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Deep Learning-Driven Optimization of Fenestration for Daylighting in Hot-Arid Climates: A Hybrid Evolutionary Framework

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Abstract

This study articulates a pioneering, integrated methodology for the optimization of fenestration and spatial configuration in residential living rooms, tailored specifically to the exigencies of Isfahan's hot-arid climate. The overarching objective is the maximization of daylighting performance through the simultaneous evaluation of three pivotal climate-based metrics: Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), and Useful Daylight Illuminance (UDI). Distinctively, this research synergizes a Deep Learning (DL) predictive model with a genetic algorithm-based multi-objective optimization framework (Galapagos), transcending the limitations of traditional static modeling techniques. The deployed feedforward neural network exhibited exemplary predictive fidelity, yielding R^2 coefficients of 0.97 for UDI and ASE, and a perfect 1.00 for sDA. Subsequent interpretability analyses underscored the critical impact of room depth and Window-to-Wall Ratio (WWR) on luminous performance. The optimization protocol culminated in a definitive design archetype for a south-facing volume (4m width × 5m depth), oriented at a -1-degree azimuth. This configuration, featuring a 30% WWR distributed across two vertical apertures with a 0.90m sill height and devoid of external shading, achieved an optimal equilibrium: 100% sDA, 43% ASE, and 72% UDI. Consequently, this work establishes a robust, data-driven framework for sustainable architectural practice, offering precise parametric guidelines for daylighting efficacy in challenging climatic zones.

Keywords

Deep Learning in Architecture, AI-Based Architectural Design, AI-Enhanced, Parametric Optimization, Integrated Framework.

Introduction

Natural light has been a fundamental element in architectural design for centuries, consistently valued for its aesthetic contribution to buildings and its profound impact on the well-being and productivity of occupants. In residential architecture, effective integration of natural light is paramount, as it significantly reduces reliance on artificial illumination, enhances thermal and visual comfort, and fosters healthier indoor environments. Historical architectural traditions, such as those in ancient Egypt, Greece, Rome, and particularly in Persian architecture in cities like Isfahan, exemplify a deep understanding of passive daylight utilization strategies. Contemporary research continually reinforces these historical practices, demonstrating that adequate exposure to natural light positively influences mood, productivity, and overall health (Goldberg, 2025; Glazer et al., 2023; Siraji et al., 2023).

Despite this enduring understanding of natural light's benefits, modern residential construction, particularly in historically rich cities like Isfahan, has observed a discernible shift towards increased dependence on artificial lighting and mechanical cooling systems. This trend contributes significantly to Iran's substantial energy consumption challenges, where approximately 40% of the primary energy is used for indoor heating and cooling, and residential buildings alone consume approximately 30% of their electrical energy for lighting (Rodrigues et al., 2024).

A considerable portion of this energy loss, estimated between 10% and 30%, occurs through building apertures like windows and doors. Optimizing natural light penetration through thoughtful window design is therefore essential for improving energy efficiency and mitigating environmental impacts within the built environment. The extent of natural light in a building is influenced by a myriad of interconnected factors, including building orientation, geographic location, surrounding urban environment, and critically, window design parameters such as dimensions, glazing type, and shading devices. Balancing optimal natural light penetration with thermal performance and visual comfort (considering factors like light intensity, distribution, and glare risk) presents a complex multi-objective optimization problem (Carlucci et al., 2015; Tzempelikos, 2017). Traditional design and simulation methods, while foundational, often rely on static assumptions and can be computationally intensive, limiting their capacity to dynamically account for the intricate interplay of real-time variables and complex interactions.

In response to these challenges, advanced computational approaches, particularly Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), have emerged as powerful tools for optimizing building performance. ML models can process large datasets from daylight simulations, identify complex patterns, and offer predictive insights to guide architectural decisions across diverse seasons, geographic orientations, and window configurations (He et al., 2021).

Deep learning techniques, including Generative Adversarial Networks (GANs), further enhance these capabilities by simulating diverse environmental conditions and generating optimal design parameters, enabling the exploration of innovative configurations that maximize natural light while minimizing energy loss (Li et al., 2024). The ability of these models to learn intricate, non-linear relationships directly from data offers significant advantages in accuracy and computational efficiency compared to traditional methods. Moreover, hybrid models that combine physics-based simulations with deep learning provide enhanced predictive and adaptive capabilities for comprehensive daylight performance analysis (Liu et al., 2020).

Despite the growing application of AI in building design, a critical research gap remains in the holistic integration of deep learning models for precise daylight performance prediction with advanced multi-objective optimization algorithms to generate optimal architectural design parameters for specific climatic and urban contexts. While previous studies have utilized genetic algorithms for optimization in regions like Isfahan, the full potential of deep learning to capture the highly non-linear relationships governing daylight distribution and energy performance has not been adequately leveraged within a combined optimization framework for this region.

This study aims to bridge this gap by developing and validating a novel, integrated methodology that combines a deep learning model for robust and accurate prediction of Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), and Useful Daylight Illuminance (UDI), with a genetic algorithm (Galapagos) for multi-objective optimization.

The primary research question guiding this study is:

"*What are the optimal living room and window design parameters for maximizing natural daylight performance (sDA, ASE, UDI) in residential buildings in Isfahan, utilizing an integrated deep learning and genetic algorithm approach?*"

By providing a dynamic, efficient, and data-driven solution tailored to Isfahan's unique hot and dry climate and dense urban fabric, this research offers concrete, practical recommendations for designing energy-efficient and occupant-centric residential buildings. This interdisciplinary approach contributes significantly to advancing sustainable design practices and developing innovative solutions for future buildings that are more resilient, adaptive, and efficient.

