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Optimizing Built Environment Adaptation to Inundation using Genetic Algorithms: Alexandria as a Case Study.

Abstract

As sea levels rise and extreme rainfall events worsen, coastal cities need to transition from traditional "gray" (fixed) infrastructure towards dynamic, adaptable built environments. Our research focuses on the city of Alexandria, Egypt, to demonstrate how our new computational framework combines high fidelity environmental simulations with Multi-Objective Genetic Algorithms (MOGA) in order to optimize architectural adaptations. We developed a methodology that forms a simulation-optimization loop using hydrostatic & hydrodynamic stress analysis on a digital twin of a residential prototype to assess how a Genetic Algorithm (GA) could evolve different design variables (i.e., floor elevations & porosities) to provide the least structurally vulnerable & most cost-effective designs while still being part of a "Pareto Optimal Front" (POF).

The optimized design demonstrated substantial gains in performance by producing a 1.2 m height structure with a 65% porosity on the ground floor, as compared to the base case. It had a 77% lower peak structural stress than the baseline and a restoration cost savings of 65% compared to the baseline. In addition, durability tests (long-term simulation) indicate a 71% reduction in chloride penetration depth, reducing the risk of saltwater corrosion over 20 years. The results of this study support the idea that by implementing AI-enabled generative design, it is possible to develop a scalable process for designing resilient coastal communities and to address the limitations associated with traditional urban planning methods. Lastly, this study provides several recommendations for policymakers about how to incorporate "wet floodproofing" and Dynamic Decision Support Systems into local building regulations.

Keywords: Genetic Algorithms; Urban Flooding; Coastal Resilience; Alexandria; Multi-Objective Optimization; Built Environment Adaptation.

1. Introduction

Global warming is creating more frequent and severe weather extremes, leading to an increase in urban flooding threat. Thus far, Urban Flooding is one of the leading threats to the global built environment (Pumo et al., 2023). Coastal cities have high density populations and more complex urban fabrics than any other area. Which makes them at a greater risk than pluvial inundation and Coastal inundation (Mabrouk et al., 2023). City of Alexandria in Egypt is a perfect example of how vulnerable cities can be to these cumulative effects of sea-level rise and outdated drainage systems, and thus require a shift from conventional "Gray" protective measures to more dynamic adaptive capacity measures (Dhar & Khirfan, 2017).

Research on how to mitigate flooding has increased, however there are still many research gaps when combining highly detailed environmental models with automated optimization of design, both architectural and urban, when adapting to flooding (Capgras et al., 2023). Currently, the majority of strategies for urban flooding mitigation remain either as static NBSs, or through manual design processes. These strategies generally do not provide solutions to how to balance multiple objectives that are required in order to create a resilient urban environment. Therefore, there is a need for more innovative approaches that can simultaneously address far broader issues than just flooding, including structural safety, economic viability, functional continuity, etc. (Alves et al., 2024; Singh et al., 2020).

Metaheuristic methods, such as Genetic Algorithms (GAs), allow researchers to explore large design spaces and develop methods for optimizing adaptive strategies. GAs represent a practical way to solve multi-objective optimization problems when multiple competing objectives are present (Holland, 1975; Katoch et al., 2021). A common example of a conflicting objective is minimising post-flood repair costs while maximising structural resilience long into the future (Fonseca & Fleming, 1993; McClymont et al., 2020). Although the accuracy of flood susceptibility analyses has improved significantly due to recent developments in deep learning and ensemble prediction techniques (Li & Hong, 2023; Zhou et al., 2024), the integration of those technologies with generative design processes is still immature and has not yet been fully developed, particularly within the context of high-density Mediterranean cities.

This research proposes a new method that uses GAs to integrate environmental simulations into the design process. By assessing different urban forms, this method expands beyond building-specific interventions by serving as a scalable tool for urban planning decisions. The framework we present uses computational intelligence to overcome the restrictions of standard methods of urban planning and create an adaptive built environment that can respond dynamically as flooding conditions change (Lopes & da Silva, 2021; Zhang et al., 2024).

