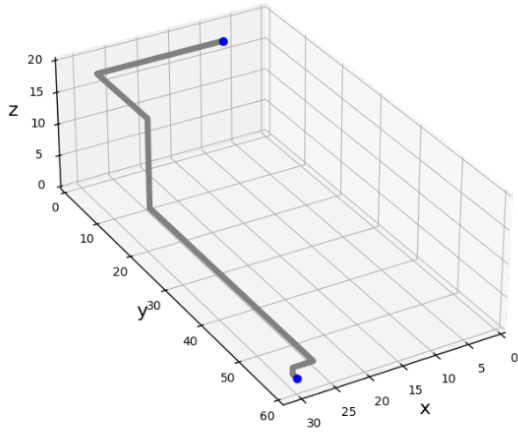
Table 4 Comparative evaluation and structural dataset of the elite individuals in Generation 3 and Generation 4

Metric Parameter	Generation 3	Generation 4
Total evaluation index F [-]	4.43 (Unpenalized)	3.72
Peak Seismic Stress [MPa]	957.15	254.42
Total Piping Length l [m]	98	120
Obstacle Collision Status [-]	Yes	No
Total Bend Count n_b [-]	7	11

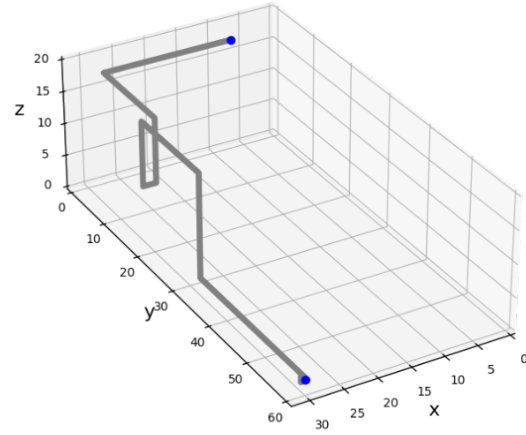
The physical routing topologies of these two intermediate generations are visually contrasted in Figure 13. In Generation 3 (Fig. (a)), the layout executed a highly direct, near-linear orthogonal path between the terminals. While this configuration optimized material volume, it synthesized an excessively rigid structural framework whose fundamental natural

frequency coincided directly with the high-amplification resonance band of the input seismic floor response spectrum.

Conversely, the Generation 4 individual (Figure 13(b)) autonomously evolved an extended "S-curve" detour corridor. While this topological modification increased both the material length index f_L and the bend index f_B , the expanded geometry lowered the global structural stiffness matrix profile, successfully shifting the system's fundamental natural frequency away from the dynamic resonance peak. In industrial seismic piping engineering, the strategic integration of orthogonal bends and localized detours functions identically to a structural expansion loop; it enables the pipeline to absorb extreme dynamic inertial energy through distributed elastic, flexible bending deformation rather than concentrating lethal, destructive forces at fixed equipment nozzle connections or rigid support structures. This behavior proves that the MOGA-A* hybrid routine can systematically discover non-intuitive, highly effective, flexible layouts that satisfy stringent structural safety criteria without requiring manual engineering guidance.



(a) Generation 3



(b) Generation 4

Figure 13: 3D spatial routing trajectories of intermediate generations: (a) the highly rigid and non-compliant layout of Generation 3, and (b) the seismically decoupled flexible detour layout of Generation 4.

6.3. Qualitative Comparison of Initial and Final Converged Layouts

Visualizing the spatial routing pathways provides a clear qualitative validation of the topological evolution from the early stochastic generations to the final converged Pareto-optimal solution. The structural layout configurations are shown in Figure 14, where the blue spheres denote the terminal nozzle coordinates, the light blue triangles indicate the automated intermediate support locations assigned via the midpoint splitting rule, and the red markers mark the peak-generated seismic stress coordinates.

The early-stage routing configurations, represented by the elite individual of Generation 1 (Figure 14(a)), were characterized by highly fragmented, erratic trajectories containing numerous redundant bends that contributed nothing to obstacle avoidance or seismic decoupling. Furthermore, because the straight-segment geometries were poorly coordinated, the automated support allocation module left excessively long unsupported

spans vulnerable to severe low-frequency gravitational sagging and high seismic inertial stress concentrations at the fixed boundaries.

