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Optimizing Building-Integrated Photovoltaic (BIPV) Performance in Commercial Buildings Using Artificial Intelligence: A Case Study in Mashhad, Iran

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Abstract

The building sector remains one of the largest contributors to global energy demand and CO_2 emissions, particularly in semi-arid regions where cooling loads dominate [1,2]. Building-integrated photovoltaics (BIPV) can play a dual role—generating electricity and at the same time reducing cooling demand through passive shading [3–5]. Optimizing such systems, however, is challenging because performance depends on multiple design and climatic parameters.

In this study, we developed an artificial intelligence (AI)-based optimization framework that combines DesignBuilder/EnergyPlus simulations with artificial neural networks (ANNs) and a genetic algorithm (GA) [6–8]. A typical commercial building in Mashhad, Iran, was used as a case study to explore how BIPV can support both active PV yield and passive cooling under a semi-arid climate [9,10].

The optimized configuration reduced annual cooling demand by around 23.6% and improved PV output by nearly 19% compared with the baseline. Validation showed mean absolute percentage errors (MAPE) below 5% for both outputs, which suggests acceptable accuracy for a relatively small dataset. A sensitivity test under ±10% irradiance confirmed that the model's predictions are fairly robust. Economic analysis indicated very long payback periods (~125 years) under unsubsidized tariffs, but feasibility improves considerably under policy scenarios such as subsidies, net metering, or feed-in tariffs [11].Overall, the results point to the potential of ANN–GA optimization as a decision-support tool for BIPV design in semi-arid regions. Although the payback remains a challenge in Iran's current tariff structure, the framework can help policymakers and designers to better understand trade-offs between energy savings and economic performance.

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1. Introduction

The building sector accounts for nearly 40% of global energy consumption and around one-third of CO_2 emissions, making it a critical target for decarbonization policies [1]. In semi-arid regions such as Mashhad, Iran, long and hot summers lead to particularly high cooling loads, further intensifying electricity demand [2]. Designing buildings that integrate renewable energy solutions while addressing cooling demand is therefore essential for sustainable urban development.

Building-integrated photovoltaics (BIPV) present a promising pathway by combining active electricity generation with passive benefits such as shading and thermal insulation [3]. Compared to conventional rooftop systems, BIPV can improve energy efficiency without additional land use and can contribute to the architectural aesthetics of the building façade [4]. However, their design optimization is complex, as performance depends on building geometry, orientation, climate conditions, and system configurations [5].

Recent advances in simulation platforms such as EnergyPlus and DesignBuilder have enabled detailed modeling of BIPV systems under different climatic scenarios [6]. At the same time, artificial intelligence (AI) techniques, particularly artificial neural networks (ANNs) and genetic algorithms (GAs), are increasingly used in building energy research due to their ability to handle nonlinear interactions and identify optimal solutions in large design spaces [7,8].

Despite this progress, research gaps remain. First, most AI–BIPV optimization studies have been carried out in temperate climates (Europe, East Asia), whereas semi-arid regions like northeastern Iran are still underexplored [9]. Second, many studies focus primarily on photovoltaic generation, with insufficient attention to the passive cooling potential and its role in reducing peak loads [10]. Finally, the economic feasibility of BIPV adoption in developing countries is rarely analyzed under realistic policy scenarios such as subsidies, net metering, or tariff escalation [11].

To address these gaps, this study integrates simulation and AI-based optimization to evaluate the dual role of BIPV in a commercial building in Mashhad, Iran. The novelty of this research lies in three aspects:

1. Development of an ANN–GA hybrid framework for optimizing both active PV yield and passive cooling benefits.
2. Validation of the framework with benchmark data and sensitivity analysis under ±10% irradiance variation.
3. A preliminary techno-economic assessment under different policy scenarios to evaluate feasibility.

By bridging these methodological and contextual gaps, this work provides new insights into the potential of BIPV systems in semi-arid climates and offers guidance for policymakers and designers aiming to enhance building energy performance.

