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A METHOD FOR AI-DRIVEN OPTIMIZATION OF FUNCTIONAL ZONING IN EDUCATIONAL DEVELOPMENT PROJECTS

Abstract. *Traditional management of educational development projects relies heavily on a subjective, experience-based approach to spatial planning, which leads to a limited exploration of design alternatives and a weak connection between initial decisions and long-term lifecycle performance. This linear process lacks a methodical toolkit for navigating the complex trade-offs between cost, functionality, and future adaptability under conditions of high uncertainty. To address these limitations, this study develops and proposes a method for the AI-optimization of functional zoning in educational development projects. This method is based on a structured framework that integrates a Genetic Algorithm with a Multi-Criteria Decision Analysis (MCDA) model by formalizing stakeholder requirements into a set of mathematically verified and comparable project scenarios. The core of the developed method is a formalized algorithmic process that functions as a generative decision support system. The process begins with the digitization of project constraints, including building codes, budget limits, and a weighted adjacency graph representing the topological requirements between functional zones. The generative engine then initializes a population of random layouts and iteratively refines them through the genetic operators of selection, crossover, and mutation. The fitness of each candidate is evaluated using an objective function vector that simultaneously optimizes three conflicting criteria: (1) minimization of Lifecycle Cost (LCC), which includes both capital and operational expenditures; (2) maximization of Functional Utility, measured through student flow efficiency and adjacency compliance; and (3) maximization of Adaptability, assessed by the layout's modularity and potential for future expansion. The output of the method is not a single solution but a Pareto set, which presents a collection of non-dominated solutions for managerial analysis. The proposed method for AI-optimization of functional zoning marks a paradigm shift from conventional, reactive project management to a proactive, predictive approach. It is anticipated that this method will enhance the effectiveness of decision-making during the pre-investment phase of a development project and provide managers with a reliable, evidence-based foundation for selecting the optimal configuration. The practical significance of the method lies in the generation of a Pareto set, which enables stakeholders to make informed and defensible trade-off decisions among financial, pedagogical, and strategic goals. This enhances the project's digital resilience, minimizes the risks of scope creep and functional obsolescence, and ultimately ensures that the capital investment creates a sustainable, efficient, and adaptive educational asset.*

Keywords: project management; decision support system; genetic algorithm; multi-objective optimization; generative design; space layout planning; educational environments

Introduction

The increasing complexity of modern development projects, characterized by intricate design constraints and the need for high functional efficiency, has exposed the limitations of traditional planning methods. Historically, architectural space layout planning relied heavily on the intuition and experience of designers, a process often criticized for its subjectivity and inability to manage non-linear variables effectively. A bibliometric analysis of the field reveals a significant paradigm shift towards the integration of Artificial Intelligence (AI). Zhang and Yu classify this evolution into three distinct methodological categories: optimization-based, generative, and interactive approaches. Their research highlights that while generative methods, such as Generative Adversarial Networks (GANs), offer novel creative possibilities, optimization algorithms are crucial for enhancing quantifiable performance metrics, marking a transition from experience-based to data-driven design decision-making [1].

This algorithmic approach allows for the transformation of abstract planning problems into mathematical optimization functions. For instance, in the related domain of urban infrastructure, Liu demonstrates the efficacy of combining K-means clustering with improved Genetic Algorithms (GA) to optimize spatial layouts. By treating the layout problem as an objective function based on supply-demand accessibility, this method proves that algorithmic solutions can significantly outperform traditional qualitative analysis in achieving spatial equity and resource efficiency [2]. Such mathematical modeling provides a robust framework for balancing cost, distance, and utility, which is directly applicable to the functional zoning of complex environments.

Furthermore, effective spatial planning extends beyond static geometry to include the dynamic behaviors of the environment's users. Xu et al. emphasize the importance of integrating crowd simulation and psychological factors into the layout planning process. In their study on healthcare facilities, they developed a «Low-Trust Social Force Model» to simulate pedestrian dynamics and infection risks, subsequently using these insights to optimize the spatial configuration. This underscores that a comprehensive AI-optimization method must not only arrange physical spaces but also predict and accommodate the complex flows and psychological needs of the occupants, thereby reducing congestion and enhancing operational safety [3].

In the broader context of construction project management, the integration of AI is evolving into sophisticated Decision Support Systems (DSS). Smith and Wong provide a systematic review indicating that while early-stage project prediction dominates the field, there is a notable upward trend in using AI for design optimization and sustainability assessment. Their analysis highlights a critical shift in project success criteria: moving beyond the traditional «iron triangle» of cost, time, and quality to include broader economic, environmental, and social sustainability goals. This necessitates the use of hybrid AI models capable of handling complex, multi-dimensional data during the pre-construction phase, specifically to support decision-making in environments with high uncertainty [4].

Addressing the technical implementation of such systems, Nisztuk and Myszkowski propose a functional computational tool (ELISi) based on a Hybrid Evolutionary Algorithm (HEA). Their work demonstrates how the Automated Floor Plan Generation (AFPG) problem can be treated as a multi-objective optimization task. By utilizing non-sorting genetic algorithms (NSGA-II), they illustrate that it is possible to generate a Pareto front of solutions that balance conflicting design constraints such as topology, room adjacency, and compactness. This approach shifts the paradigm from manual drafting to selecting from a range of mathematically optimized trade-offs, allowing the project manager to evaluate the «fitness» of a layout against specific project goals [5].

However, the successful adoption of these algorithmic tools depends heavily on their alignment with professional workflows and stakeholder expectations. Nisztuk, Kościuk, and Myszkowski conducted an extensive survey of practitioners to define the guidelines for AFPG software. Their findings reveal a strong preference for tools that support the conceptual phase without limiting the architect's control, emphasizing that optimization criteria must be customizable (e.g., room connectivity, evacuation routes, and solar orientation). Crucially, they identify acceptable computational timeframes relative to project complexity, providing a benchmark for the non-functional requirements (NFRs) of any proposed AI-based management tool. This highlights that for an AI method to be viable in a development project, it must act as an intelligent assistant that respects the iterative nature of the design process rather than a «black box» generator [6].