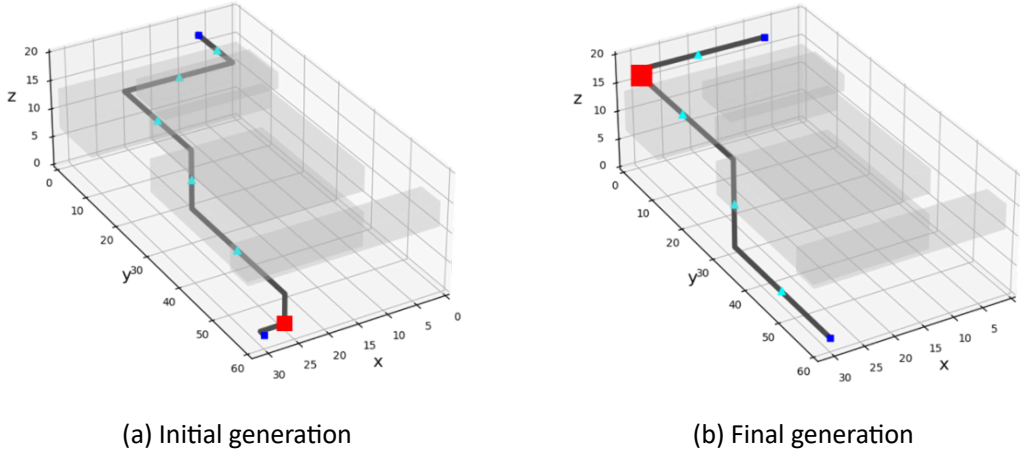


Figure 14: Visual comparison of the 3D piping layout evolution: (a) the chaotic, unoptimized trajectory of the initial generation, and (b) the regular, highly regular converged layout topology achieved at Generation 100.

In complete contrast, the final optimized layout synthesized at Generation 100 (Fig. (b)) exhibits a highly regular, balanced orthogonal geometry. The total number of elbows was strictly pruned to the absolute mathematical minimum required to clear the spatial obstacle blocks while preserving localized seismic flexibility. The automated intermediate supports are optimally distributed in full compliance with the structural span threshold. This coordinated configuration successfully controlled the global response, ensuring that the maximum calculated equivalent stress was restricted to 145.46 MPa—safely below the code-permissible P_{al} limit of 309 MPa. The clean routing corridors eliminate unnecessary directional deviations, demonstrating that the automated optimization framework aligns perfectly with standard plant engineering design requirements.

6.4. Results Focused on Individual Objective Minimization

To rigorously map the multi-objective sensitivity and validate the behavior of the balanced fitness function F , a series of isolated optimization runs were executed by focusing exclusively on single independent objectives.

When the optimization routine was configured to minimize the seismic dynamic performance index f_S solely, the resulting layout topology converged to the highly flexible configuration illustrated in Figure 15. This specialized structure yielded an exceptionally low peak dynamic stress of 20.21 MPa. Compared to the balanced multi-objective solution of Generation 100 (Figure 14(b)), which generated 145.46 MPa, the peak structural stress was reduced by an additional 86.1%. However, this extreme seismic optimization requires massive material expenditures, tortuous detours, and a high density of automated supports, which severely penalizes spatial and procurement efficiency.

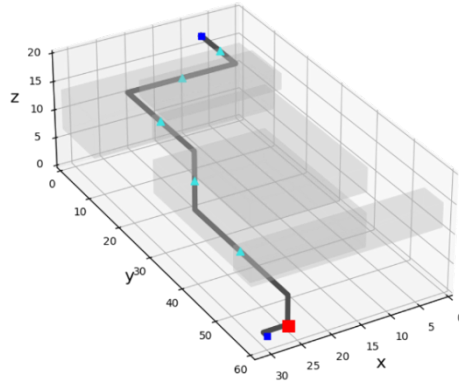


Figure 15: 3D piping routing layout synthesized by minimizing the seismic resistance objective function f_S exclusively, prioritizing extreme flexibility at the expense of material efficiency

Conversely, when the evolutionary pipeline was restricted to minimizing the piping length index f_L , the layout converged to the absolute shortest trajectory plotted in Figure 16. This path is topologically identical to the direct, linear candidates observed in the initial

generation, operating at the absolute lower bound length of 98 m. While highly cost-effective from a procurement and insulation standpoint, this unyielding linear path possesses extreme structural stiffness. Consequently, under design-basis seismic excitation, it triggers severe dynamic amplification and resonance, yielding stress values that violate code compliance.

