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Optimising L-Shaped Courtyard Building Design Using Prescriptive Analytics

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Abstract— Buildings in tropical climates are predominantly cooling-dominated, making architectural design decisions an important factor in reducing operational energy demand. While machine learning has been widely applied to predict building energy performance, most existing studies focus primarily on predictive accuracy and provide limited guidance on translating predictions into practical design decisions. Consequently, architects and designers often know the expected energy performance of a design but remain uncertain about which configuration should be selected to achieve specific energy objectives. This study proposes a prescriptive analytics framework that extends machine learning beyond prediction to support architectural decision-making for L-shaped courtyard buildings in Malaysia's tropical climate. A Gradient Boosting (GB) model was identified as the best-performing predictive model, achieving R^2 values of 0.999684, 0.998808, and 0.999695 for cooling load, heating load, and total load prediction, respectively. The trained model was subsequently integrated into a prescriptive optimisation engine to identify energy-efficient architectural configurations. The optimal cooling- and total-load designs converged towards compact building forms with a window-to-wall ratio (WWR) of 0.10, producing predicted cooling and total energy loads of 43.81 kWh/m² and 45.55 kWh/m², respectively. In contrast, the heating-load optimum was achieved with a WWR of 0.40, resulting in a predicted heating load of 0.68 kWh/m². A scenario-based "what-if" analysis further confirmed that the cooling-oriented design package consistently achieved the lowest overall energy demand. The results identify the window-to-wall ratio as the most influential architectural parameter affecting building energy performance and demonstrate that cooling and heating objectives cannot be optimised simultaneously. The proposed framework transforms machine learning from a predictive model into a practical decision-support tool that provides interpretable and actionable design guidance for architects during the early stages of building design.

Keywords— Prescriptive Analytics, Machine Learning, Building Energy Prediction, Gradient Boosting, Courtyard Buildings

I. Introduction

Buildings account for almost 40% of global energy demand, making the built environment one of the largest contributors to energy consumption and greenhouse gas emissions worldwide [1]. In Malaysia, the building sector consumes nearly half of the national electricity supply, with energy demand continuing to increase because of rapid urbanisation and growing cooling requirements under the country's hot-humid tropical climate [17][14]. These challenges highlight the importance of improving building energy efficiency through architectural design decisions made during the early stages of project development. Passive design strategies, particularly those related to building geometry and envelope characteristics, offer significant opportunities to reduce cooling demand before mechanical systems are considered [1] [15].

Among passive design strategies, courtyard buildings have long been recognised for their ability to improve natural ventilation, daylight distribution, and thermal performance. In Malaysia, courtyard configurations have evolved from traditional shophouses to contemporary educational, residential, and commercial developments, demonstrating their continued relevance in climate-responsive architecture [11] [23]. Previous studies have shown that courtyard geometry, orientation, and envelope characteristics influence solar exposure, airflow, and building energy performance [15] [10] [2]. However, evaluating these design alternatives using conventional simulation tools remains computationally expensive and time-consuming, limiting their practicality during conceptual design where multiple design options must be explored efficiently [6].

Machine learning has emerged as an effective surrogate modelling approach capable of predicting building energy performance from architectural design variables with substantially lower computational cost than conventional simulation methods [20][21]. Algorithms such as Random Forest (RF), Gradient Boosting (GB), and Artificial Neural Networks (ANN) have demonstrated strong predictive capabilities in estimating cooling load, heating load, and total energy consumption based on building geometry, orientation, and façade characteristics [6] [7] [18]. Nevertheless, most existing studies focus primarily on improving predictive accuracy, while providing limited support for practical architectural decision-making. Although designers can estimate the expected performance of a building, predictive models alone do not indicate which design configuration should be selected to achieve specific energy objectives [8].

This limitation highlights an important gap between predictive analytics and design practice. Predictive analytics answers the question of what will happen, whereas architects require guidance on what should be done to achieve better building performance. Prescriptive analytics addresses this limitation by combining predictive models with optimisation techniques capable of recommending design solutions based on predefined objectives [22] [13]. Despite its potential, the application of prescriptive analytics for courtyard building design remains limited, particularly within Malaysia's tropical context where cooling demand dominates operational energy consumption.

This study proposes a prescriptive analytics framework that extends machine learning from prediction to architectural recommendation. Building upon the best-performing Gradient Boosting model, the framework integrates an optimisation engine capable of evaluating thousands of potential L-shaped courtyard configurations to identify designs that minimise cooling load, heating load, and total energy load. In addition, a scenario-based "what-if" analysis is introduced through three representative design packages to provide architects with interpretable and practical design alternatives. Rather than simply predicting energy performance, the proposed framework supports evidence-based decision-making by translating machine learning outputs into actionable design recommendations for early-stage architectural design [3].