Beyond the internal configuration of a single building, the effectiveness of educational infrastructure management is increasingly dependent on spatial analysis at the urban scale. Chen et al. utilized Point of Interest (POI) data and Geographic Information Systems (GIS) to analyze the distribution of educational facilities in the Greater Bay Area. Their study reveals significant regional disparities, where facility density is highly correlated with population size and economic development, following a «multi-center clustering» pattern. This underscores that for a project management methodology to be truly effective, it must incorporate geospatial data to address macro-level imbalances and ensure equitable resource allocation across diverse urban landscapes [7].

However, optimizing for spatial distribution and functional layout is insufficient without considering the long-term environmental impact. The integration of Life Cycle Assessment (LCA) into the early stages of Space Layout Planning (SLP) is becoming a pivotal requirement for sustainable development. Sokhangoo et al. argue that specific design parameters such as module geometry, material selection, and prefabrication levels significantly influence the embodied carbon of modular buildings. By identifying these «influencing factors» early in the design phase, project managers can shift from reactive compliance to proactive carbon minimization. This dual focus on spatial efficiency and environmental sustainability represents a holistic approach to managing the development of educational environments [8].

Case studies in developing contexts further highlight the gap between theoretical sustainability criteria and actual implementation. Arsan's evaluation of a standard primary school project in Turkey demonstrates that rigid «type projects» often fail to adapt to local climatic and physical conditions, leading to poor energy performance and user comfort. This suggests that a one-size-fits-all approach in project management is detrimental to sustainability. Instead, a flexible, site-specific methodology that integrates ecological design criteria such as natural lighting, orientation, and renewable energy integration is essential for creating resilient educational buildings [9].

The successful implementation of AI-driven optimization in development projects is predicated on the existence of a robust digital ecosystem. Opara et al. argue that digital resilience in construction is not merely a technological goal but a strategic necessity achieved through the integration of Data Governance, Building Information Modelling (BIM), and Real-Time Decision Support Systems (RT-DSS). Their research emphasizes that without a structured governance framework to ensure data integrity and security, the application of advanced analytics remains fragmented and unreliable. Consequently, any proposed AI optimization method must be embedded within a «digital resilience» framework that facilitates continuous feedback loops and adaptive decision-making throughout the project lifecycle [10].

This central role of BIM as an integration platform is exemplified across various scales of project management. At the macro-level of urban planning, Honcharenko et al. demonstrate the necessity of a BIM-concept for the effective design of engineering networks. Their research highlights that early-stage integration of complex systems within a unified digital model is critical for ensuring the long-term functionality and sustainability of urban infrastructure [11]. Zooming into the micro-level of project execution, Dolhopolov et al. propose a multi-stage approach that leverages both AI and BIM technology for detailed construction site modeling. Their work shows that a well-structured digital model serves as the foundation for applying artificial intelligence to manage site logistics, monitor progress, and ensure compliance, thereby bridging the gap between design intent and physical realization [12]. Both studies underscore the principle that a robust, data-rich digital model is a prerequisite for intelligent project management, whether at the scale of a city or a single construction site.

However, the optimization of educational spaces cannot rely solely on generative algorithms; it must strictly adhere to physical and safety constraints. Hassan et al. highlight the critical importance of structural analysis in the design of primary school buildings, particularly in seismically active regions. Their comparative analysis of structural models reveals that the configuration of the floor plan specifically the arrangement of columns and beams directly impacts the building's lateral displacement and drift ratios. This suggests that an effective AI-based zoning method for educational facilities must incorporate structural performance metrics and safety codes (such as BNBC and ASCE) as fundamental constraints to ensure that the generated layouts are not only functionally efficient but also structurally resilient and cost-effective [13].

In the broader context of construction management, Intelligent Decision Support Systems (IDSS) are emerging as essential tools for handling «Big Data» and navigating complex project environments. Evstratov proposes a unified IDSS architecture that integrates data collection, mining, and predictive modeling layers. His work on monolithic construction demonstrates how multivariate regression models within an IDSS can evaluate the economic feasibility of resuming suspended projects by analyzing factors such as technical condition, weather impact, and resource availability. This highlights the capacity of intelligent systems to process multi-threaded data streams and support strategic decision-making in scenarios with high uncertainty [14].

However, the adoption of such AI-driven systems in professional practice is often hindered by the «black box» nature of complex algorithms. Love et al. argue that for AI to be truly effective in construction management, it must be explainable. They introduce a «means-end framework» for Explainable Artificial Intelligence (XAI), emphasizing that Decision Support Systems must provide «Meaningful Human Explanations» (MHEs). Their review indicates that simply generating an optimal layout is insufficient; the system must also provide evidence-based justifications such as feature importance or counterfactual scenarios to build trust and enable end-users (project managers) to validate the AI's recommendations against their professional judgment and domain knowledge [15].

Main Research

The traditional approach to managing development projects in the educational sector is characterized by a significant discontinuity between the definition of stakeholder requirements and the spatial materialization of these requirements. In conventional practice, the project manager operates with abstract constraints regarding budget, capacity, and functional zoning, while the architect translates these into a limited number of static layout alternatives based on heuristic experience. This linear process often leads to suboptimal decisions where the full impact of spatial configuration on the project's lifecycle cost and functional utility remains obscure until the detailed design or even operation phase. To address this structural inefficiency, this study proposes a formal method for iterative multi-objective optimization of the functional-spatial configuration of educational environments. The proposed method operates as a cybernetic decision support system that transforms unstructured or semi-structured project requirements into a set of mathematically verified implementation scenarios.