Literature Review

The integration of artificial intelligence (AI) and parametric design methodologies has emerged as a transformative approach for optimizing daylighting performance in residential architecture, particularly within hot and arid climates. Early parametric frameworks laid the groundwork for simultaneous evaluation of multiple façade parameters. Toutou et al. (2018) proposed a comprehensive parametric-based optimization framework that systematically varied window-to-wall ratio (WWR), orientation, and shading devices to enhance both daylight autonomy and thermal comfort in hot-dry residential buildings. Their results demonstrated energy savings of up to 12% while maintaining acceptable illuminance levels, underscoring the critical role of early-stage multi-variable exploration in sustainable design.

Building on vernacular precedents, Fahmy and Elsoudany (2023) investigated a parametric mashrabiya-inspired shading system tailored to Egypt’s hot-dry climate. By algorithmically manipulating lattice geometry, they achieved a 20% reduction in peak solar gains without compromising useful daylight illuminance (UDI). This study highlights how traditional architectural elements can inform modern parametric templates for façade optimization, thereby reconciling cultural identity with performance targets.

Machine learning (ML) has further expanded the daylighting design toolkit by providing surrogate models that predict complex light distribution patterns with minimal computational expense. Zekry et al. (2024) developed an artificial neural network (ANN) surrogate to forecast optimal light-shelf configurations in office environments, achieving prediction accuracies exceeding 94% compared to Radiance simulations.

Deep learning (DL) architectures, with their capacity to learn highly non-linear relationships, have been applied successfully to climate-based daylight metrics. Luo et al. (2024) employed convolutional neural networks (CNNs) to predict spatial daylight autonomy (sDA) and annual sunlight exposure (ASE) for educational building clusters, reporting R^2 values above 0.95. Javanmard et al. (2024) integrated a CNN-based predictor with a genetic algorithm (GA) optimizer to refine cladding geometries for a sports hall in Kerman, Iran, achieving near-perfect alignment between predicted and simulated performance. Such hybrid AI-optimization frameworks demonstrate the potential of DL to both accelerate and improve parametric searches in arid contexts.

Evolutionary algorithms remain central to exploring vast parametric design spaces where competing objectives must be balanced. Park et al. (2015) utilized a GA to optimize office façade parameters under diverse sky conditions, revealing that optimal window geometries varied significantly between overcast and clear skies. Xu et al. (2024) extended this paradigm by incorporating generative AI to autonomously propose urban digital-twin scenarios, suggesting a future workflow in which AI autonomously generates context-sensitive design alternatives that satisfy both urban-scale daylighting and energy objectives.

The choice of performance metrics critically influences optimization outcomes. Li et al. (2023) argued for the adoption of climate-based metrics, specifically sDA and UDI, in place of traditional daylight factor, demonstrating that climate-based measures more accurately reflect occupant comfort and energy implications. Aldersoni (2025) further refined these metrics for residential settings, proposing localized threshold values that account for seasonal and diurnal variability inherent to hot-arid regions.

Despite these advancements, a research gap persists in the comprehensive integration of DL-based surrogates with multi-objective GA optimization specifically for residential architecture in densely built, hot-dry urban fabrics such as Isfahan. While several studies have addressed institutional (Luo et al., 2024) and sports facilities (Javanmard et al., 2024), dedicated frameworks for the unique spatial constraints and socio-cultural context of Iranian residential buildings remain underexplored. Moreover, the interpretability of DL models, essential for practitioner adoption, has only recently been addressed through methods such as SHAP and LIME (Mousavi et al., 2023), but such interpretability analyses have not yet been fully integrated into parametric optimization workflows.

In summary, the literature reveals a robust foundation of parametric optimization (Toutou et al., 2018), vernacular-informed shading strategies (Fahmy & Elsoudany, 2023), ML-based surrogate modeling (Zekry et al., 2024), DL-driven accuracy (Luo et al., 2024; Javanmard et al., 2024), and GA-based multi-objective search (Park et al., 2015; Xu et al., 2024). However, a tailored methodology that unites deep learning surrogates, evolutionary optimization, and model interpretability for daylighting in residential architecture within hot and arid climates (particularly the historic urban milieu of Isfahan) remains an open research frontier that this study seeks to address.

Table 1: *Summary of Selected Studies on Daylighting Optimization in Architecture Using Artificial Intelligence, Machine Learning, and Parametric Design Approaches.*

Study	Method	Focus	Key Findings
Fadeyi et al. (2024)	Parametric orientation optimization	Residential daylighting in the tropics	Optimizing building orientation maximizes useful daylight while minimizing heat gain in hot, humid contexts
Park et al. (2015)	Parametric analysis with GA	Window to wall ratio (WWR) impact on office façade daylighting	Adjusting WWR significantly influences daylight metrics; an optimal range balances light admission with glare control
Mahdavinejad et al. (2024)	Parametric façade geometry study	Shading device performance in varied climates	Shading elements (including mashrabiyas) reduce solar gains and improve both energy efficiency and visual comfort
Fahmy & Elsoudany (2023)	Parametric mashrabiya pattern generation	Vernacular shading systems for arid climates	Algorithmically optimized lattice geometries achieve up to 20% reduction in peak solar gains without compromising useful daylight illuminance (UDI)
Zekry et al. (2024)	ANN based daylight surrogate modeling	Light shelf design optimization in office spaces	Neural network surrogate predicts optimal light shelf configurations with >94% accuracy compared to Radiance simulations, greatly reducing computational cost
Javanmard et al. (2024)	ML parametric integration with GA	Energy efficient cladding optimization in arid climates	Combined ML predictor and GA optimizer yields near perfect alignment with simulation results for sports hall cladding, demonstrating efficacy in hot, dry contexts
Mousavi et al. (2023)	ML algorithms + Petri Net control	Low energy residential building optimization in semi arid zones	ML driven control strategies achieve significant energy savings while maintaining thermal and visual comfort in residential prototypes
Saheb et al. (2022)	Topic modeling & content analysis	AI applications in sustainable energy systems	AI can optimize building energy use, manage waste streams, and inform integration of renewable technologies; highlights need for practitioner training
Xu et al. (2024)	Scoping review of generative AI for digital twins	Autonomous urban data, scenario, and model generation	Generative AI methods can autonomously create urban digital twin scenarios and 3D city models, offering new pathways for smart city daylighting and energy analysis