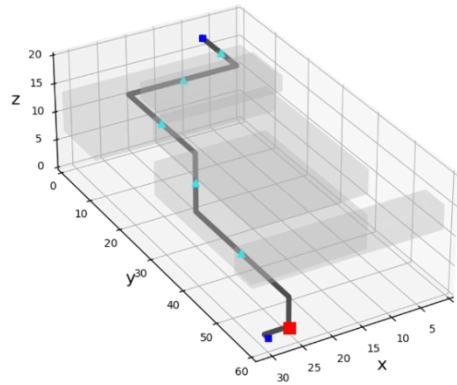


Figure 16: 3D piping routing layout synthesized by minimizing the piping length index f_L , illustrating the rigid, linear trajectory that violates seismic safety ceilings.

Finally, the layout synthesized by focusing solely on minimizing the bend frequency index f_B is illustrated in Figure 17. Although this run achieved the theoretical minimum elbow count, the individual was completely non-viable. Due to the complete lack of geometric flexibility and poor alignment with the support span limits, the peak dynamic stress at the location indicated by the red marker in Figure 17 reached a critically high, structurally catastrophic value, triggering immediate selection rejection. This cross-objective comparison confirms that the balanced solution achieved in Figure 14(b) represents the most stable, reliable, and practical layout topology for realistic industrial operations.

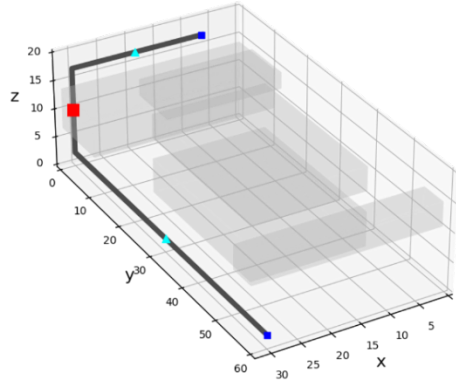


Figure 17: 3D piping routing layout synthesized by minimizing exclusively the bend number objective function f_B , resulting in severe structural stress concentrations due to inadequate geometric flexibility.

6.5. Computational Performance and Algorithmic Scalability

The practical viability of any automated optimization framework in industrial plant engineering is directly constrained by its overall computational overhead. The numerical performance results indicate that the hierarchical MOGA-A* hybrid strategy is highly efficient and scalable for real-time design support. The complete optimization run—encompassing spatial synthesis, A* path repair, support allocation, and finite-element modal evaluation of 10,000 unique layout candidates (100 individuals across 100 generations)—was completed in exactly 46 minutes and 19 seconds. This performance averages to approximately 0.28 seconds per individual layout evaluation.

This high computational speed was achieved by using linear-response spectrum modal analysis as a physics-informed surrogate model instead of performing full nonlinear transient finite-element simulations. While a single non-linear time-history FEM run across a complex multi-bend pipeline routinely requires several minutes to solve, the modal superposition approach used herein successfully captures the essential mass participation,

global stiffness matrices, and natural frequency spectra required to accurately rank candidate safety profiles within a fraction of a second. In a conventional industrial design workflow, a routing task of this geometric and structural complexity requires weeks of iterative, manual data exchange between CAD layout designers and structural stress analysts. By completely automating the "Generate-Repair-Evaluate" cycle, the proposed framework compresses the total design lead time to under an hour, enabling rapid, multi-criteria scenario analysis.

6.6. Summary of Engineering Implications

The findings of this research indicate that the hybrid MOGA-A* strategy establishes a systematic, deterministic methodology for critical infrastructure piping design. By modeling the spatial routing trajectory as an evolving sequence of coordinates that dynamically adapts to structural feedback, the framework moves beyond simple geometric collision avoidance toward a true physics-informed automated design paradigm.