The fundamental logic of the proposed method is visualized in Figure 1, which illustrates the transformation of the project lifecycle from the initiation of requirements to the final managerial decision.

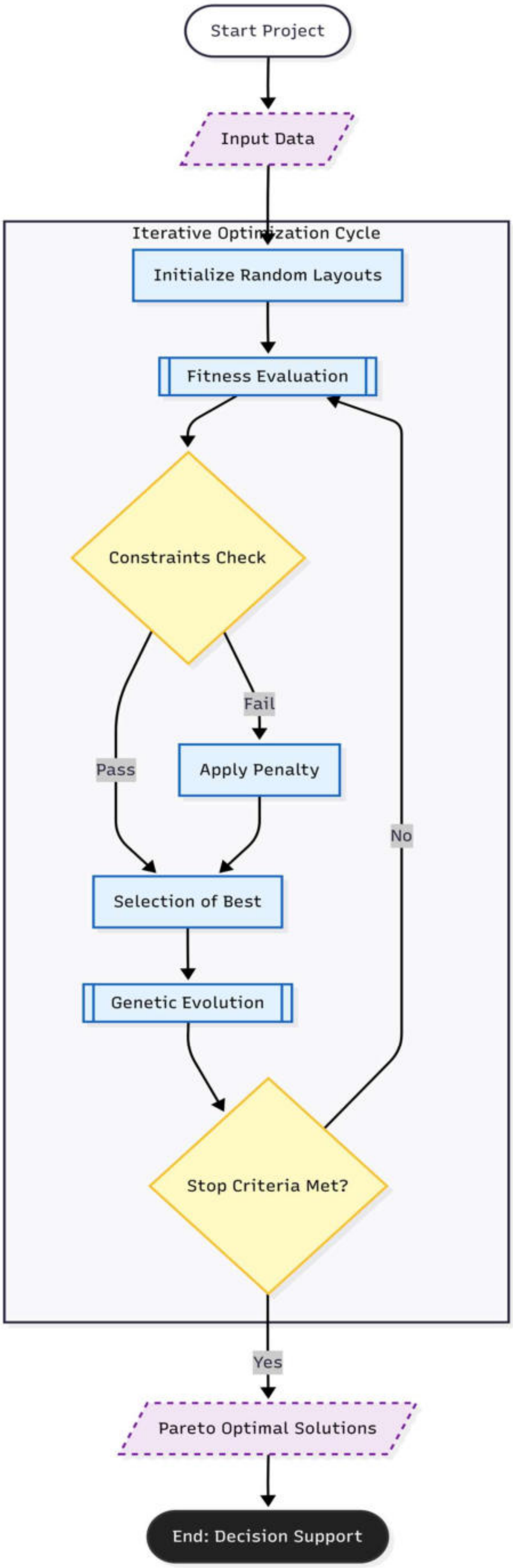

Figure 1 – Algorithmic Model of the Proposed Optimization Method

The framework is structurally divided into three distinct but interconnected cognitive spaces: the Problem Space, the Solution Space, and the Decision Space. In the Problem Space, the primary objective is the formalization of the project brief. Unlike traditional management, where requirements are often treated as static text-based directives, this method treats requirements as a dynamic set of mathematical constraints and input vectors.

The core transformation occurs within the Solution Space, where the generative engine operates. Instead of manually drafting a single solution, the system utilizes an evolutionary algorithm to explore the vast combinatorial landscape of possible spatial configurations. This generative phase does not aim to produce a single «correct» layout but rather to evolve a population of potential layouts that progressively adapt to the predefined fitness functions. The algorithmic logic ensures that every generated candidate is rigorously tested against the defined constraints, filtering out non-viable options before they consume managerial attention.

This process effectively shifts the project management focus from correcting errors in manual designs to defining the performance criteria that drive the automated generation of designs.

Finally, the Decision Space represents the interface between the computational output and the project manager's strategic judgment. The output of the optimization process is not a single master plan, but a Pareto Optimal Frontier – a set of trade-off solutions where no single objective can be improved without compromising another. This approach aligns with the principles of value engineering, as it forces the project manager to make explicit trade-offs between conflicting goals, such as capital expenditure versus operational efficiency or compactness versus functional flexibility. By presenting a range of optimized scenarios, the Decision Support System empowers the manager to select a configuration that best aligns with the specific strategic priorities of the educational institution, ensuring that the final approved master plan is both scientifically optimized and strategically valid.

The practical implementation of the proposed method requires a rigorous approach to data structuring, where the physical attributes of an educational facility are abstracted into computable units. The initial phase of the algorithm involves the decomposition of the project scope into a granular list of functional zones. Each zone is treated as an object with specific attributes, including required area, aspect ratio preferences, natural lighting requirements, and acoustic isolation needs. This object-oriented approach allows the project manager to manipulate the project scope at a parametric level. For instance, a change in the educational model from traditional classrooms to open-plan learning clusters does not require a manual redesign of the layout but simply an adjustment of the parameters within the input vector.

A critical component of the input architecture is the formalization of topological relationships between these functional zones. In educational projects, the efficiency of the facility is largely determined by the logical adjacency of related spaces. To quantify this, the method utilizes a weighted Adjacency Graph, where nodes represent rooms or zones, and edges represent the required strength of the connection between them. These connections are assigned numerical weights ranging from mandatory proximity, such as the link between a kitchen and a dining hall, to mandatory separation, such as the distance between a noisy gymnasium and a quiet library. This graph serves as the primary genotype for the generative algorithm, guiding the spatial arrangement process to minimize the weighted distance between interacting zones.