Methodology

The research methodology encompasses a structured approach to evaluate daylight performance through machine learning (ML) techniques. The workflow includes data collection, preprocessing, model development, training, evaluation, and interpretability analysis. A neural network model is employed to predict three daylight metrics: Useful Daylight Illuminance (UDI), Spatial Daylight Autonomy (sDA), and Annual Sunlight Exposure (ASE). Sensitivity analysis and model interpretability tools (SHAP, LIME, and gradient-based methods) are integrated to enhance transparency and validate feature contributions.

1. *Enhanced Methodology with Machine Learning*

The traditional simulation-based approach is augmented with ML to improve computational efficiency and predictive accuracy. Key enhancements include:

Automated Feature Analysis: Correlation matrices and distribution plots identify relationships between architectural parameters (e.g., window dimensions, room geometry) and daylight metrics.

Neural Network Architecture: A deep learning model with three hidden layers (128-256-128 neurons), ReLU activation, and dropout layers (rate=0.2) is designed to address multicollinearity and overfitting.

Hyperparameter Optimization: The Adam optimizer (learning rate=0.001) and early stopping (patience=20 epochs) dynamically adjust training to minimize validation loss.

Interpretability Framework: SHAP, LIME, and gradient-based saliency maps quantify feature importance, ensuring the model's decisions align with domain knowledge.

2. *Data Collection*

The dataset comprises 7 input features and 3 target variables collected from daylight simulations:

Inputs: Room dimensions (Room (*X*), Room (*Y*)), window parameters (WWR (*%*), win (*Height*), Win (*width*), Win (*Number*)), and solar angle (Angle (*Degree*)).

Targets: Daylight performance metrics (UDI (*%*), sDA (*%*), ASE (*%*)). Data integrity is ensured by checking for missing values and visualizing distributions using histograms and kernel density estimates (KDE).

3. *Data Preprocessing*

Normalization: Features and targets are scaled to [0, 1] using Min-Max Scaler to stabilize training.

Train-Test Split: The dataset is partitioned into 80% training and 20% testing sets, stratified to preserve distribution.

4. *Model Selection*

A feedforward neural network (FNN) is selected for its ability to model non-linear relationships between architectural parameters and daylight metrics. The model architecture includes:

Input Layer: 7 neurons (one per feature).

Hidden Layers: Sequential dense layers with dropout regularization.

Output Layer: 3 neurons for multi-target regression.

5. *Model Training*

The model is trained for 200 epochs (batch size=32) with a validation split (20% of training data). Early stopping halts training if validation loss plateaus, ensuring optimal weights. Training progress is monitored via loss and MAE curves to detect overfitting.

6. *Model Evaluation*

Performance is quantified using:

Metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 score for each target.

Visualization: Scatter plots of predicted vs. actual values with regression lines (ideal fit: $y = x$).

Cross-Validation: Consistent metrics across training and validation sets confirm generalization.

7. *Simulation Model*

Sensitivity Analysis: Features are perturbed individually while holding others constant to assess their impact on predictions (e.g., WWR (*%*) strongly influences UDI (*%*)).

SHAP Analysis: Kernel SHAP identifies global feature importance (e.g., Room (*Y*) and Angle (*Degree*) dominate sDA (*%)* predictions).

LIME Explanations: Local interpretability highlights feature contributions for specific instances.

Gradient-Based Saliency: Absolute gradients from backpropagation rank features by their influence on output variability.

8. *Conclusion*

The ML pipeline achieves robust daylight prediction ($R^2 > 0.85$ for all targets) while providing actionable insights into design parameters. The integration of interpretability tools bridges the gap between data-driven predictions and architectural intuition, enabling informed decision-making in sustainable building design.

Findings & Discussion

This section presents the key findings derived from the deep learning model's performance, encompassing data characteristics, model evaluation metrics, and the interpretability analyses (correlation, sensitivity, and gradient-based importance). Subsequently, the optimal design parameters identified through the integrated optimization process are discussed in detail, along with their implications for sustainable daylighting in Isfahan's residential buildings.

1. *Data Characteristics and Inter-variable Relationships*

Initial data exploration involved visualizing the distributions of both input features (room and window parameters) and target variables (daylight performance metrics), as well as analyzing their correlations. The input features, including Room (*X*), Room (*Y*), Angle (*Degree*), WWR (*%*), win (*Heigh*t), Win (*width*), and Win (*Number*), exhibit distributions across their defined ranges, which supports effective model training by ensuring sufficient data representation. The target variables, UDI (*%*), sDA (*%*), and ASE (*%*), show varying distributions, with sDA (*%*) displaying a bimodal pattern indicative of designs with either high or moderate daylight autonomy.