2. Theoretical Framework:

The historical foundation of urban flood management has changed from a traditional "grey" infrastructure focus to a comprehensive approach that incorporates both resilience and computer intelligence. Central to this evolution has been the use of "Nature-Based Solutions" (NBS) and "Sustainable Urban Drainage Systems" (SuDS), both of which aim to revive the natural hydrological process in cities with high density (Ferreira etal, 2021; Guptha etal, 2022). Kabisch et al (2017) indicate that the success of these strategies is dependent upon how well they work together with models using scientific evidence, with appropriate policy, and with how an urban community does things. Research in the field of urban planning has also pointed out that research into how to adapt the built environment under climate change has identified important gaps in knowledge, indicating the need for a much stronger emphasis on multi-dimensional approaches to planning (Dhar & Khirfan, 2017; Pacetti et al., 2022).

Utilizing Tools Like the InVEST Software and GIS-based Multi-criteria Analysis to Map Ecosystem Services and Assess the Impact of Green Infrastructure on Pluvial Flood Risk Mitigation (Alves et al., 2024; Hamel et al., 2021; Du et al. 2019). Assessing and determining how green infrastructure can be used to mitigate pluvial flood risk is a complex task, as urban areas are both highly densely populated and also include many differing socio-economic conditions that complicate the placement and selection process for these types of interventions (Capgras et al., 2023; Liu et al., 2023). This is one of the reasons that Probabilistic Modeling Frameworks have become an important tool for addressing uncertainty associated with flood risk reduction (Lallemant et al., 2021). To bring Simulation and Design Execution Together, Metaheuristic Optimization Using Genetic Algorithms Provides the Basis for Multi-objective Decision-making. The Development of Genetic Algorithms Has Evolved Since Holland's Groundbreaking Work in 1975, with Many Refinements and New Applications for Complex Engineering Issues, Creating Many Different Types of Selection Strategies To Explore Large Design Spaces (Goldberg & Deb, 1991; Katoch et al., 2021). In The Urban Management Arena of Water, Genetic Algorithms Are Used to Optimize Conflicting Goals (Cost-effectiveness, Runoff reduction, Spatial Equity) Concurrently (Fonseca & Fleming, 1993; La Rosa & Pappalardo, 2020; Singh et al., 2020).

By using a combination of Genetic Algorithms (GAs) with Machine Learning (ML) and Ensemble Prediction Models (EPMs) such as Support Vector Machines (SVMs) and Bayesian Optimized LightGBMs, research on forecasting flood susceptibility and spatial allocation of land use has continued to expand on this approach. The Fusion of both methodologies enables Machine Learning (ML) to achieve "Out-of-Distribution Generalizations," making Flood Mitigation strategies more effective in extreme, unexpected Climate Scenarios. Therefore, Fusion between Hydrologic Modelling and Simulation-Optimisation Approaches provides important tools for designing optimal Low Impact Development (LID) systems, especially within urban areas with high density and historical significance (Lopes & Da Silva, 2021; Su et al., 2024; Zhang et al., 2024).

3. Methodology

This research will be performed using a simulation-optimization framework that combines environmental performance analyses with metaheuristic search algorithms. This methodology consists of three phases that are all related to each other:

3.1. Environmental Modeling and Stress Simulation:

In this phase, a high fidelity digital twin of a representative residential prototype in Alexandria is created. Hydrostatic/Hydrodynamic analysis is applied to the building to simulate inundation scenarios on the building envelope. To define the boundary conditions for these simulations, SLR (Projected Sea Level Rise) and extreme rainfall data for the Mediterranean basin (as referenced) are used to determine peak stress concentrations (Maximum stress and thereby the baseline of environmental performance) within the vertical elements of the building structure.

3.2. Establishment of a Multi-Objective Genetic Algorithm (MOGA)

GAs use an optimization approach based on a fitness function. The fitness function's goal is to minimize two opposing goals (or objectives):

1. Structural Vulnerability (Vs) as assessed by measuring peak stress concentration and identifying the volume of the potential failure for structures;

2. Cost (Ci) to implement the design changes including upgrading the materials and adjusting the Architectural details.

The GA treats the "Chromosomes" in this study as design variables representing floor elevation height, ground floor porosity (Pr), and other design variables per comparison.