Furthermore, the input data structure incorporates a comprehensive set of financial and physical constraints. The budget constraint is not treated merely as a final cap on the cost but as a dynamic variable that influences the geometric compactness of the generated layouts. Similarly, the site boundaries are digitized into a polygon that acts as a hard geometric limit for the generative engine. Table 1 summarizes the classification of input parameters utilized by the system, categorizing them into geometric, topological, and economic variables. This structured data input ensures that the subsequent evolutionary process is grounded in the specific realities of the project context, preventing the generation of theoretically optimal but practically unfeasible solutions.

The central computational mechanism of the proposed method is built upon a non-dominated sorting genetic algorithm, specifically adapted for spatial topology optimization. The logic of this generative engine follows a cyclical evolutionary process, designed to mimic the principles of natural selection to iteratively improve the quality of spatial layouts. As illustrated in Figure 2, the workflow initiates with the generation of an initial population of random layouts. At this nascent stage, the system places functional zones within the defined site boundaries in a stochastic manner, ensuring only that they do not overlap physically. While these initial candidates are functionally rudimentary and likely suboptimal, they provide the necessary genetic diversity required for the subsequent evolutionary exploration of the solution space.

Once the initial population is established, the system enters the primary evolutionary optimization loop. This continuous cycle is the engine that drives the transition from chaos to order. The process begins with the evaluation of each candidate layout against the defined fitness functions, which quantify the performance of the design across multiple dimensions such as cost and utility. Crucially, before a layout is assigned a performance score, it must pass through a rigorous constraint verification module. As depicted in Figure 3, this module acts as a gatekeeper, checking each generated solution against hard constraints derived from building codes and safety regulations.

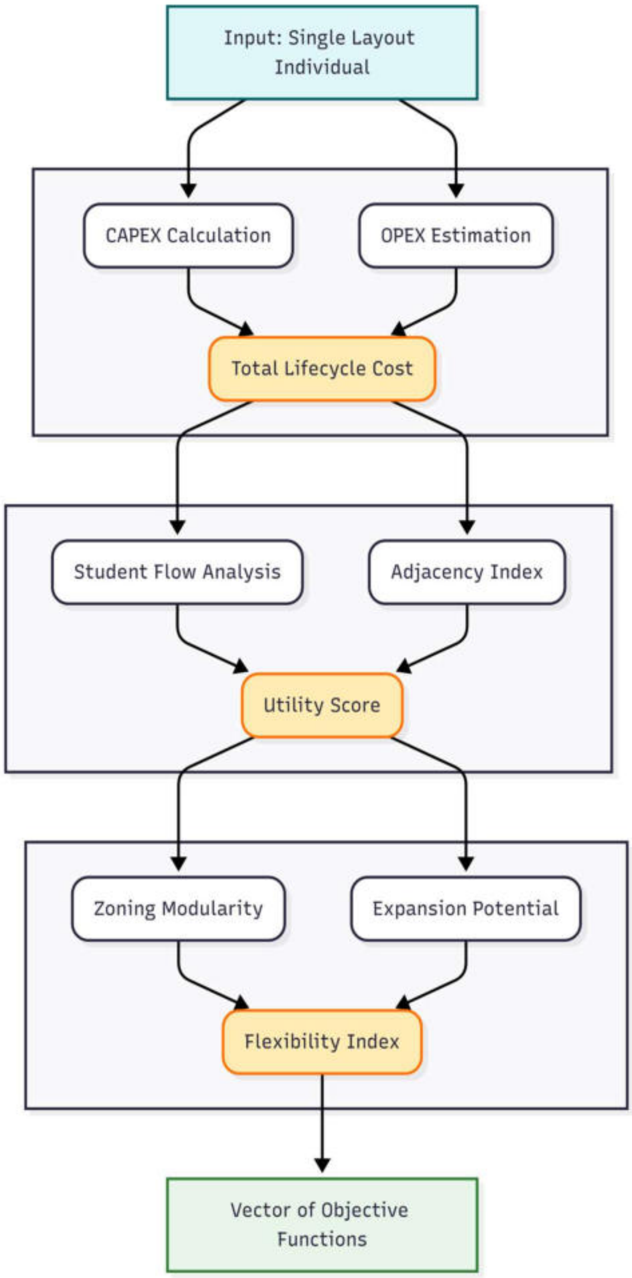

Figure 2 – Conceptual Model of the Method's Implementation

If a layout violates critical parameters, for example, by blocking an emergency evacuation route or failing to meet minimum daylight requirements it is not immediately discarded but is instead heavily penalized. This penalty function significantly reduces the candidate's likelihood of being selected for reproduction, thereby steering the evolutionary drift away from non-compliant regions of the search space while maintaining the genetic material that might be useful in future generations.

*Table 1 – **Classification of Input Parameters for the Generative Model***

Parameter Category	Variable Name	Description	Role in Optimization
Geometric Scope	S_{total}	Total allowable gross floor area	Defines the maximum buildable volume limit
	AR_{zone}	Aspect Ratio constraints per zone	Ensures room shapes remain functional (not too narrow)
Topology	W_{ij}	Adjacency Weight	Quantifies the necessity of proximity between zone i and j
	G_{site}	Site Boundary Polygon	Acts as a hard geometric constraint for the building footprint
Economic	C_{unit}	Unit construction cost	Used to calculate CAPEX estimates for each candidate
	B_{limit}	Total Investment Budget	Threshold value for filtering economically unviable options
Pedagogical	$N_{students}$	Maximum student capacity	Determines the required width of corridors and evacuation routes