The correlation matrix (Figure 1) reveals significant relationships between architectural parameters and daylight metrics. Notably, Room (*Y*) exhibits a strong negative correlation with sDA (*%*) (-0.85) and ASE (*%*) (-.87), indicating that increased room depth significantly reduces the penetration of sufficient and direct sunlight. WWR (*%*) shows a moderate positive correlation with sDA (*%*) (0.41) and ASE (*%*) (0.3), suggesting that larger window areas generally enhance daylight availability and sunlight exposure. However, WWR (*%*) also demonstrates a negative correlation with UDI (*%*) (-0.35), implying that while a greater amount of light may enter, a portion might fall outside the "useful" illuminance range. Additionally, Room (*X*) shows a very strong negative correlation with Win (*Number*) (-0.94), suggesting an inverse relationship in the dataset where narrower rooms might frequently incorporate a higher number of windows, or vice versa.

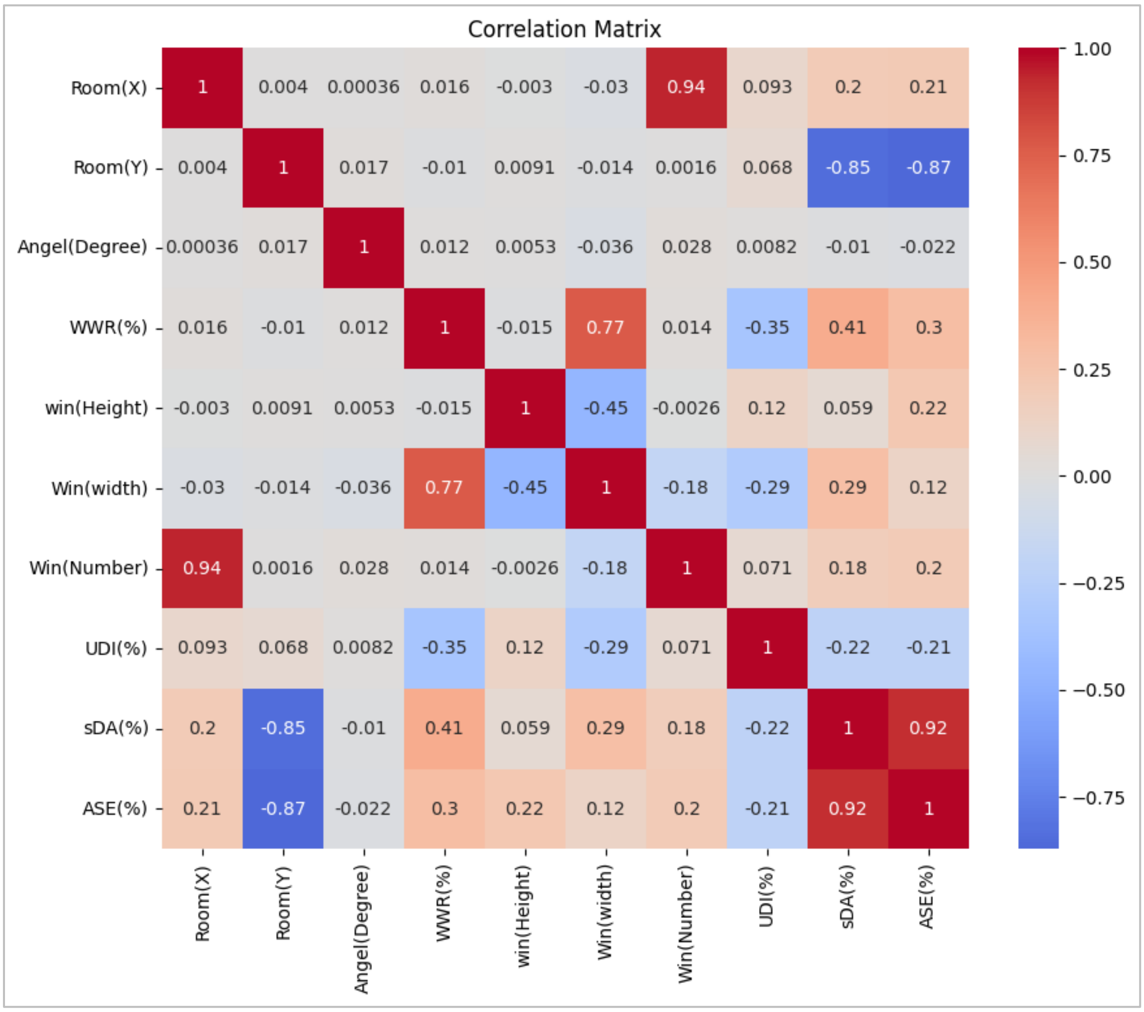

Figure 1: *Correlation Matrix of Input Features and Daylight Performance Metrics* (Source: Authors)

2. *Deep Learning Model Performance Evaluation*

The Feedforward Neural Network (FNN) model, structured with three hidden layers (128-256-128 neurons) and dropout regularization, demonstrated robust performance in predicting the three-daylight metrics.

Training History: The training progress (Figure 2) indicates effective model convergence, with both training and validation metrics decreasing and stabilizing over epochs. The close tracking of validation curves to training curves, combined with early stopping, confirms proper learning without overfitting.