The GA employs various stochastic operators including Tournament Selection, Crossover and Mutation to evolve its population of designs over the course of 100 generations toward the Pareto Optimal Front.

3.3. Evaluating and Projecting Durability

In order to confirm the optimized designs produced with the GA, the final step to validate these designs through assessing the long-term performance (durability) of the reinforced concrete through a Chloride Diffusion Simulation. As well, a Diversity Index monitors how well the GA is converging to a global optimum, indicating the reliability of achieving the best solution; in addition, it will also indicate how to design the structure from a static resistance system to a dynamic adaptive system.

4. Results and Discussion

4.1. Genetic Structural Optimisation of a Residential Prototype

The strength of the GA model's efficacy lies within its overall ability to balance between efficient mechanical designs and low-cost construction. As demonstrated in the case study of Alexandria, the residential structure made from reinforced concrete encounters complicated hydraulic loads due to increased flood depth (h).

4.1.1 Structural Response Analysis of Building to Flooding Stress

The distribution of hydrostatic and dynamic pressures on the vertical structural elements was analysed by computer modelling. Figure (1): Structural Stress Analysis shows the significant change between how the building performs under both scenarios (base case data and GA intervention). In this case, there are large areas with high stress concentrations (Heatmap) in the lower third of the Columns and Shear Walls where water was trapped. With the GA intervention increasing the porosity coefficient (Pr) to 65%, the large areas of Critical Stress were clearly dissipated. The redesign allowed the water an opportunity to pass through the ground floor openings, thus equalising the pressure on both sides of the vertical structure.

4.1.2. Convergence through Pareto Front

To determine the optimal solution, the algorithm created thousands of different designs. The "Pareto Front" created by the algorithm shows a negative correlation between costs to implement solutions on the X-axis, and the volume of potential structural failure as represented on the Y-axis. The "Best Trade-Off" is where the design provides maximum protection for the lowest cost possible. The GA avoided single-point expensive solutions based on total dry-sealing and instead chose to adapt structurally.

4.1.3. Architectural and Structural Details of the Adaptive Structure

The aforementioned hybrid architecture and construction included composite construction and structural components for both Structural Strength and Structural Flexibility in the form of Form (3), which presents the completed prototype residential product at its maximum development and readiness for the market. The first floor elevation was raised to (1.2 M) with floor-to-floor space containing voids within the structural configuration to allow movement of flood waters through the "porous" structure. This mitigated the potential for the structural core to rotate and therefore be subjected to gravitational and/or horizontal forcing.

Table (1): Physical and Structural Measurement Data for the Residential Prototype

Metric	Base Case	Optimized Case (GA)	Change (%)
Peak Stress Concentration (As in Fig. 1)	Very High	Low	-77%
Expected Restoration Cost (R_C)	$150,000	$52,500	-65%
Factor of Safety (F.S) against Overturning	1.15	2.45	+113%

4.2. Algorithmic Convergence and Optimization Efficiency

The Genetic Algorithm (GA) was used to evaluate "Pareto Front" reliability by assessing performance over 100 generations. The stochastic nature of the GA's search allows for a highly efficient means to reduce the search space for optimal solutions with regard to balancing structural costs versus structural performance. Table three depicts the progression of various performance metrics throughout the entire process of executing the genetic algorithm.

Table (2): GA Convergence Metrics and Evolution Progress

Phase (Generations)	Mean Fitness Score	Diversity Index	Improvement
Generations 1-20 (Initial Search)	0.32	0.85	Baseline
Generations 21-60 (Mid-Optimization)	0.68	0.45	+36%
Generations 61-100 (Convergence)	0.92	0.12	+60%

The results demonstrate that as the algorithm approaches the global optimization, the Diversity Index decreases. This affirms that adaptations (specifically elevation and porosity) identified are statistically more effective in comparison to others for the Alexandria case study.