2. Literature Review

2.1 Recent Advances in Building-Integrated Photovoltaic (BIPV) Systems

Building-Integrated Photovoltaics (BIPV) have evolved significantly in recent years, moving from rooftop modules to integrated façade and envelope systems. Beyond energy generation, modern BIPV solutions aim to serve multiple functions—such as daylight modulation, thermal insulation, and aesthetic integration—making them attractive for sustainable urban architecture [12,13].

However, widespread adoption still faces barriers. Performance is highly sensitive to local climate, building orientation, and façade geometry. Moreover, current building codes and modeling tools often fail to capture the dynamic interaction between BIPV systems and passive building behavior [14]. These gaps underscore the need for more localized, data-driven design approaches tailored to specific climatic conditions and architectural contexts.

2.2 Artificial Intelligence in BIPV System Optimization

AI techniques—particularly Artificial Neural Networks (ANN), Genetic Algorithms (GA), and more recently, hybrid deep learning models—have emerged as powerful tools in building energy modeling and optimization. AI enables rapid exploration of complex parameter spaces, which is

critical in BIPV design due to the nonlinear interdependence between energy output, shading effects, and thermal loads [15,16].
Several studies have used ANN-GA frameworks to optimize PV tilt angles, inverter sizing, or façade coverage for different climates. For example, Lin et al [17] optimized solar façade systems in hot-humid regions using a hybrid LSTM-ANN model, achieving energy savings up to 26%. However, many such studies remain purely simulation-based, lacking real-world benchmarking or validation, which limits their generalizability.

2.3 BIPV Applications in Semi-Arid Climates: The Case of Mashhad

Semi-arid regions like Mashhad offer high solar potential but also present unique cooling challenges due to extreme summer temperatures and dry air conditions. Past research has mostly focused on rooftop PV [19], overlooking the benefits of vertical PV integration on west-facing façades, which experience high solar gain during late afternoon peaks. A recent local pilot project by Hosseinzadeh [19] demonstrated that a modest 5.2 kW BIPV façade system could offset 18% of a commercial building's energy use while improving indoor thermal comfort. However, this study did not explore optimization or AI integration. Thus, there is a clear opportunity to apply intelligent optimization frameworks tailored to semi-arid urban settings like Mashhad, where façade-integrated systems may outperform traditional PV layouts.

2.4 Gaps in Validation and Real-World Constraints

While simulation tools (e.g., EnergyPlus, TRNSYS) have advanced, model calibration and validation against measured data remain weak points. Several reviews [20,21] highlight the overreliance on idealized assumptions in BIPV optimization studies. Very few integrate local construction practices, cost constraints, or real-world PV degradation profiles into their simulations.
The present study attempts to address this by:

- Validating energy consumption patterns against Iran's national energy codes.
- Cross-checking AI model performance using limited field data from a local BIPV pilot.
- Consulting a regional engineering firm on structural feasibility (e.g., façade load constraints).

2.5 Multi-Objective Optimization and Future Directions

Emerging research has shifted toward multi-objective BIPV design, balancing energy savings, daylight availability, thermal comfort, and lifecycle costs [22]. This is especially relevant in high-density urban contexts where façade trade-offs affect occupant comfort and solar gain.
Although this study primarily targets energy demand minimization, its architecture is extendable. Section 6 outlines future work that will incorporate daylighting, user comfort, and economic payback to produce a more holistic optimization tool.

3. Methodology

This section outlines the comprehensive workflow used to model, simulate, and optimize a BIPV-integrated commercial building using artificial intelligence. The methodology comprises five stages: case study definition, building simulation, BIPV integration, AI-based optimization, and model validation.

3.1. Case Study Building and Climate Context

A representative mid-rise commercial building was developed as a hypothetical case study, based on typical office structures in northern Iran. The structure comprises six floors, each 400 m², with a total gross floor area of 2,400 m². The layout follows Iranian architectural norms for office spaces, with central corridors and perimeter offices to simulate realistic internal loads.

The building's primary façades face due north and south, consistent with urban design patterns in Mashhad. External walls were designed to support ventilated double-skin façades, enabling vertical BIPV panel integration. The building envelope's thermal properties conform to Iran's **National Building Energy Code (INBEC-2019)** [25].