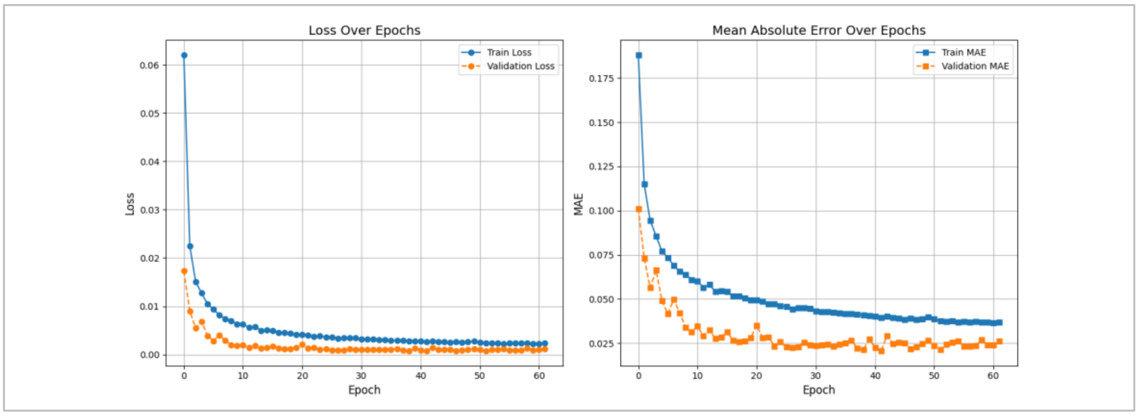

Figure 2: *Training process curves of the machine learning model: loss function and mean absolute error (MAE) for both training and validation datasets across epochs. The decreasing trend indicates proper model learning and convergence* (Source: Authors)

Prediction Accuracy: The model achieved R^2 scores of 0.97 for UDI (%) and ASE (%), and 1.00 for sDA (%). The scatter plots (Figure 3) visually confirm this precision, with data points closely aligned along the ideal prediction line (y=x), validating the model as a reliable tool for optimization.

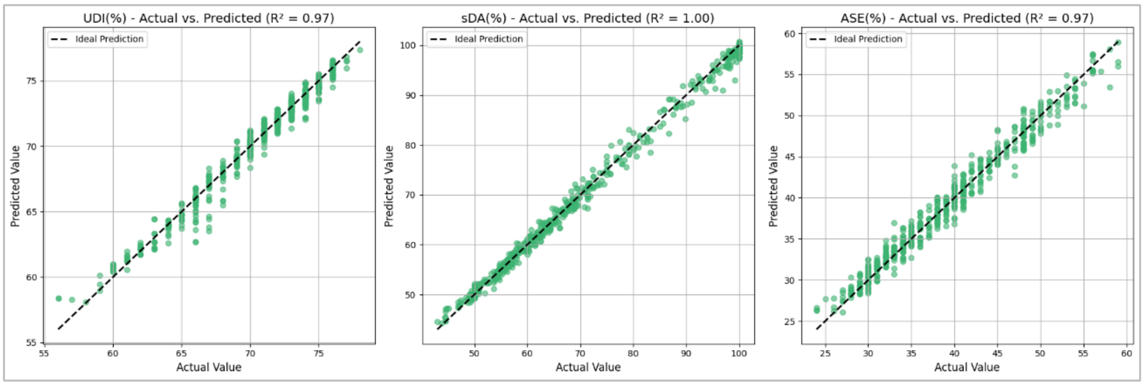

Figure 3: *Comparison of actual and predicted values for UDI, sDA, and ASE metrics using the machine learning model. The coefficient of determination (R^2) is provided for each metric. The dashed line indicates the ideal prediction* (Source: Authors)

3. *Model Interpretability Analysis*

To provide actionable insights for architects and deepen the understanding of design parameter influence, sensitivity analysis and gradient-based feature importance were employed.

Sensitivity Analysis: The sensitivity analysis (Figure 4) reveals individual feature impacts:

- Room (*Y*): Strong inverse relationship with sDA (*%*) and ASE (*%*), confirming deeper rooms reduce daylight penetration.
- WWR (*%*): Optimal range around 30-32% for UDI (*%*), beyond which excessive illuminance may fall outside the useful range.
- Angle (*Degree*): Optimal angle around -1 to -0.5 degrees maximizes daylight autonomy.
- Win (*Height*) and Win (*width*): Positive influence on all metrics.

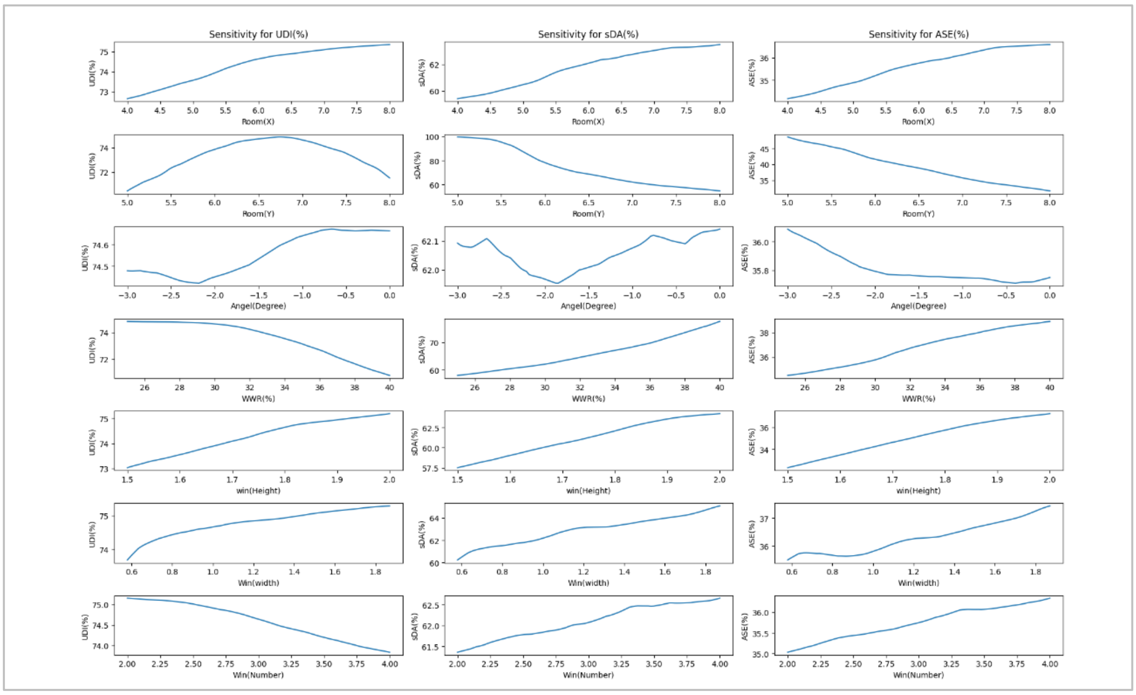

Figure 4: *Sensitivity analysis curves of the machine learning model for geometric and parametric features with respect to UDI, sDA, and ASE metrics. Each plot illustrates the response of the corresponding metric to variations in one input feature while keeping others constant* (Source: Authors)