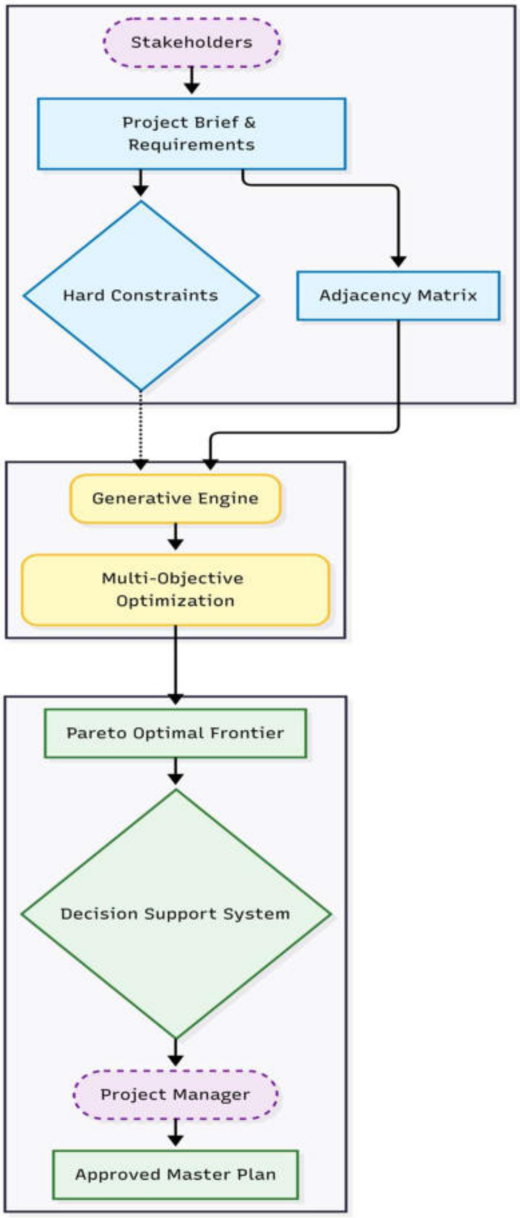

Figure 3 – Decision Model for the Multi-Criteria Evaluation of Optimized Scenarios

The mechanism for creating new, potentially better layouts relies on genetic operations applied to the selected «parent» designs. Figure 4 provides a detailed decomposition of this generative logic. The process begins with the selection phase, where layouts with superior fitness scores are chosen to fill the mating pool.

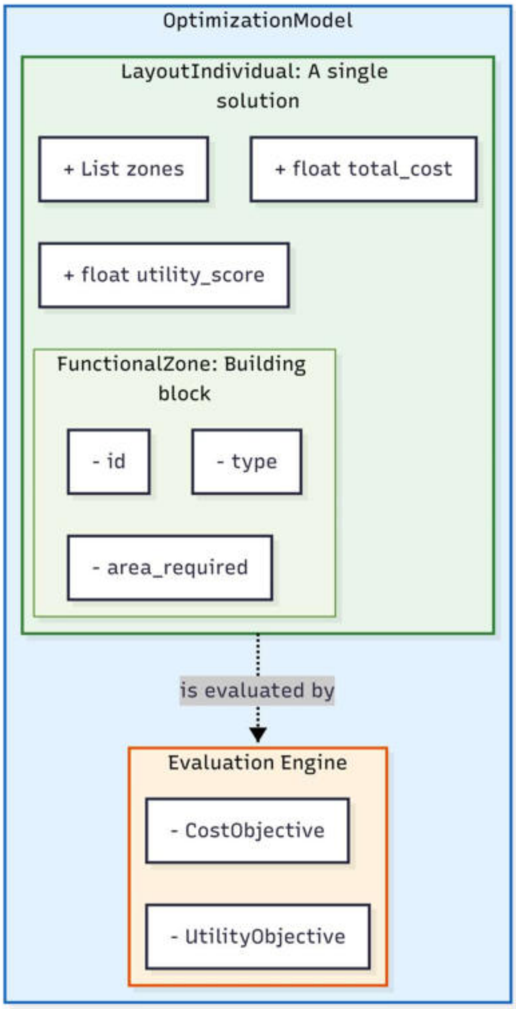

Figure 4 – Data Model of the Method's Core Components in UML Format

The algorithm then applies a crossover operator, which acts as a recombination mechanism. In the context of spatial planning, crossover involves swapping clusters of functional zones between two parent layouts. For instance, an efficient classroom wing from one layout might be combined with a compact administrative core from another, theoretically producing an offspring that inherits the strengths of both parents. This recombination allows the system to exploit known good configurations and propagate them through the population.

However, relying solely on crossover can lead to premature convergence, where the algorithm gets stuck in a local optimum – a «good enough» solution that is not truly the best possible outcome. To prevent this, the method incorporates a mutation operator, which introduces random variations into the offspring. As shown in the logic flow of Figure 4, mutation occurs with a specific probability and involves stochastic modifications such as shifting a wall position, rotating a room, or swapping the functions of two adjacent zones.