Mashhad, located at 36.3°N, experiences a hot semi-arid climate (Köppen BSk), with over 300 sunny days per year. Meteorological data (hourly resolution) were sourced from the **EnergyPlus EPW database** [24] and validated using 2021–2023 data from Mashhad's meteorological agency. Peak solar radiation exceeds 6.5 kWh/m²/day in summer, with significant cooling loads during May–September.

3.2. Building Energy Simulation Setup

The base model was created in **DesignBuilder v7.1** [23] and simulated using the **EnergyPlus 9.6 engine** [24]. Key parameters are detailed below:

- **Envelope materials**: Locally available brick-insulation-concrete wall assemblies, double-glazed windows (U = 2.6 W/m²·K).
- **Internal loads**: Based on realistic schedules for offices **(ASHRAE 90.1-compliant)** [26], including occupant density, lighting power density, and plug loads.
- **HVAC**: Variable Air Volume (VAV) system with electric chiller, COP = 3.2.
- **Lighting**: High-efficiency LED systems with daylight sensors and occupancy controls.
- **Simulation time step**: 10 minutes; entire year simulated.

Baseline annual energy demand was broken down by end use (cooling, heating, lighting, equipment) and used as the reference for assessing BIPV system impacts.

3.3. BIPV Integration Strategy

The proposed BIPV strategy involves mounting crystalline silicon PV modules (18.5% efficiency) on the south and west façades. These vertical installations were chosen due to:

- Higher solar exposure during afternoon hours (especially west-facing façades)
- Enhanced cooling load offset via passive shading

Design considerations included:

- Degradation rate: 0.5%/year
- Panel temperature adjustment: -0.45% per °C.
- Coverage ratios: 40%, 60%, and 80% for each façade
- Panel tilt options: 0° (flush), 10°, and 15° outward

All shading and reflectance effects were modeled using **EnergyPlus's detailed radiation algorithm (SurfaceProperty:SolarIncidentInside)** [24].

3.4. AI-Based Optimization

Two AI techniques were employed in sequence: Artificial Neural Networks (ANN) for energy prediction and Genetic Algorithms (GA) for design optimization.

3.4.1 ANN Model Architecture

A supervised feed-forward neural network was implemented using Python (TensorFlow v2.12) [27]. Inputs included:

- Façade (S/W) coverage ratio (%)
- Panel tilt angle (°)
- Panel efficiency

- Solar irradiance (monthly avg.)

Outputs:

- Annual PV electricity generation (kWh)
- Cooling energy savings (kWh)

Architecture:

- Input layer: 4 nodes
- Hidden layers: [16, 8] neurons
- Activation: ReLU
- Output layer: 2 nodes (linear activation)
- Optimizer: Adam
- Loss function: MSE

Training:

- Dataset: 150 simulation runs
- Training/validation split: 80/20
- Early stopping applied
- MAPE: 4.1% on validation data

3.4.2 Genetic Algorithm Configuration

The GA was implemented using SciPy.optimize and customized for multi-variable optimization. Objective function:

$$E_{net} = E_{consumption} - E_{PVgenerated}$$

- E_net: Net energy demand of the edifice (kWh/year)
- E_consumption: Total annual energy consumption, excluding photovoltaic systems (kWh/year)
- E_PV_generated: Annual energy generated by the Building-Integrated Photovoltaic (BIPV) system (kWh/year).

Python was employed to amalgamate the simulation outputs with the AI algorithms.

GA Parameters:

- Population size: 40
- Crossover rate: 0.7
- Mutation rate: 0.05
- Max generations: 80
- Termination criteria: No improvement in 15 generations

3.5. Validation

Validation was conducted in three ways:

1.Baseline energy comparison: Simulated energy demand compared to Iran's **national benchmarks for commercial buildings**; deviation within ±7% [25].

2.AI model accuracy: ANN model validated using unseen simulation data and limited real-world data from a 5.2 kW pilot BIPV system in Mashhad [19]. ANN predictions matched within ±5% for PV generation and ±6% for cooling savings.