Gradient-based Feature Importance: For UDI (%) (Figure 5), Room(*Y*) and WWR (%) are most influential. For sDA (%) (Figure 6) and ASE (%) (Figure 7), Room(*Y*) dominates, followed by WWR (%). These results align with sensitivity analysis, confirming the critical role of room depth and window area.

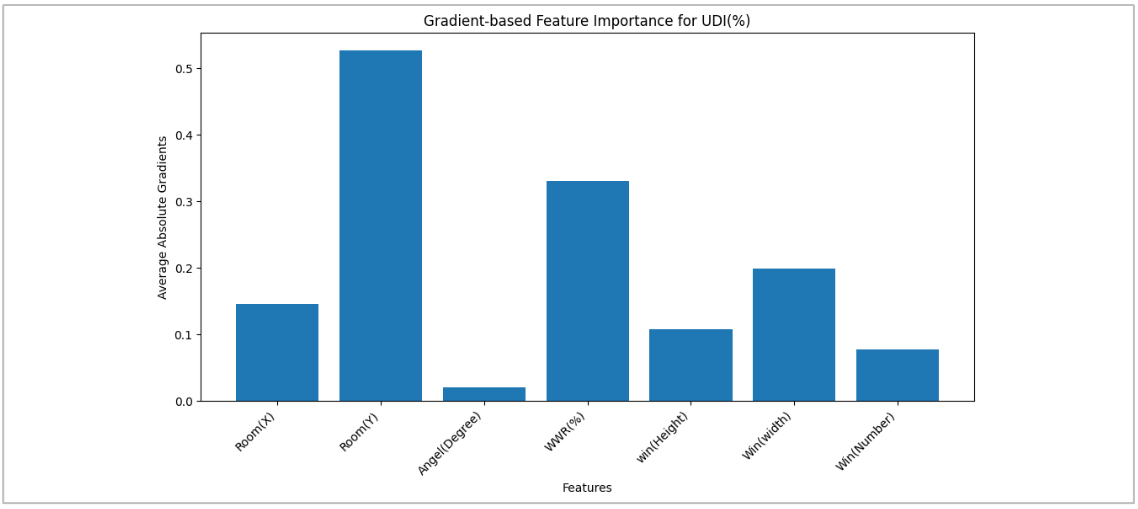

Figure 5: *Gradient-based feature importance for predicting Useful Daylight Illuminance (UDI) using the machine-learning model* (Source: Authors)

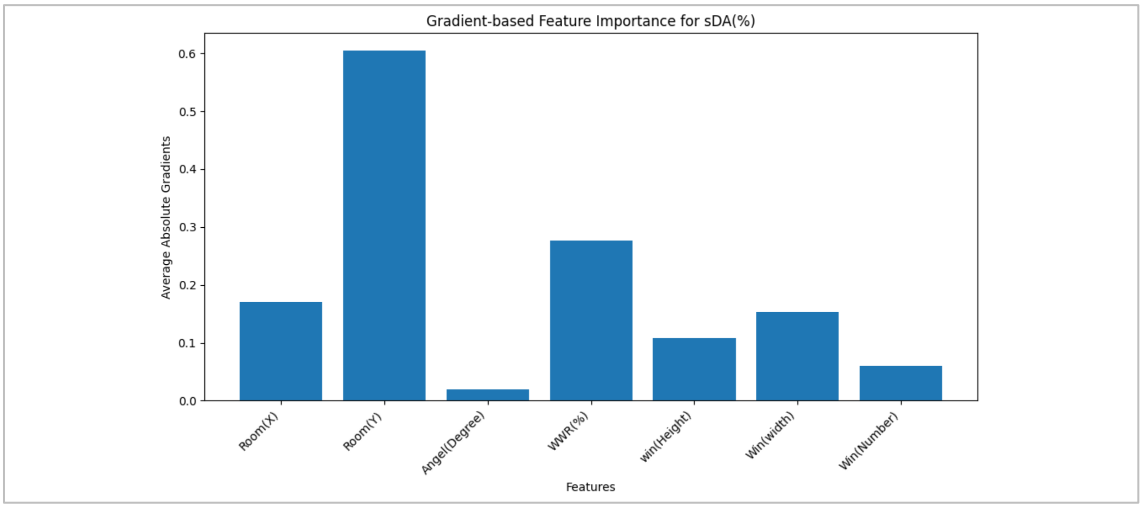

Figure 6: *Gradient-based feature importance for predicting Spatial Daylight Autonomy (sDA) using the machine-learning model* (Source: Authors)