II. LITERATURE REVIEW

A. Machine Learning for Building Energy Prediction

Building energy prediction has traditionally relied on analytical and simulation-based methods, such as the Cooling Load Temperature Difference (CLTD), Radiant Time Series Method (RTSM), Total Equivalent Temperature Difference (TETD), and dynamic building simulation software. Although these methods provide reliable estimates of cooling and heating loads, they require detailed building information, extensive computational resources, and considerable modelling effort, making them less suitable for rapid evaluation during the conceptual design stage [5]. Furthermore, traditional approaches operate as deterministic models that do not learn from data, cannot capture complex nonlinear relationships, and are unable to generate prescriptive recommendations for design optimisation.

Recent advances in machine learning have provided an alternative approach for predicting building energy performance by modelling the nonlinear relationship between architectural variables and energy loads. Ensemble learning algorithms, particularly Random Forest (RF) and Gradient Boosting (GB), together with Artificial Neural Networks (ANN), have demonstrated high predictive accuracy in estimating cooling load, heating load, and total energy consumption based on geometric and envelope characteristics [6][7][18]. These surrogate models significantly reduce computational time while maintaining prediction accuracy, enabling designers to evaluate multiple design alternatives more efficiently than conventional simulation-based workflow [21] [20].

Despite these advances, most existing machine learning studies remain focused on predictive performance. Model evaluation is typically based on statistical indicators such as Root Mean Square Error (RMSE) and the coefficient of determination (R^2), with limited attention given to how prediction results can support architectural decision-making during the early design stage [7]. Consequently, machine learning is often used to answer what will happen rather than what designers should do.

B. Prescriptive Analytics for Building Design Optimisation

Prescriptive analytics extends predictive modelling by combining machine learning with optimisation techniques to recommend the most suitable decisions for achieving predefined objectives. Recent building energy studies have begun integrating machine learning surrogate models with optimisation and scenario evaluation to support early-stage design decision-making [13] [22]. Rather than predicting energy performance alone, prescriptive analytics identifies architectural configurations that minimise energy demand while satisfying specified design constraints.

Recent studies also emphasise that optimisation should acknowledge trade-offs between competing design objectives rather than seeking a single universal optimum. Building energy optimisation frequently requires balancing cooling demand, heating demand, thermal comfort, daylight availability, and other performance criteria, resulting in objective-specific solutions rather than one optimal design [9] [16]. This perspective is particularly relevant in tropical climates, where cooling demand dominates annual energy consumption and envelope characteristics, especially the window-to-wall ratio, play a decisive role in determining operational energy use. Consequently, prescriptive recommendations should be climate-specific and aligned with the primary energy objective of the building.

However, despite the growing application of machine learning in building energy prediction, limited research has

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integrated predictive models with prescriptive optimisation for courtyard buildings. Existing studies rarely combine multi-output machine learning, optimisation search, and scenario-based what-if analysis within a unified framework capable of producing actionable architectural recommendations, particularly in Malaysia's tropical climate [5].

Therefore, this study addresses this research gap by integrating Gradient Boosting with a prescriptive optimisation framework to identify energy-efficient L-shaped courtyard building configurations. Unlike conventional predictive models that estimate energy performance, the proposed framework systematically evaluates multiple architectural configurations and translates prediction results into practical design recommendations through optimisation and scenario-based analysis, thereby supporting evidence-based architectural decision-making.

C. Architectural Variables Affecting Building Energy Performance

Previous studies consistently demonstrate that architectural and envelope characteristics significantly influence building energy performance. Among these variables, the window-to-wall ratio (WWR) has been identified as one of the most influential parameters affecting cooling demand in tropical climates because larger glazed areas increase solar heat gain and consequently cooling energy consumption [12]. Similarly, building geometry, including form factor and surface-to-volume ratio, influences heat transfer between the building envelope and the external environment, affecting both cooling and heating loads [13].

Courtyard geometry further contributes to building energy performance by influencing solar exposure, shading, and natural ventilation. Previous studies have reported that courtyard dimensions, orientation, and geometric proportions affect thermal behaviour and energy demand, particularly in hot-humid climates [15] [10] [2]. These findings indicate that optimising architectural variables rather than relying solely on mechanical systems can substantially improve building energy efficiency during the early stages of design.