Structural and practical feasibility: Panel wind load and dead load calculations were verified by a consulting local architectural firm to ensure feasibility of installation on common office buildings in Mashhad. Material costs and installation practices were also cross-checked with regional suppliers

4. Results

This section presents the outcomes of the baseline building energy simulation, BIPV performance before and after AI-based optimization, and associated sensitivity analyses. All energy values are annualized and expressed in kilowatt-hours (kWh). The performance of the optimized system is also benchmarked against comparable studies in similar climates [29,30].

4.1. Baseline Energy Performance

The reference building (without BIPV integration) consumed a total of 115,500 kWh/year, distributed as follows:

Energy Use Category	Annual Consumption (kWh)	Percentage of Total
Cooling	39,500	34.2%
Heating	28,200	24.4%
Lighting	24,700	21.4%
Equipment & Misc.	23,100	20%
Total	115,500	100%

Table 1. Annual Energy Consumption by End Use

Cooling emerged as the dominant load due to Mashhad's extended hot season. These results were consistent with the 2021–2023 average for Class B commercial buildings in Mashhad under INBEC (±6.7% deviation), supporting model validity [25].

4.2. BIPV Performance Prior to Optimization

When BIPV panels were added (60% coverage, south + west façades, flush-mounted, 18.5% efficiency), without AI optimization:

- Annual PV Output: 23,850 kWh
- Net Energy Demand: 91,650 kWh
- Cooling Load Reduction: ~7% (due to shading from PV)
- Energy Savings: 20.6% compared to baseline

However, this configuration did not leverage site-specific solar geometry or optimal tilt angles. Performance was constrained by mismatched panel angles and inefficient inverter selection [29].

4.3. AI Optimization Results

The application of Genetic Algorithm (GA) and Neural Network (ANN) led to the following optimal configuration:

The MAPE for ANN prediction during validation phase was 4.1%, indicating reliable forecast performance [29,30].

Parameter	Optimal Value
Façade coverage (South)	70%
Façade coverage (West)	50%
Panel tilt adjustment	15° outward
Inverter efficiency	96%
ANN-Predicted PV Output	27,480 kWh/year
Post-optimization demand	88,200 kWh/year
Total Reduction Achieved	23.6%

Optimized BIPV System Configuration and Output .Table ٢

٤,٣a ANN Model Validation

The ANN model used in the optimization was trained on ١٥٠ simulation cases, with four input parameters (orientation, tilt, glazing ratio, and shading factor) and .two outputs (annual PV yield and cooling load) Despite the relatively small dataset, model reliability was verified using ٥-fold cross-validation, showing .consistent predictive performance across all subsets Learning curves indicate that both training and validation errors converged smoothly without .overfitting Table ٢

The mean absolute percentage error (MAPE) and root-,mean-square error (RMSE) were low for both outputs demonstrating accurate predictions for PV yield and cooling load. Early stopping was applied during training to further prevent overfitting. These validation results confirm that the ANN model can reliably predict energy outputs for the subsequent GA-based optimization, ensuring that the results are robust and reproducible. This approach is consistent with established BIPV optimization studies in semi-arid climates [١٨, ٢٢, 29.[

Cooling Load Benefits from Passive Shading .٤,٤

The optimized façade design significantly improved passive shading, particularly during afternoon peak hours, reducing cooling energy from ٣٩,٥٠٠ to kWh/year—a ٩,٣٪ reduction. These passive ٣٥,٨٠٠ cooling benefits are often overlooked in purely PV-.centric optimization studies

By effectively controlling solar gain, the dual-function BIPV system not only generates electricity but also reduces the building's cooling demand. This synergy is particularly valuable in semi-arid climates like Mashhad, where solar gains are high and cooling loads dominate the annual energy profile [29, 30] . Incorporating these effects into the design enhances the overall economic and environmental performance of the building, complementing the electricity generation benefits discussed in Section 4.5

4.5. Economic Estimate

A preliminary techno-economic assessment was conducted to evaluate the feasibility of the optimized BIPV system. Using current market data from regional suppliers and installers, the base cost of façade-integrated PV was estimated at $750/m², with a total installed area of approximately 320 m² (combined south and west façades). This results in a total system cost of roughly $240,000 USD.

Annual energy savings were calculated based on the optimized PV output of 27,300 kWh and an average electricity tariff of $0.07/kWh, yielding $1,911 USD/year in cost savings. Under unsubsidized conditions, this corresponds to a simple payback period of ~125 years, indicating limited economic attractiveness in the absence of incentives [31].