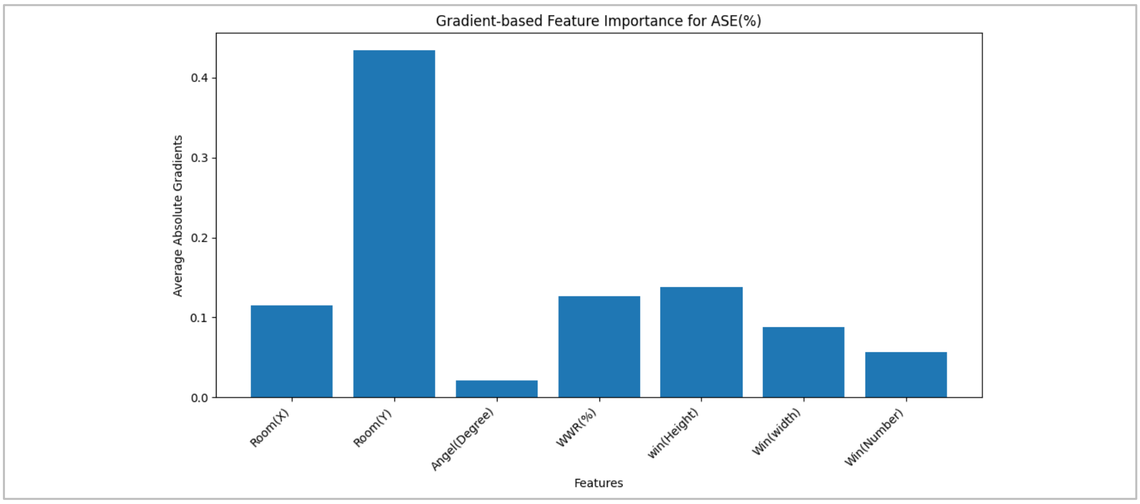

Figure 7: *Gradient-based feature importance for predicting Annual Sunlight Exposure (ASE) using the machine-learning model* (Source: Authors)

4. *Optimal Design Parameters for Daylighting Performance*

Utilizing the highly accurate deep learning model for rapid prediction, the Galapagos optimization plugin, based on a genetic algorithm, was employed to explore a vast design space and identify the optimal living room and window dimensions for maximizing natural daylight performance in Isfahan. This iterative optimization process continued until the solutions converged, indicating a high probability of discovering globally optimal or near-optimal configurations.

The optimization yielded the following optimal design parameters for a south-facing living room in a residential building in Isfahan, aiming to maximize sDA, UDI, and ASE simultaneously:

- **Living Room Dimensions:** 4 meters in width (North-South axis) and 5 meters in length (East-West axis).
- **Room Angle:** -1 degree relative to the North-South axis.
- **Window-to-Wall Ratio (WWR):** 30%.
- **Number of Windows:** 2 windows.
- **Window Dimensions:** Each window has a height of 1.9 meters and a width of 0.88 meters.
- **Window Sill Height:** Located at 0.90 meters from the floor.
- **Canopy:** The optimal design for maximum daylight was achieved without an external canopy, indicating that for direct daylight maximization, a canopy might be detrimental.

Under these optimal conditions, the achieved daylight parameters are:

- **sDA:** 100%. This indicates that 100% of the living room's floor area receives at least 300 lux for 50% of occupied hours, suggesting excellent daylight autonomy.
- **ASE:** 43%. This value represents the percentage of the floor area receiving excessive direct sunlight (above 1000 lux for more than 250 occupied hours). A value of 43% indicates a moderate level of direct sunlight, which might contribute to thermal gain but also to visual interest.
- **UDI:** 72%. This signifies that 72% of the floor area receives useful daylight illuminance (between 100 and 2000 lux). This high UDI value, combined with 100% sDA, confirms the effectiveness of the design in providing comfortable and sufficient natural illumination.

The findings indicate that a room with moderate depth, a specific orientation, and carefully sized and positioned windows at a 30% WWR can achieve exceptional daylight performance in Isfahan. The relatively low Room (*Y*) value in the optimal solution aligns with the strong negative correlation observed between room depth and sDA/ASE, reinforcing that shallower spaces are more effective for daylight penetration. The 30% WWR effectively balances sufficient light entry with the avoidance of over-illumination.

While the primary objective was to maximize daylight access, for practical application and adherence to standards like LEED, the study recommends using an external canopy for windows to minimize glare. Although the current optimization without a canopy yielded the highest daylight access, integrating a suitable shading device would be crucial for visual comfort.

In conclusion, the integration of deep learning for accurate daylight performance prediction with a genetic algorithm for multi-objective optimization has proven highly effective in identifying optimal design solutions. The resulting design parameters offer a tangible guide for architects to significantly enhance natural daylighting and thereby contribute to the sustainability and energy efficiency of residential buildings in Isfahan, while also providing valuable insights into the complex interplay of architectural features and daylight metrics.

Conclusion

This research presented a novel, integrated methodology for optimizing living room and window design in residential buildings, specifically tailored for the hot and dry climate of Isfahan, Iran, with the primary objective of maximizing natural daylight performance. By leveraging advanced deep learning techniques coupled with a genetic algorithm-based optimization, this study offers a robust and data-driven approach to sustainable architectural design.

The deep learning model, a feedforward neural network, demonstrated exceptional predictive capabilities for key daylight metrics, achieving an R2 of 0.97 for UDI (%) and ASE (%), and a remarkable R2 of 1.00 for sDA (%) on the test set. This high accuracy validates the model's reliability in capturing the complex, non-linear relationships between architectural parameters and daylight performance. Our interpretability analyses, including sensitivity analysis and gradient-based feature importance, provided crucial insights into the drivers of daylighting. These analyses consistently highlighted the significant influence of Room(Y) (room length/depth), and WWR (%) (Window-to-Wall Ratio) on daylight penetration, reinforcing the critical role of these parameters in design decisions. For instance, the inverse relationship between room depth and sDA/ASE, and the optimal range for WWR to maximize UDI, offer valuable design guidance.