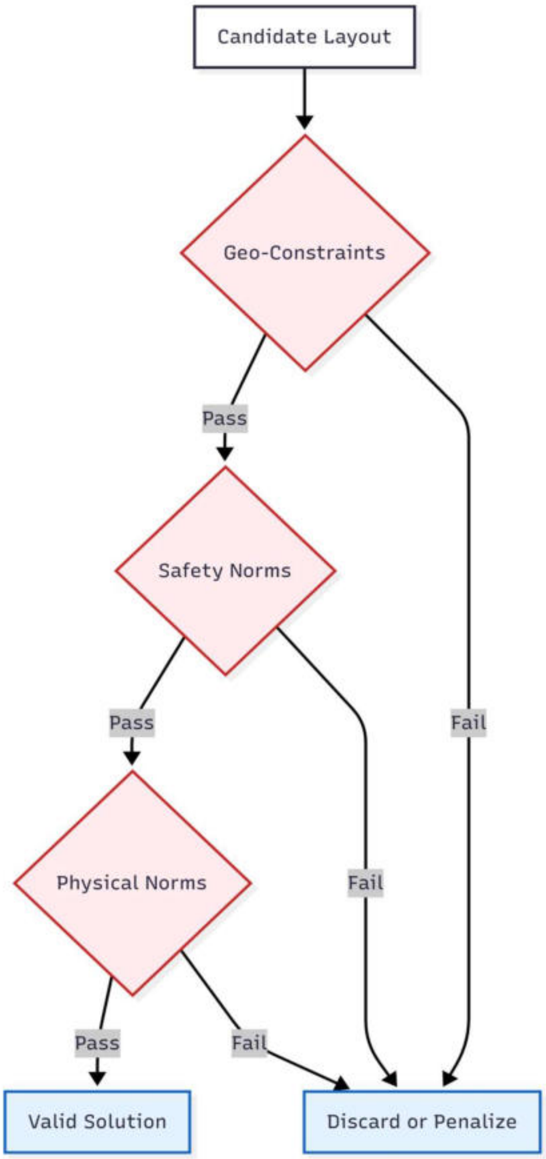

Figure 5 – Model of the Constraint Handling Algorithm for Layout Validation

From a project management perspective, mutation represents the innovative element of the design process, allowing the system to test unconventional configurations that a human designer might not intuitively consider. These genetic operations (selection, crossover, and mutation) are repeated over hundreds of generations. With each iteration, the population of layouts becomes increasingly refined, gradually converging towards a set of optimized solutions that balance the conflicting objectives of the project.

The efficacy of an evolutionary algorithm is fundamentally dependent on its ability to accurately measure the «fitness» or quality of each candidate solution. In the context of this method, fitness is not a monolithic score but a multi-dimensional vector representing the project's performance against a set of conflicting managerial objectives. This multi-objective approach is critical for educational projects, where success is defined by a complex interplay of economic viability, functional effectiveness, and long-term adaptability. The method employs a set of three distinct objective functions often referred to as fitness functions to guide the optimization process. As illustrated in the fitness evaluation sub-system diagram (Figure 5), each layout generated by the algorithm is systematically deconstructed and assessed against these three core criteria. The resulting vector of scores provides a nuanced performance profile, allowing for a comparative analysis that goes beyond simplistic, single-metric evaluations.

The first objective function, F1, is designed to quantify the economic performance of each layout. Moving beyond the traditional project management focus on initial capital expenditure (CAPEX), this function adopts a lifecycle cost (LCC) perspective. The algorithm estimates the CAPEX by calculating the total quantity of primary construction materials required. This is achieved by measuring the aggregate length of all internal and external walls and the total floor area of each candidate design. Layouts with a higher degree of geometric compactness and a lower ratio of circulation space (e.g., corridors) to functional space (e.g., classrooms) naturally require fewer materials, resulting in a more favorable CAPEX score.

Furthermore, the function incorporates an estimation of long-term operational expenditure (OPEX), primarily focusing on energy consumption for heating and cooling. This is calculated by analyzing the building's form factor – the ratio of its external surface area to its enclosed volume. A layout with a more compact, regularized form has a lower surface area through which thermal energy can be lost, leading to lower projected energy costs over the building's operational life. By integrating both CAPEX and OPEX into a single economic objective, the algorithm provides a holistic financial assessment that aligns with the principles of total cost of ownership. This empowers the project manager to make decisions that are not only cost-effective at the construction stage but also financially sustainable throughout the facility's lifecycle.

The second objective function, F2, measures the functional effectiveness of the spatial configuration, directly addressing the question of how well the building will serve its primary users – students and staff. This function translates the pedagogical and operational requirements of the educational environment into a quantifiable utility score. A primary component of this score is derived from a student flow analysis. The algorithm simulates the typical daily movement patterns of students between key functional zones, such as the main entrance, classrooms, library, and cafeteria. By calculating the total aggregated walking distance for these common pathways, the system can objectively assess the logistical efficiency of a layout. Designs that minimize these distances are rewarded with a higher utility score, as they reduce transition times and create a more seamless educational experience.

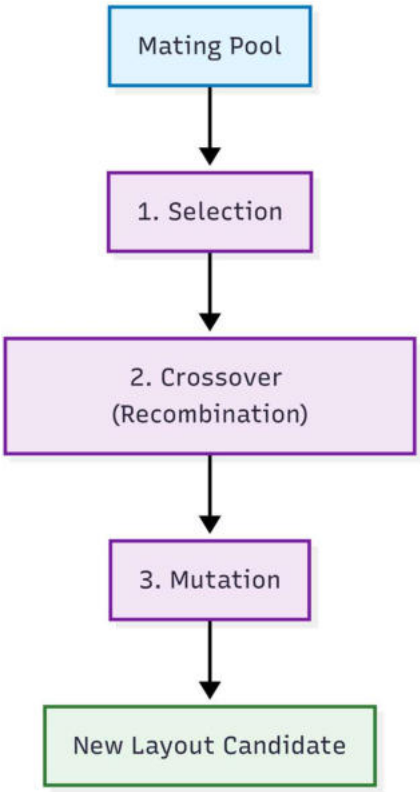

Figure 6 – Model of the Generative Algorithm: Selection, Crossover, and Mutation

This data-driven approach ensures that the generated layouts are not just geometrically plausible but are also logically coherent and aligned with the operational needs of the institution, thereby managing the project's quality and scope requirements at a fundamental level. The class diagram in Figure 6 illustrates this structure, where the *UtilityObjective* class encapsulates these evaluation methods.

The third objective function, F3, introduces a strategic, forward-looking dimension to the evaluation process by assessing the layout's adaptability and resilience to future changes. Educational paradigms and student populations are dynamic, and a building designed for today's needs may become obsolete within a decade. This function quantifies a layout's «future-proofing» potential, ensuring that the project delivers a long-term strategic asset. One of the key metrics for this objective is zoning modularity. The algorithm analyzes the structural grid of the layout, rewarding designs that utilize a regular, modular grid and minimize the number of internal load-bearing walls. Such configurations offer greater flexibility for future reconfiguration, allowing, for example, two smaller classrooms to be easily combined into a larger collaborative learning space with minimal structural intervention.