The algorithm's capacity to autonomously discover that a longer, more tortuous route can significantly improve global structural safety margins by serving as a flexible expansion loop has direct implications for high-safety-tier nuclear and chemical facility engineering. It ensures that dynamic seismic resilience is embedded directly into the pipeline's macro-geometry from the initial conceptual design phase, rather than being treated as a reactive, expensive remediation step that involves the secondary addition of heavy snubbers, spring hangers, or massive structural steel supports. Ultimately, the framework demonstrates that partitioning optimization tasks into hierarchical layers—delegating deterministic constraints to pathfinding heuristics and multi-objective trade-offs

to evolutionary selection—is an exceptionally powerful methodology for resolving high-dimensional engineering problems in congested 3D environments.

7. Conclusion

This study established a physics-informed automated 3D piping routing framework by hierarchically coupling the deterministic pathfinding capabilities of the A* algorithm with the global multi-objective exploration of the NSGA-II metaheuristic. The framework concurrently optimized piping length, bend frequency, and peak equivalent seismic stress derived via linear response spectrum modal analysis, while embedding spatial obstacle interference as a strict step-barrier penalty function. The quantitative and qualitative validation of this hybrid system within a congested 3D benchmark space modeled after the Onagawa Nuclear Power Plant yielded the following core engineering conclusions:

- **Complete Population Feasibility Preservation:** The integration of the local A* pathfinding routine as a segment-wise connector within the genetic pipeline guaranteed a 100% population feasibility rate across all generations. This hierarchical architecture successfully eliminated the chronic issue of invalid or disjointed path topologies during stochastic crossover and mutation operations, ensuring stable geometric convergence even within highly restricted design corridors.
- **Autonomous Synthesis of Seismic Flexibility Mechanisms:** The multi-objective optimization successfully mapped the non-linear trade-offs between material routing efficiency and dynamic structural safety margins. The framework autonomously discovered that a strategic increase in total piping length (from 98 m to 120 m) and

elbow count (from 7 to 11) could lower the peak equivalent seismic stress by 73.4% (from 957.15 MPa down to 254.42 MPa). This explicitly demonstrates that the algorithm can systematically synthesize non-intuitive flexible layouts that shift the system's fundamental natural frequency away from seismic resonance peaks.

- **High Computational Throughput via Surrogate Modeling:** Using lightweight response-spectrum modal analysis as a structural surrogate model enabled the framework to complete the generation, real-time repair, and physics-based evaluation of 10,000 unique design candidates in exactly 46 minutes and 19 seconds. This average evaluation rate of 0.28 seconds per individual confirms that the proposed framework is highly scalable for rapid, interactive industrial engineering deployment.

By embedding structural material characteristics and code-defined design stress limits (such as $P_{al} = 309$ MPa for STPT410 carbon steel) directly into the conceptual routing phase, the proposed framework compresses the traditional, fragmented design cycle from weeks to under an hour. Furthermore, this geometry-based flexible layout strategy effectively minimizes the project's reliance on expensive, reactive secondary mitigation hardware, such as heavy seismic snubbers, spring hangers, or rigid structural bracing networks.

The technical scope of this methodology is bounded by several mathematical simplifications that establish explicit directions for future investigations:

1. **Algorithmic Robustness and Stochastic Verification (Part II):** The spatial routing configurations and dynamic stress reductions captured in these macro-computational profiles require extensive validation of algorithmic robustness. Part II of this co-

authored investigation will focus exclusively on the statistical reproducibility, trial-to-trial reliability, and initial-value dependency of the hierarchical optimization framework, building directly upon the preliminary numerical assessments to establish a mathematically rigorous verification protocol for the synthesized design spaces.

2. **Advanced Boundary Condition Modeling:** The automated support allocation routine used in this work assumed idealized, rigid translational constraints. Subsequent iterations must incorporate complex, non-linear boundary constraints, including pipe-support friction coefficients, physical structural gaps, and the localized flexibility matrices of equipment nozzles.
3. **Multi-Physics Fitness Integration:** While the current total evaluation index F isolates seismic stress, piping length, and elbow counts, future framework expansions will integrate thermal expansion loading states, internal fluid-induced pressure drops, and strict maintenance access envelopes into a unified, multi-physics optimization environment.

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DECLARATION ON THE USE OF ARTIFICIAL INTELLIGENCE (AI) TOOLS

The authors utilized the Gemini large language model (Google LLC) and Grammarly

(Grammarly, Inc.), accessed via a web browser environment in June 2026, exclusively for language editing, structural refinement, and text readability improvements. No substantive research content, data, or conclusions were generated by these tools. The authors verified all outputs and assumed full responsibility for the paper's technical integrity.