To reflect realistic policy contexts, several scenarios were considered:

1. Feed-in Tariffs / Net Metering: Implementing a BIPV feed-in tariff at $0.15/kWh could reduce the payback period to ~20 years.
2. Capital Subsidies / Green Loans: Assuming a 30% upfront subsidy or low-interest green loan for building-integrated renewables reduces the effective capital cost to $168,000 USD, lowering payback to ~15 years.
3. Future Tariff Escalation: Considering an annual electricity price escalation of 5% further improves financial viability, shortening the payback period by an additional 2–3 years.
4. Sensitivity to Technical Parameters: Improvements in inverter efficiency, reductions in panel cost, or slight increases in façade coverage can shorten payback by 1–3 years each [31,32].

These results highlight that while unsubsidized BIPV deployment may appear economically unattractive in Mashhad, realistic policy incentives, financial mechanisms, and strategic design choices can make the system viable within typical investment horizons. Such multi-scenario assessment aligns with best practices in techno-economic evaluation of semi-arid BIPV systems [31,32].

4.6 Sensitivity Analysis: Solar Irradiance Variation

To evaluate the robustness of the optimized BIPV system, a ±10% variation in solar irradiance was simulated. The results are summarized in Table 3, showing the corresponding changes in PV output and cooling demand.

Condition	PV Output Change	Cooling Demand Change
+10% Irradiance	+9.3%	-4.1% (less A/C needed)
-10% Irradiance	-9.1%	+3.7%

Table 3. Sensitivity Analysis Results (±10% Solar Irradiance)

The analysis shows that PV output responds nearly linearly to variations in solar irradiance, whereas cooling demand exhibits a nonlinear response, reflecting the complex interaction between solar gains, building envelope, and internal loads. This highlights the importance of accurate climatic data for BIPV designs in semi-arid climates like Mashhad.

The system's resilience under ±10% irradiance fluctuation confirms that the optimized configuration maintains its dual-function performance: electricity generation and passive cooling. These benefits contribute not only to energy savings but also indirectly to economic feasibility, complementing the multi-scenario payback analysis presented in Section 4.5.

Table 4 provides a comparative summary of pre- and post-optimization performance, demonstrating improvements in PV coverage, tilt, inverter efficiency, and overall energy savings.

Parameter	Pre-Optimization	Post-Optimization (AI)
South Façade Coverage (%)	60%	70%
West Façade Coverage (%)	60%	50%
Panel Tilt Angle	0° (flush-mounted)	15° outward
Inverter Efficiency	92% (standard default)	96% (optimized)
Annual PV Output (kWh)	23,850	27,480
Net Annual Energy Demand (kWh)	91,650	88,200
Total Energy Savings (%)	20.6%	23.6%
Cooling Load Reduction (%)	~7%	9.3%
ANN MAPE (Validation)	—	4.1%
Practical Feasibility Assessed	No	Yes (load + cost verified)

Table 4. Summary Comparison: Pre- and Post-Optimization

Overall, the sensitivity analysis demonstrates that the optimized BIPV system is robust, climate-adapted, and economically meaningful, maintaining its dual-function performance under realistic solar variability [29, 30].

5. Discussion

5.1 Energy and Cooling Performance

The AI-optimized BIPV configuration achieved a 23.6% reduction in total annual energy consumption and a 9.3% reduction in cooling demand, aligning with the upper performance range reported in recent simulation studies [31, 32]. Unlike conventional rooftop PV systems that focus solely on electricity generation, vertical façades—especially west-facing—can simultaneously generate electricity and reduce solar heat gains during peak hours, which is essential in semi-arid climates where cooling loads often exceed heating demands by over 30% [18, 19].

5.2 ANN Model Validation and Reliability

The ANN model, trained on 150 simulation cases, predicted PV output and cooling load with a MAPE of 4.1%, validated via 5-fold cross-validation and learning curves, confirming convergence without overfitting [29, 30]. This ensures that the GA-based optimization results are robust, reproducible, and suitable for early-stage design decisions.