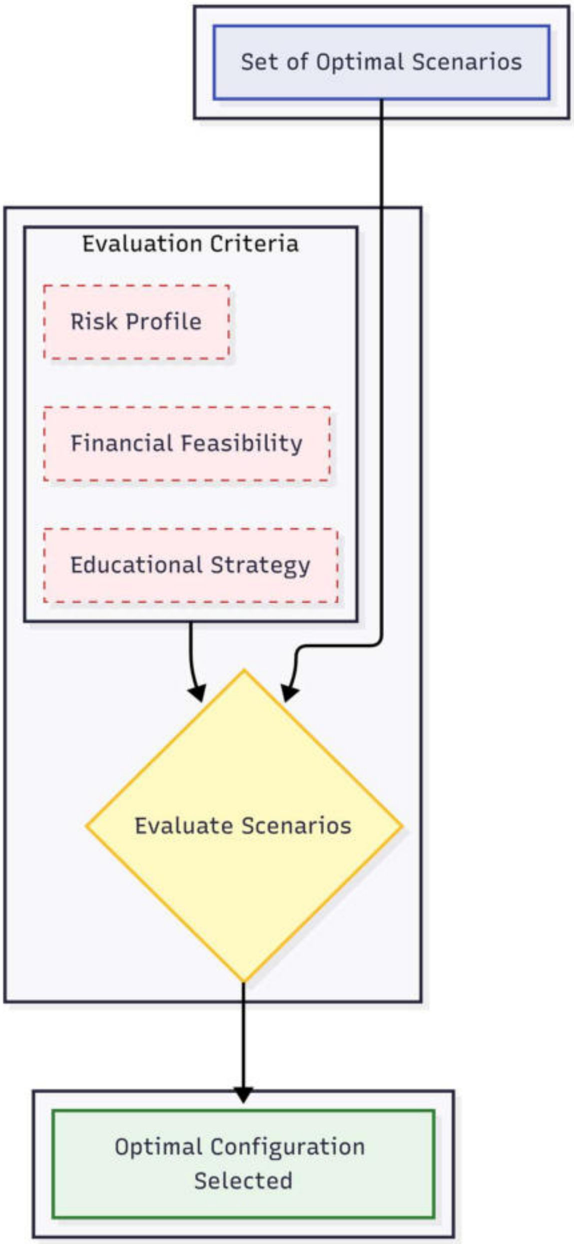

Figure 7 – Model of the Multi-Objective Fitness Evaluation Function

The final output of the generative optimization process is fundamentally different from that of traditional design methods. Instead of delivering a single, prescriptive «best» solution, the algorithm generates a Pareto Optimal Frontier. This frontier represents a curated set of non-dominated solutions, where each point on the frontier corresponds to a unique and fully detailed spatial layout. A solution is considered non-dominated if it is impossible to improve its performance in one objective function (e.g., reducing lifecycle cost) without incurring a performance penalty in at least one other objective (e.g., decreasing functional utility). From a project management perspective, this set of solutions serves as a strategic map of the decision landscape, transforming the abstract challenge of balancing competing project objectives into a tangible and explorable set of data-driven alternatives.

Each point on this frontier represents a distinct trade-off. For instance, one solution might offer the lowest possible construction cost by utilizing a highly compact building form with minimal circulation space, but this may come at the expense of lower functional utility due to longer internal travel distances or less daylight access. Conversely, another solution might achieve a near-perfect utility score by prioritizing short travel paths and optimal room adjacencies, but at the cost of a 20% increase in the estimated budget due to a more complex and materially intensive building footprint.

The existence of a Pareto Optimal Frontier, while computationally elegant, presents a new challenge for the project manager: how to select the single best configuration from a set of equally optimal – albeit different – alternatives. This selection process cannot be arbitrary; it must be guided by a structured framework that aligns the quantitative outputs of the AI with the qualitative strategic goals of the organization. As illustrated in the decision logic diagram (Figure 7), the proposed method incorporates a multi-criteria decision analysis (MCDA) framework to facilitate this final selection.

This framework acts as a critical bridge between the data-driven solution space generated by the algorithm and the value-driven decision space inhabited by project stakeholders. The MCDA process formalizes what is often an intuitive or unstructured debate, providing a systematic methodology for weighing the strategic importance of various performance indicators. It acknowledges that the «best» solution is not an absolute, mathematical truth but is contingent upon the specific priorities of the educational institution. For example, a publicly funded community school might prioritize long-term operational cost savings and durability, while a private, specialized academy may place a higher premium on functional layouts that support a unique pedagogical model, even at a higher initial cost. This structured evaluation ensures that the final selection is not merely a preference but a defensible decision aligned with the core mission and business case of the project.

The evaluation within this framework is structured around three primary pillars of managerial concern, which extend beyond the algorithm's core fitness functions. The first pillar is Financial Feasibility, which moves beyond the simple LCC calculation to assess each scenario's alignment with the investor's financial strategy, including cash flow projections, potential for phased implementation, and overall return on investment (ROI). The second pillar, Strategic Alignment, evaluates how effectively each layout supports the institution's pedagogical vision and brand identity. This qualitative assessment considers factors such as the potential to foster collaborative learning, the quality of student experience, and the building's capacity to attract and retain faculty and students. The third pillar, Risk Profile, provides a holistic risk assessment for each scenario, considering not only technical risks like construction complexity but also market risks, regulatory hurdles, and potential community opposition.