D. Optimisation Techniques for Building Energy Design

Building energy optimisation has gained increasing attention as researchers seek to identify architectural configurations that minimise energy consumption while satisfying multiple design objectives. Conventional optimisation approaches are commonly integrated with building energy simulation to evaluate alternative design solutions. However, simulation-based optimisation is computationally intensive because each design iteration requires repeated energy simulations, limiting its practicality during the conceptual design stage when numerous design alternatives must be explored [21] [20].

The emergence of machine learning surrogate models has significantly improved optimisation efficiency by replacing repeated simulations with rapid prediction models. Once trained, surrogate models can estimate building energy performance almost instantaneously, allowing optimisation frameworks to evaluate a substantially larger number of design alternatives within a shorter computational time. This capability enables designers to explore the influence of architectural variables on energy performance more effectively during the early stages of design [21] [20].

Despite these developments, most optimisation studies *focus on identifying optimal numerical solutions and rarely translate the optimisation outcomes into interpretable recommendations for architectural practice [19]. Designers often receive optimal parameter values without understanding how different design strategies perform under varying objectives. Consequently, optimisation results remain difficult to apply in practical decision-making. This limitation highlights the need for prescriptive frameworks that integrate optimisation with scenario-based analysis to provide architects with actionable and interpretable design recommendations.*

E. Research Gap

Although machine learning has demonstrated strong capability in predicting building energy performance, most existing studies focus primarily on improving predictive accuracy rather than supporting architectural decision-making [18][6]. Furthermore, relatively few studies have specifically investigated courtyard geometry despite evidence that building form, orientation, surface exposure, and window-to-wall ratio significantly influence thermal performance [15] [10] [2].

More importantly, predictive modelling alone does not provide actionable design recommendations. The integration of prescriptive analytics with machine learning to optimise courtyard building configurations remains largely absent, particularly within the Malaysian tropical context [22] [13]. Consequently, architects are able to estimate building energy performance but still lack practical guidance on selecting the most energy-efficient design configuration during the early stages of design. This study addresses this gap by integrating Gradient Boosting with a prescriptive optimisation framework and scenario-based what-if analysis to transform energy prediction into practical design recommendations for L-shaped courtyard buildings.

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III. METHODOLOGY

This study proposes a prescriptive analytics framework that extends machine learning beyond prediction by transforming predicted building energy performance into practical architectural recommendations. The framework follows the Cross-Industry Standard Process for Data Mining (CRISP-DM), consisting of business understanding, data understanding, data preparation, modelling, evaluation, and prescriptive analytics. While the predictive modelling stage identifies the most accurate machine learning model, the prescriptive stage applies optimisation and scenario analysis to recommend energy-efficient courtyard building configurations.

A. *Dataset and Predictive Model*

The study utilised the L-shaped courtyard building dataset developed by [4], which contains validated thermal performance and energy simulation data representing buildings located in Kuala Lumpur, Malaysia. The dataset includes seven architectural design variables, namely WIDTH, LENGTH, HEIGHT, ORIENTATION, WINDOWS_RATIO, FORM_FACTOR, and S_V_RATIO, while the response variables consist of COOLING_LOAD, HEATING_LOAD, and TOTAL_LOAD. These architectural parameters represent key geometric and envelope characteristics that influence building energy performance under Malaysia's tropical climate.

Three machine learning algorithms, namely Random Forest (RF), Gradient Boosting (GB), and Artificial Neural Network (ANN), were evaluated for predicting cooling load, heating load, and total energy load. Model performance was assessed using statistical error measures, and Gradient Boosting consistently demonstrated the most stable and accurate predictive performance across both single-output and multi-output prediction tasks. Consequently, the trained Gradient Boosting model was selected as the surrogate model for the subsequent prescriptive analytics stage.

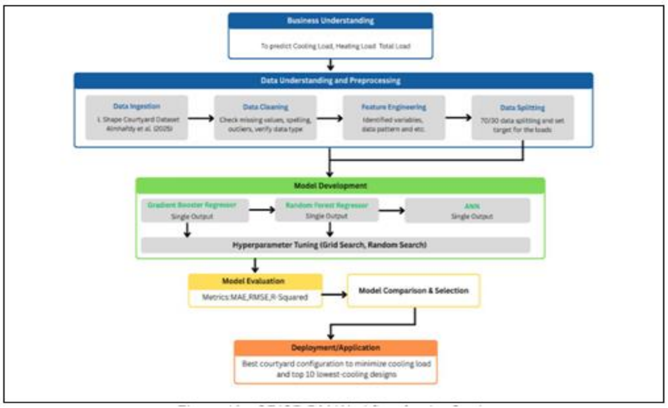

Fig 1. Machine Learning Model Development Workflow for L-Shaped Courtyard Energy Prediction.