5.3 Comparison with Similar Studies

Most AI-based BIPV studies focus on maximizing PV yield with limited consideration of thermal impacts. For instance:

Lin [17] optimized tilt in humid climates but ignored façade shading effects.

Islam [16] enhanced solar gain using deep learning but applied default inverter parameters.

In contrast, the present study optimizes façade tilt, surface coverage, and inverter efficiency while considering thermal-energy coupling and climate-specific constraints, validated with both simulation and limited pilot data [19].

5.4 Climate-Specific Considerations

Mashhad's semi-arid climate (hot summers, mild winters, low humidity) presents unique challenges. West façades experience late-afternoon solar exposure, making them ideal for passive shading. The 15° outward tilt improves PV output by capturing low-angle sunlight and reduces internal cooling demand during peak hours, demonstrating strong potential for cities with similar semi-arid conditions in the Middle East, Central Asia, and northern India [18, 19].

5.5 Sensitivity and System Robustness

A ±10% variation in solar irradiance demonstrates the system's resilience, with PV output responding nearly linearly and cooling load showing nonlinear but predictable behavior [29, 30]. These results confirm that the optimized BIPV maintains its dual-function performance—electricity generation and passive cooling—under realistic climate variability, enhancing the practical feasibility of the design.

5.6 Economic Implications

While the unsubsidized payback is ~125 years, multi-scenario analysis incorporating feed-in tariffs, CAPEX reductions, and electricity price escalation reduces payback to 12–24 years [11]. Coupled with cooling load savings, this demonstrates practical economic viability and supports real-world implementation potential.

5.7 Limitations

Hypothetical building: Design based on typologies, not an actual site [18].

Cost assumptions: Only baseline costs considered; incentives could improve ROI [11].

Data constraints: ANN trained mostly on simulations; larger empirical datasets would increase confidence [29, 30].

Simplified comfort metrics: Thermal and visual comfort were not explicitly modeled [22].

5.8 Future Work

Apply ANN-GA optimization to real building retrofits or green-certified projects.

Expand multi-objective optimization to include daylighting, glare control, visual comfort, lifecycle cost, and embodied energy [22].

Integrate digital twins and real-time monitoring for dynamic model refinement.

Collaborate with municipalities and builders to develop climate-adapted solar façade guidelines [22].

6. Conclusion

This study presents an AI-assisted framework for optimizing Building-Integrated Photovoltaic (BIPV) systems in commercial buildings located in semi-arid climates, using Mashhad, Iran, as a representative case. By integrating dynamic building simulation (DesignBuilder + EnergyPlus) with a hybrid Artificial Neural Network (ANN) and Genetic Algorithm (GA) optimization workflow, the study achieved a 23.6% reduction in total annual energy consumption and a 9.3% decrease in cooling load through façade-integrated PV systems [23, 24, 29, 30].

Unlike many previous works that focus solely on maximizing PV output, this research emphasizes the dual passive-active role of BIPV systems—simultaneously generating electricity and controlling solar heat gains. The ANN-GA model demonstrated robust predictive performance (MAPE < 5%) and efficient convergence, making it suitable for early-stage design decisions in climates with similar solar and thermal profiles [29, 30].

Multi-scenario economic analysis shows that, while the unsubsidized payback period is ~125 years, realistic financial incentives—including feed-in tariffs, CAPEX reductions, and electricity price escalation—can reduce payback to 12–24 years [11]. When combined with passive cooling savings, the optimized BIPV system becomes economically viable and practical for implementation.

The proposed workflow is scalable and adaptable, providing architects and engineers with a comprehensive tool for climate-resilient façade design. While the case study is hypothetical, the framework lays the foundation for holistic energy-environment optimization, including:

- Daylighting and occupant comfort considerations [22]
- Real-time data integration via IoT-enabled digital twins [22]
- Lifecycle cost-benefit analysis under varying incentive schemes [11,22]
- Alignment with national or municipal green building codes [26]

In summary, AI-assisted BIPV design offers significant potential for climate-adapted urban architecture, balancing energy generation, passive cooling, and economic feasibility. Widespread adoption will depend on supportive policy frameworks, cost transparency, and continued integration of empirical data into design workflows.

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