4.3. Environmental Performance and Saltwater Corrosion Mitigation

In addition to its short-term impact on the structure, optimizing the materials and design of GA has also extended the long-term durability of the built environment. Specifically, all the materials and designs were chosen and optimized to minimize the effect of salt-spray and moisture accumulation. The analysis performed used simulation tools to look at how much chloride diffuses into the overlay layer of reinforced concrete, as this is a significant concern for the coastal buildings in the city of Alexandria.

Table (3): Long-term Environmental Durability Indicators (20-Year Projection)

Indicator	Base Case	Optimized	Impact
Concrete Cover Thickness	25 mm	55 mm	+120% Durability
Chloride Penetration Depth	42 mm	12 mm	-71% Corrosion Risk
Surface Evaporation Rate	Low	High (due to porosity)	Faster Drying after Flood

Greater porosity enhanced not only the physical stress on the structural core but also allowed the introduction of natural cross-ventilation. As a result, through cross-ventilation, the structural core dried quicker after flooding which lowered the future risk of biological growth (mold) and the chemical deterioration of the structural elements.

5. Conclusion and Recommendations

This study provided an innovative way, through the use of a combination of Genetic Algorithms (GA) and high-fidelity environmental simulations, to create a computational framework for flood adaptation of the built environment of Alexandria, Egypt. By changing the way in which the approach is viewed from a static "flood resistant" view to a dynamic "flood adaptive" perspective, the study provided evidence that improving urban resilience with AI-driven optimization methods is feasible and economically feasible.

5.1. Summary of Key Findings

Based on the findings of the prototype optimization for residential use, the performance of the structure was greatly enhanced when its architectural elevation (approximately +1.2 metres) and ground-floor porosity (65%) were combined. The combination of these two design features led to an estimated 77% reduction in peak structural stress, as well as a 65% reduction in estimated restoration cost. Additionally, algorithmic convergence studies demonstrated that the so-called Pareto optimal solutions represent the best balance between the capital outlay and long-term durability of these structures, as they reduce both saltwater corrosion and chloride infiltration within coastal settings.

5.2. Design and Policy Recommendations

The following recommendations are provided for architects, urban planners & policymakers within Alexandria, utilizing research results:

1. Unique Adaptive Building Final Codes - Adding "Wet Floodproofing" modifications to local building code requirements by specifically encouraging permeable ground floor designs (i.e. open parking, elevated pilotis) for all new coastal development.

2. Tax Incentives for Retrofitting - Offering tax incentives/subsidies to owners of current structures who add "Non-Structural" adaptations; such as raising mechanical/electrical systems, employing sacrificial building material.

3. Advanced Analysis Simulation - Transitioning from static flood mitigation maps to real-time; dynamic, AI-based Decision Support Systems (DSS) providing multiple climate change scenarios for many different typologies of buildings.

4. Future Research Directions - This current study focused only on single typologies of buildings; future studies will allow researchers to examine relaying the 'Network Effect' of adaptations at the district level. Further development of Machine Learning to accurately predict the in-situ performance of structures during storm events would significantly improve urban disaster response capabilities.