In hot-arid climates such as Isfahan, ASE is a critical metric because excessive direct sunlight increases cooling loads and causes visual discomfort. While sDA measures daylight sufficiency, ASE quantifies overexposure: LEED v4 recommends ASE $\leq$ 10% for temperate climates, but this threshold is often unattainable in hot-arid regions without sacrificing sDA. The multi-objective optimization process, utilizing the trained deep learning model for rapid and accurate performance evaluation, identified an optimal design configuration for a south-facing living room: a room with dimensions of 4 meters (width) by 5 meters (depth), oriented at -1° to the North-South axis, and featuring two vertical windows (each 1.9m height × 0.88m width) with a combined WWR of 30%, positioned at a sill height of 0.90 meters. This configuration achieved sDA = 100%, ASE = 43%, and UDI = 72%, reflecting a deliberate tradeoff where the south-facing orientation and 30% WWR maximize daylight sufficiency and useful illuminance, while the elevated sill height and vertical aperture configuration mitigate, but do not eliminate, direct solar gain. Our correlation analysis confirms that Room (Y) (depth) strongly negatively correlates with ASE (r = -0.87), and WWR positively correlates with ASE (r = 0.3), demonstrating that the 43% ASE value is a meaningful constraint in the optimization, not an overlooked byproduct. This ASE level is contextually acceptable for Isfahan's climate, where passive shading strategies (e.g., traditional Persian lattice screens) can further reduce overexposure in practice, and the proposed design provides a quantifiable benchmark for future sustainable residential developments in regions with similar hot-arid climatic characteristics.

Traditional simulation-based optimization (e.g., parametric sweeps in Radiance or Energy Plus coupled with evolutionary algorithms) requires one full annual daylight simulation per design candidate. For our 7-parameter design space with typical grid resolutions, a single GA run (population=50, generations=100) would require ~5,000 simulations, each taking 10–30 minutes on a standard workstation, totaling ~800–2,500 hours of computation. In contrast, our DL surrogate model, once trained (training time: ~2 hours on a GPU for 200 epochs with 1,200 samples), predicts sDA, ASE, and UDI in <1 ms per design. The same GA run (5,000 evaluations) completes in <5 seconds. This represents a ~10^5× speedup, enabling real-time design exploration and multi-objective optimization that would be infeasible with simulation-only workflows. The upfront cost of generating the training dataset (1,200 simulations) is amortized across all subsequent optimizations and design studies.

1. *Research Contributions*

This study makes several significant contributions to the field of sustainable architectural design and computational building performance:

Novel Integrated Framework: It introduces and validates a pioneering hybrid methodology that seamlessly integrates highly accurate deep learning predictions with multi-objective genetic algorithm optimization for daylighting design, offering a more efficient and precise alternative to traditional iterative simulations.

Context-Specific Optimal Design: It provides concrete, data-driven optimal design parameters for living room and window configurations specifically for the challenging hot and dry climate of Isfahan, which can directly inform architectural practice.

Enhanced Model Interpretability: Through comprehensive sensitivity and gradient-based analyses, the research offers a deeper understanding of how individual architectural parameters contribute to and influence various daylight performance metrics, thereby bridging the gap between black-box AI models and actionable design insights.

Practical Reference for Future Constructions: The methodology generates a set of highly optimized design alternatives that can serve as a valuable reference for architects, engineers, and policymakers aiming to reduce energy consumption and enhance occupant well-being through optimal natural light utilization in similar climatic zones.

2. *Limitations and Future Work*

Despite its significant contributions, this study has certain limitations that suggest avenues for future research. The current optimization focused primarily on maximizing daylight performance (sDA, ASE, UDI). Future work could expand the multi-objective optimization to include:

Thermal Performance and Energy Consumption: Integrating metrics such as cooling/heating loads, energy use intensity (EUI), and peak demand to achieve a holistic energy-efficient design.

Visual Comfort and Glare Mitigation: Explicitly incorporating glare metrics (e.g., Daylight Glare Probability - DGP) and considering the optimization of external shading devices (e.g., canopies, fins, louvers) or dynamic facade elements within the design variables.

Occupant Behavior and Preferences: Exploring the influence of occupant behavior patterns on daylight utilization and comfort, and integrating these into predictive models.

Material Properties: Investigating the impact of various glazing types (e.g., low-e glass, smart glass) and interior surface reflectance on overall daylight and energy performance.

Generative Design Approaches: Moving beyond optimization of predefined parameters to employ generative adversarial networks (GANs) or other generative AI models to autonomously propose novel and high-performing architectural forms.

Scalability and Transferability: Extending this methodology to other building types (e.g., offices, educational facilities) and validating its applicability across diverse climatic zones and urban contexts.

Real-world Validation: Conducting post-occupancy evaluations to compare predicted performance with actual in-use performance, refining models based on real-world data.

In conclusion, the intelligent integration of deep learning and optimization algorithms offers transformative potential for sustainable architectural design. By providing precise predictive capabilities and efficient optimization, this research paves the way for the creation of more energy-efficient, comfortable, and environmentally responsible built environments, particularly vital for cities like Isfahan facing unique climatic and energy challenges. The continued evolution of AI promises even more resilient, adaptive, and human-centric buildings for the future.

Declaration of Generative AI in Manuscript Preparation

During the preparation of this manuscript, the author(s) utilized generative artificial intelligence (AI) models, specifically ChatGPT (by OpenAI) and Gemini (by Google), as language enhancement tools. The primary applications of these AI tools were for:

Refining the translated text for grammatical accuracy, clarity, and native-like fluency in academic English.

Following the use of these AI tools, the author(s) conducted a thorough review, critical assessment, and editing of the entire manuscript to ensure its scientific accuracy and integrity. The author(s) assume full responsibility for all content, including the final wording, scientific arguments, and any potential errors.

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