B. *Prescriptive Optimisation Framework*

Unlike conventional machine learning studies that terminate after prediction, this research integrates the Gradient Boosting model into a prescriptive optimisation framework to identify energy-efficient architectural configurations. The predictive model serves as a surrogate model capable of rapidly estimating building energy performance without repeatedly performing computationally intensive building simulations.

The optimisation process began by generating thousands of possible combinations of the architectural design variables within the ranges defined by the dataset. Each generated design alternative was evaluated using the trained Gradient Boosting model to predict its corresponding cooling load, heating load, and total energy load. The predicted results were subsequently ranked according to three optimisation objectives:

- minimisation of cooling load,
- minimisation of heating load, and
- minimisation of total energy load.

For each objective, the design configuration with the lowest predicted energy demand was selected as the recommended solution. This optimisation process transforms predictive outputs into actionable architectural recommendations by identifying the most suitable design parameters for different performance objectives rather than merely estimating energy consumption.

C. *Scenario-Based What-If Analysis*

To improve the practical applicability of the proposed framework, a scenario-based what-if analysis was conducted following the optimisation stage. Rather than evaluating individual design variables independently, three representative architectural design packages were developed to simulate realistic design strategies commonly encountered during the early stages of building design. These packages enable designers to compare the expected energy performance of different architectural approaches before finalising a building configuration.

The three design scenarios consist of:

- Package A: Cooling-optimised design characterised by a compact building form with a low window-to-wall ratio.
- Package B: Conventional design representing moderate values across the principal architectural variables.
- Package C: A design with relatively higher glazing ratio and a vertically compact configuration.

Each package was evaluated using the trained Gradient Boosting model, allowing the predicted cooling load, heating load, and total energy load to be compared across alternative design strategies. This scenario-based evaluation

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provides architects with interpretable design guidance by illustrating the consequences of selecting different architectural configurations instead of relying solely on individual optimisation results.

IV. RESULTS AND DISCUSSION

A. *Gradient Boosting Performance*

Among the three machine learning models evaluated, Gradient Boosting achieved the highest predictive accuracy across all target variables and was therefore selected as the surrogate model for prescriptive optimisation. In the multi-output framework, Gradient Boosting achieved an RMSE of 0.01967 and R^2 = 0.999684 for Cooling Load, RMSE = 0.01012 and R^2 = 0.998808 for Heating Load, and RMSE = 0.01434 and R^2 = 0.999695 for Total Load. These values consistently outperformed Random Forest and Artificial Neural Network models, demonstrating the robustness of Gradient Boosting for subsequent optimisation tasks.

Since the objective of this study is to provide design recommendations rather than improve prediction accuracy alone, the trained Gradient Boosting model was subsequently employed as the optimisation engine for prescriptive analytics.

B. *Optimal Design Configuration*

The optimisation process evaluated multiple feasible L-shaped courtyard configurations to identify the architectural design that minimised each energy objective independently. The results indicate that different optimisation objectives produce different architectural solutions, confirming that no single design simultaneously minimises cooling, heating, and total energy demand.

TABLE 1 –
OPTIMAL DESIGN CONFIGURATIONS IDENTIFIED BY THE PRESCRIPTIVE OPTIMISATION FRAMEWORK

Parameter	Cooling Load	Heating Load	Total Load
Width (m)	60	60	60
Length (m)	60	30	60
Height (m)	8	16	8
Orientation	45°	0°	45°
Window-to-Wall Ratio	0.10	0.40	0.10
Form Factor	1.8007	1.3007	1.8007
S/V Ratio	0.4502	0.3476	0.4502
Predicted Load (kWh/m²)	43.81	0.68	45.55

For cooling load minimisation, the optimisation converged towards a 60 m × 60 m building footprint with a building height of 8 m, an orientation of 45°, and a window-to-wall ratio (WWR) of 0.10, producing a predicted cooling load of 43.81 kWh/m². Interestingly, the optimisation for total energy load converged to an almost identical configuration, yielding a predicted total load of 45.55 kWh/m². This finding indicates that, under Malaysia's hot-humid climate, cooling demand dominates total building energy consumption. Consequently, architectural strategies that minimise cooling load also minimise total energy demand.

Conversely, the optimal configuration for heating load differed substantially. The optimisation recommended a 60 m × 30 m footprint, 16 m building height, 0° orientation, and a WWR of 0.40, producing the lowest predicted heating load of 0.68 kWh/m². Compared with the cooling-optimised configuration, this design exhibits a lower form factor and lower surface-to-volume ratio, reflecting a more vertically compact geometry with greater façade transparency.