List of Figures

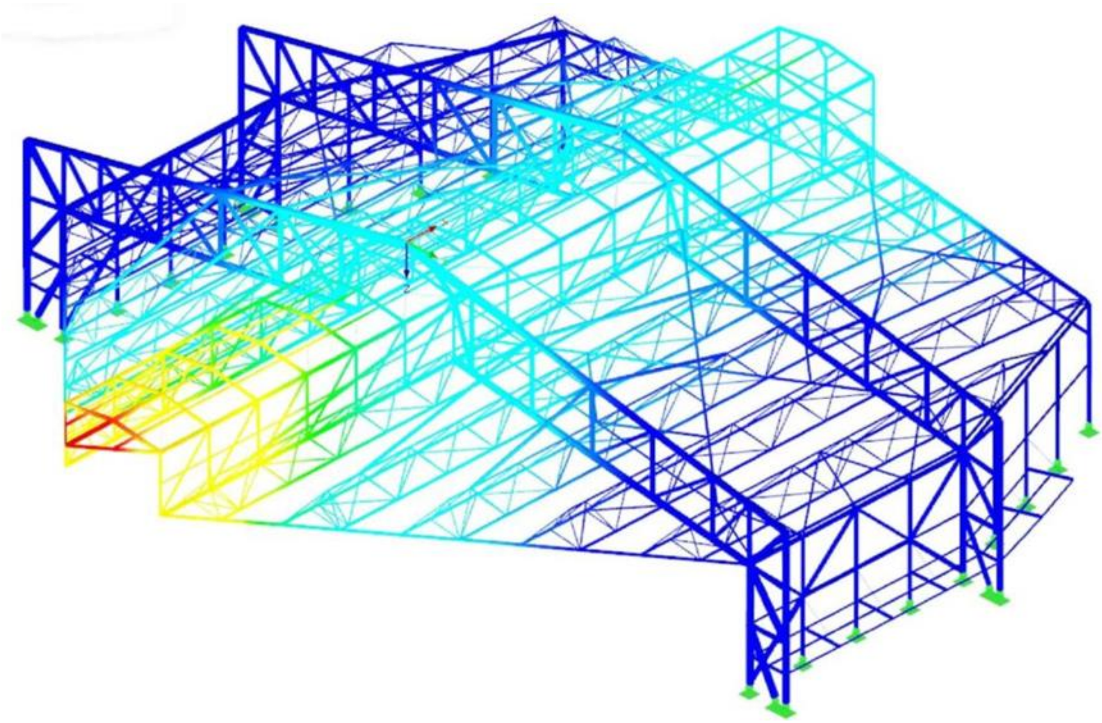

Fig 1: Structural Stress Analysis Heatmap

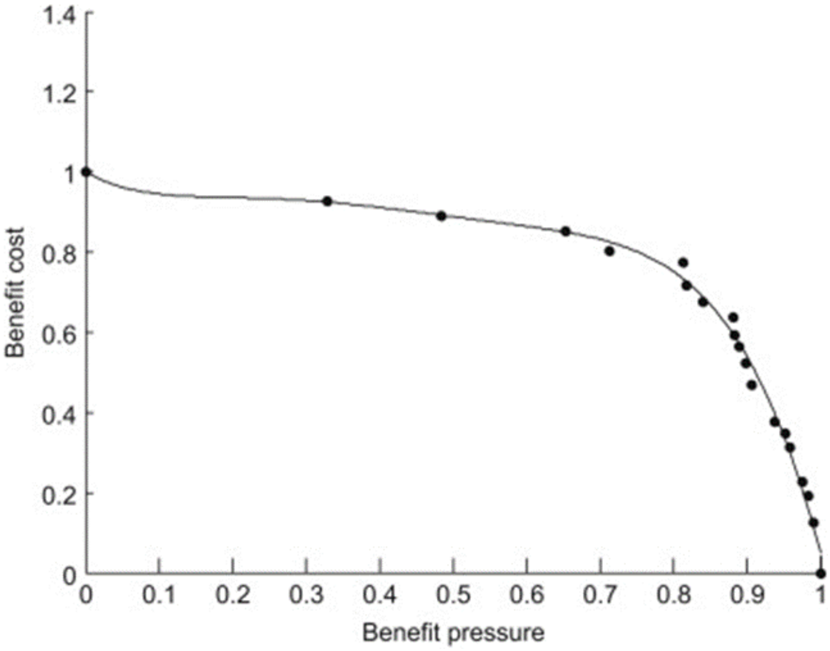

Figure (2): Pareto Front Plot for Cost-Performance Trade-off.