Conclusions

This study addressed the inherent subjectivity and limitations of traditional, experience-based approaches in the project management of educational facility development. Conventional methods restrict the exploration of design alternatives and fail to provide a clear, evidence-based link between spatial configurations and long-term performance indicators. To overcome these challenges, this paper introduced and detailed a formal method for the AI-driven, multi-objective optimization of functional-spatial layouts. The proposed framework, built upon a Genetic Algorithm, successfully transforms abstract project requirements into a tangible set of mathematically validated, Pareto-optimal scenarios, thereby objectifying the critical pre-investment phase of project management.

The principal finding of this research is that the generative optimization approach provides a paradigm shift from a reactive to a proactive and predictive management model. By simultaneously evaluating candidate layouts against conflicting criteria of lifecycle cost, functional utility, and adaptability, the method externalizes the complex trade-offs inherent in any development project. The generation of a Pareto Optimal Frontier empowers the project manager to move beyond the role of a passive decision-approver to that of a strategic decision-maker. This enables a data-driven dialogue with stakeholders, where choices between different high-performance scenarios can be justified based on their alignment with the organization's financial, pedagogical, and long-term strategic goals. Consequently, the method serves as a powerful tool for value engineering and risk mitigation, enhancing the project's digital resilience against future uncertainties.

The scientific contribution of this work lies in bridging the gap between computational design and project management theory. By formalizing the architectural design problem as a multi-objective optimization task within a managerial decision-making context, the proposed method provides an actionable framework for implementing principles of systems thinking and digital twin concepts at the earliest stages of the project lifecycle. This structured approach ensures traceability and defensibility in decision-making, transforming the «art» of layout planning into a more rigorous «science» of spatial configuration management. However, the proposed method has several limitations that must be acknowledged. Firstly, the efficacy of the algorithm is fundamentally contingent upon the quality and accuracy of the input data, including the formalization of the adjacency matrix and constraint parameters. Inaccurate or incomplete inputs will inevitably lead to suboptimal outputs (GIGO principle). Secondly, the current model does not incorporate qualitative or aesthetic criteria, which remain a critical component of architectural design. The role of the human architect is therefore not eliminated but transformed into that of a «curator» and «parameter tuner» who guides the AI towards aesthetically and culturally appropriate solutions. Lastly, the framework presented is conceptual and has been validated through simulation; its performance in a live, large-scale project environment is yet to be empirically tested.

Future research should focus on addressing these limitations through three primary avenues. First, empirical validation of the method through a real-world case study is essential to quantify its practical benefits against traditional design processes. Second, the model should be extended to incorporate more complex constraints, such as structural engineering requirements, detailed energy simulations, and human behavior models.

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МЕТОД AI-ОПТИМІЗАЦІЇ ФУНКЦІОНАЛЬНОГО ЗОНУВАННЯ В ДЕВЕЛОПЕРСЬКИХ ПРОЄКТАХ ОСВІТНІХ СЕРЕДОВИЩ

Анотація. *Традиційне управління девелоперськими проєктами освітніх середовищ значною мірою спирається на суб'єктивний, базований на досвіді підхід до просторового планування, що призводить до обмеженого дослідження альтернативних рішень та слабкого зв'язку між початковими рішеннями та довгостроковими показниками життєвого циклу. Такий лінійний процес не має методичного інструментарію для навігації складними компромісами між вартістю, функціональністю та майбутньою адаптивністю в умовах високої невизначеності. Для розв'язання цих обмежень у дослідженні розроблено та запропоновано метод AI-оптимізації функціонального зонування в девелоперських проєктах освітніх середовищ. Цей метод базується на структурованій моделі, що інтегрує генетичний алгоритм з моделлю багатокритеріального аналізу (англ. Multi-Criteria Decision Analysis, MCDA) шляхом формалізації вимог стейкхолдерів у набір математично верифікованих і порівнянних сценаріїв проєкту. Ядром розробленого методу є формалізований алгоритмічний процес, що функціонує як генеративна система підтримки прийняття рішень. Процес починається з цифровізації проєктних обмежень, включаючи будівельні норми, бюджетні ліміти та зважений граф суміжності, що представляє топологічні вимоги між функціональними зонами. Потім генеративний рушій ініціалізує популяцію випадкових планувань та ітеративно вдосконалює їх за допомогою генетичних операторів селекції, кросоверу та мутації. Пристосованість кожного кандидата оцінюється за допомогою векторної функції, яка одночасно оптимізує три конфліктні критерії: (1) мінімізацію вартості життєвого циклу (англ. Lifecycle Cost, LCC), що враховує капітальні та операційні витрати; (2) максимізацію функціональної корисності, що вимірюється через ефективність потоків студентів та дотримання суміжності; (3) максимізацію адаптивності, що оцінюється за модульністю та потенціалом для майбутнього розширення. Результатом роботи методу є не єдине рішення, а множина Парето, що представляє набір недомінованих рішень для управлінського аналізу. Запропонований метод AI-оптимізації функціонального зонування знаменує парадигмальний зсув від конвенційного, реактивного управління проєктами до проактивного, предиктивного підходу. Передбачається, що він підвищить ефективність прийняття управлінських рішень на передінвестиційній фазі девелоперського проєкту та надасть менеджерам надійну, доказову основу для вибору оптимальної конфігурації. Практична значущість методу полягає в тому, що генерація множини Парето дає змогу стейкхолдерам приймати обґрунтовані та захищені компромісні рішення між фінансовими, педагогічними та стратегічними цілями. Це підвищує цифрову стійкість проєкту, мінімізує ризики розповзання змісту та функціонального старіння, та в кінцевому підсумку гарантує, що капітальні інвестиції створюють стійкий, ефективний та адаптивний освітній актив.*

Ключові слова: проєктний менеджмент; система підтримки прийняття рішень; генетичний алгоритм; багатокритеріальна оптимізація; генеративний дизайн; планування просторових рішень; освітні середовища

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