These results clearly demonstrate that optimisation objectives are conflicting. While cooling and total energy optimisation favour compact horizontal buildings with minimal glazing, heating optimisation benefits from taller buildings with larger glazing areas.

C. *Scenario-Based What-If Analysis*

To improve practical applicability, the optimisation results were translated into three representative architectural design packages.

TABLE 2
SCENARIO-BASED DESIGN PACKAGES

Package	Cooling (kWh/m²)	Heating (kWh/m²)	Total (kWh/m²)
Package A	43.847	1.727	45.553
Package B	45.651	1.194	46.845
Package C	47.279	0.681	47.964

Package A, representing the cooling-oriented design, achieved the lowest cooling load (43.847 kWh/m²) and total energy load (45.553 kWh/m²). This package adopted a low-rise configuration (8 m), a 60 m × 60 m footprint, a diagonal orientation (45°), and the minimum WWR of 0.10. Despite exhibiting the highest form factor (1.80) and surface-to-volume ratio (0.45), it consistently outperformed the remaining scenarios.

Package B represents conventional Malaysian design practice. Compared with Package A, cooling load increased from 43.847 to 45.651 kWh/m², while total load increased to 46.845 kWh/m², indicating that moderate glazing and increased building height reduce overall energy efficiency.

Package C produced the highest cooling (47.279 kWh/m²) and total energy loads (47.964 kWh/m²), despite achieving the most compact geometry. Although heating demand decreased to 0.681 kWh/m², the increase in cooling demand

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outweighed this benefit. Relative to Package A, cooling load increased by 3.432 kWh/m² (7.8%), confirming that increasing glazing ratio substantially increases operational energy demand under tropical climatic conditions.

V. CONCLUSIONS

This study proposed a prescriptive analytics framework that extends machine learning beyond prediction to support architectural decision-making for L-shaped courtyard buildings in Malaysia's tropical climate. While previous studies have primarily focused on predicting building energy performance, the proposed framework demonstrates how predictive models can be transformed into practical decision-support tools through optimization and scenario-based what-if analysis. Gradient Boosting was identified as the best-performing predictive model and subsequently employed as the optimization engine to recommend energy-efficient courtyard building configurations. By integrating prediction, optimization, and scenario analysis within a single framework, this study addresses the gap between predictive modelling and practical architectural decision-making [22][13].

The optimization results demonstrate that compact building forms with a low window-to-wall ratio (WWR = 0.10) consistently minimize cooling load (43.81 kWh/m²) and total energy load (45.55 kWh/m²), whereas heating load is minimized by a taller configuration with a higher window-to-wall ratio (WWR = 0.40), producing a predicted heating load of 0.68 kWh/m². Furthermore, the scenario-based what-if analysis confirmed that the cooling-oriented design package achieved the lowest overall energy demand, while the high-glazing package produced the highest cooling and total energy consumption. These findings demonstrate that cooling and heating objectives cannot be optimized simultaneously, highlighting the importance of objective-specific design recommendations for architects during the conceptual design stage.

The study further confirms that the window-to-wall ratio is the dominant architectural parameter governing cooling and total energy demand in tropical courtyard buildings. By transforming predictive machine learning into a prescriptive optimization framework, the proposed approach provides architects with practical guidance for selecting energy-efficient courtyard configurations instead of relying solely on predicted energy values. This contribution demonstrates how machine learning can evolve from a predictive technique into an evidence-based decision-support tool for sustainable building design.

Despite these contributions, several limitations should be acknowledged. The proposed framework was developed using a parametric simulation dataset for L-shaped courtyard buildings and therefore does not capture real-world operational variability, occupant behavior, shading devices, natural ventilation strategies, material thermal properties, or active building system performance. In addition, the optimization recommendations were generated using surrogate model predictions rather than direct field validation. These limitations may affect the generalizability of the findings to other building typologies and climatic conditions.

Future research should validate the recommended design configurations using real-world building case studies and measured operational data to further verify the effectiveness of the proposed framework. The framework may also be extended to other courtyard typologies and different climatic regions to improve its broader applicability. In addition, incorporating additional architectural variables such as shading devices, natural ventilation strategies, material thermal properties, and active building system efficiencies would enable a more comprehensive evaluation of building energy performance. Future studies may also investigate advanced neural network architectures and enhanced optimization techniques to further improve predictive performance and strengthen prescriptive decision support for sustainable building design.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR(S) CONTRIBUTION STATEMENT

All authors contributed equally to this work.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

This study did not require ethical approval.

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