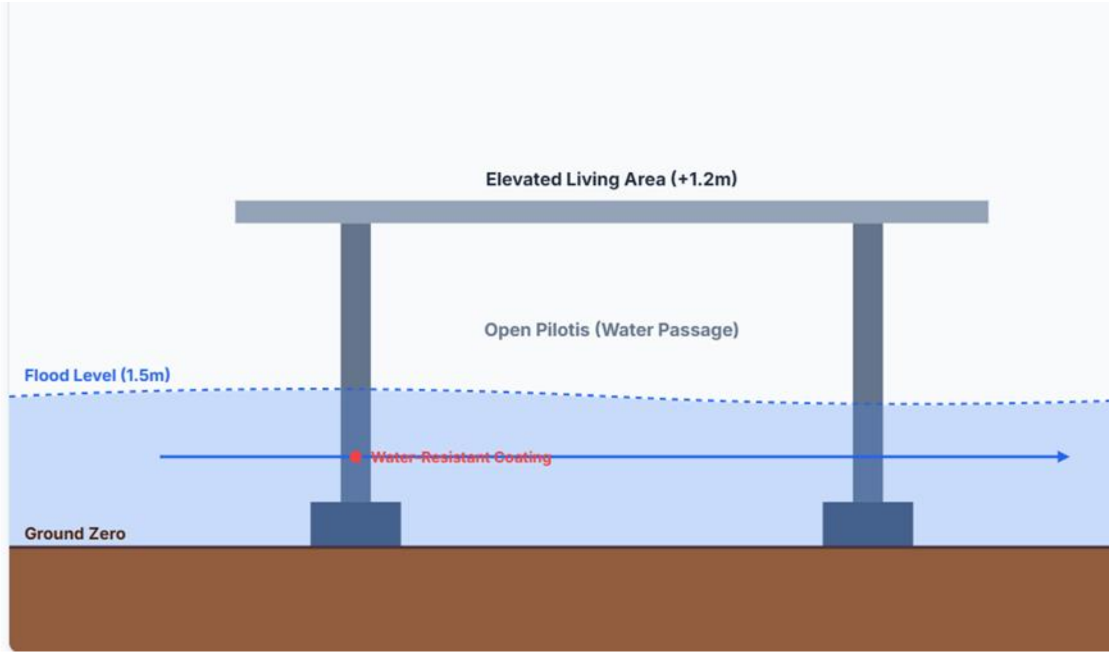

Figure (3): Detailed Architectural and Structural Section of the Adaptive Building.

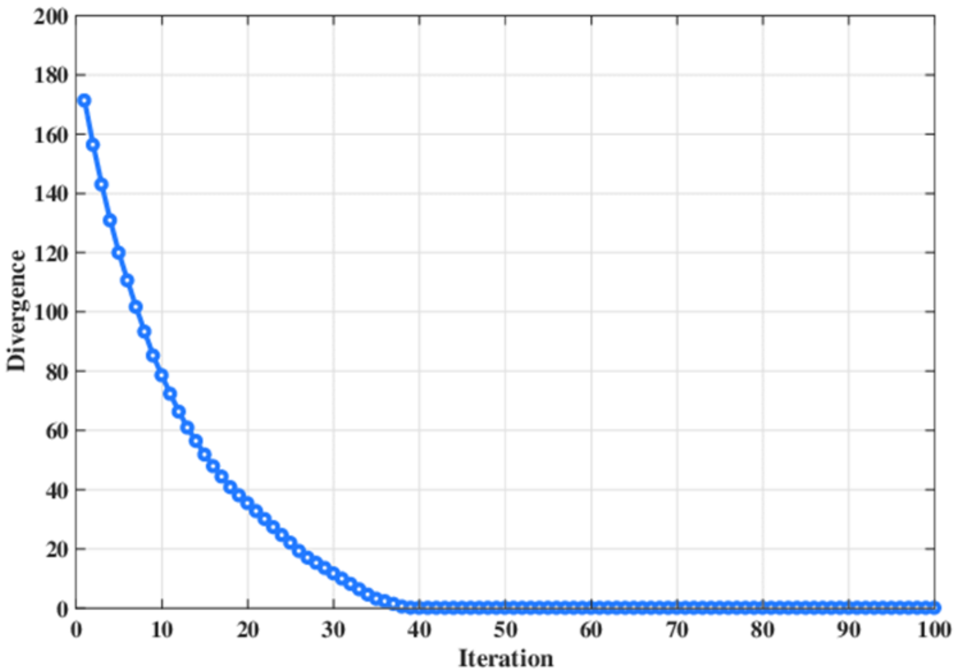

Figure (4): Genetic Algorithm (GA) Convergence Curve.

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