COPYRIGHT STATEMENT

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CONFLICT 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.

DATA AVAILABILITY STATEMENT

The primary data supporting the engineering findings of this study are available within the article. The raw datasets generated and analyzed during the evolutionary optimization process are available from the corresponding author upon reasonable request.

NOMENCLATURE

a_i	Spectral acceleration for the i -th mode, m/s^2
B_1, B_2	Standardized primary code stress coefficients for straight sections and elbows
$\mathbb{C}$	Spatial coordinate vector representing the layout chromosome
D	Outer diameter of the piping system, m
E	Young's modulus of the piping material, Pa
F	Overarching total evaluation index / objective function
f_0	Reference target dynamic cutoff frequency, Hz
f_B	Evaluation index of bend number
f_L	Evaluation index of piping length
f_S	Evaluation index of seismic resistance
g	Acceleration of gravity, m/s^2
I	Sectional second moment of area m^4
k	Total number of intermediate midway points within a chromosome
$[K]$	Global structural stiffness matrix, N/m
l	Cumulative physical length of the synthesized piping layout, m
l_i	Physical length of the i -th individual straight pipe segment, m
$l_{\min}$	Minimum theoretical orthogonal distance based on 3D Manhattan distance, m
l_{span}	Maximum allowable theoretical support span determined via frequency span method, m
L_x, L_y, L_z	Global dimensional boundaries of the rectangular plant search space, m
M	Total resultant dynamic seismic moment vector, $\text{N}\cdot\text{m}$
$[M]$	Global finite-element structural mass matrix, kg

M_i	Modal seismic bending moment vector for the i -th individual eigenmode, N·m
M_j	Total resultant seismic moment at node coordinate j , N·m
M_x, M_y, M_z	Directional synthesized seismic moment vectors along coordinate axes, N·m
n_b	Total number of 90-degree elbows present in the synthesized layout
$n_{b,min}$	Theoretical minimum number of bends required to clear spatial obstructions
P	Internal operating pressure of the pipeline, Pa
P_{al}	Code-defined design allowable seismic stress threshold, Pa
P_o	Penalty function of obstacle interference
P_{start}, P_{end}	Fixed Cartesian coordinates of the start and end equipment nozzle terminals
$P_{w,i}$	Spatial Cartesian coordinates of the i -th evolving intermediate midway point
S_j	Total generated code-equivalent stress calculated at specific node coordinate j , Pa
S_m	Design stress intensity ceiling parameter specified by structural codes, Pa
S_u	Ultimate tensile strength of the structural material, Pa
S_y	Minimum yield point of the structural material, Pa
t	Nominal wall thickness of the pipe section, m
$\{u\}_i$	Structural eigenmode vector associated with the i -th natural frequency
w	Aggregate structural weight distributed per unit length of the pipeline, N/m
w_x, w_y, w_z	Orthogonal spatial width dimensions of rectangular obstacle blocks, m
X_i	Dimensional displacement response vector computed for the i -th mode, m
x_s, y_s, z_s	Individual Cartesian components of the start nozzle terminal, m

x_e, y_e, z_e Individual Cartesian components of the end nozzle terminal, m

Z Sectional modulus of the piping configuration, m³

Greek Characters

β_i Modal participation factor derived for the i -th natural frequency

ω_i Natural angular frequency computed for the i -th structural mode, rad/s

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Figure Caption List

- Figure 1: Schematic representation of the piping length calculation, illustrating the relation between the synthesized path length l and the baseline minimum orthogonal distance l_{min} .
- Figure 2: Schematic flowchart of the overarching MOGA-A* hybrid layout optimization framework, delineating the iterative loop between deterministic segment-wise path generation and multi-objective evolutionary selection.
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Figure 16: 3D piping routing layout synthesized by minimizing the piping length index fL , illustrating the rigid, linear trajectory that violates seismic safety ceilings.

Figure 17: 3D piping routing layout synthesized by minimizing exclusively the bend number objective function fB , resulting in severe structural stress concentrations due to inadequate geometric flexibility.

Table Caption List

Table 1: Center coordinates and width of obstacles (unit: m)

Table 2: Mechanical Properties of STPT410

Table 3: GA Configuration Parameters

Table 4 Comparative evaluation and structural dataset of the elite individuals in
Generation 3 and Generation 4