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Skipping Energy Simulation with S-TCML: A Surrogate Machine Learning Sustainable Framework for Real-Time Thermal Comfort Evaluation in Office Buildings

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Abstract

The digital and green transitions in the AEC sector require rapid, data-driven workflows to redefine sustainability through real-time performance evaluation. However, the high computational cost of traditional energy simulations often lacks evidence-based feedback during early-stage design. This study introduces a surrogate machine learning framework (S-TCML) designed to bypass traditional energy simulation by providing an instantaneous assessment of thermal comfort. Using a parametric Grasshopper–Honeybee environment, a dataset of 3072 configurations was generated for an office room in Cairo, Egypt. Six machine learning algorithms were benchmarked, with Gradient Boosting and Random Forest demonstrating superior performance in capturing non-linear thermal physics. Validation against the EnergyPlus engine confirmed that S-TCML models deliver predictions in milliseconds—a 99.9% reduction in computational time. The Gradient Boosting model achieved exceptional accuracy with an R^2 of 0.999 and RMSE of 0.013 for PMV and an R^2 of 0.995 and RMSE of 0.46% for PPD prediction. Feature importance analysis proved that a tree-based ML model can capture the underlying physical relationship between variables. To bridge the feedback gap, a web-based graphical user interface (GUI) was developed to facilitate proactive design exploration. This framework supports sustainable decision-making and design efficiency, offering scalable, user-friendly tools that protect occupant health and ensure thermal resilience in hot-arid environments.

Keywords: surrogate modeling; machine learning; thermal comfort; early-stage design; hot-arid climates; PMV/PPD; data-driven workflow; office buildings



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1. Introduction

The transition from traditional vernacular architecture to modern, glass-heavy “International Style” offices in the MENA region has created significant thermal challenges [1], as high Window-to-Wall Ratios (WWRs) intensify solar heat gain and reliance on mechanical cooling. Fanger’s PMV/PPD model remains the standard for evaluating thermal comfort [2,3]. Its complex, non-linear variables make traditional Building Performance Simulation (BPS) a “computational bottleneck” during early design.

In the early design stage, architects need to evaluate a vast number of design alternatives (“what if” scenarios) quickly. Current BPS tools create a bottleneck because of

(A) simulation time, where standard building energy simulation tools may take between 20 s and 5 min for a single simulation. While individually short, this becomes prohibitive when thousands of iterations are required for optimization [4]; (B) large-scale parametric modeling—when using Multi-Objective Evolutionary Algorithms (MOEAs) or parametric modeling without sampling techniques, the process becomes costly in terms of time and computational resources [5]; (C) iterative process lag—the need for repeated simulations to find optimal solutions (e.g., for thermal comfort or energy efficiency) creates a lag that discourages architects from using BPS, leading them to rely on “rules of thumb” instead [4].

Rapid urbanization has increased pressure on energy systems, particularly in hot-arid regions such as North Africa and the Middle East [6]. In Cairo, Egypt, the climate is characterized by high solar radiation and large temperature variations during daytime hours. Recent studies show that the building sector accounts for approximately 40% of national electricity consumption, with cooling in residential and commercial buildings responsible for nearly half of this demand during the peak summer months [7]. As global temperatures continue to rise, cooling degree days in West Cairo are expected to increase further, leading to higher energy demand, increased carbon emissions, and growing energy affordability challenges. Architectural design in hot-arid climates has traditionally focused on reducing heat gains. However, contemporary office buildings—often defined by deep plans, extensive glazing, and high internal loads—frequently fail to maintain acceptable indoor conditions without continuous dependence on Mechanical Ventilation and Air Conditioning (HVAC) systems [8,9]. The core issue lies in early envelope design decisions. Parameters such as the Window-to-Wall Ratio (WWR) and room depth are typically fixed during the conceptual phase and remain unchanged throughout the building’s lifecycle [10]. These decisions remain unchanged lifecycle-wide due to high retrofit costs and the cost of modifying related structure/BIM models [4,11,12]. When poorly selected, these parameters result in long-term thermal discomfort that cannot be fully reduced, even by high-efficiency HVAC systems, due to excessive radiant heat from overheated surfaces.

1.1. Scientific Gap: Beyond Air Temperature

A clear gap exists in how thermal comfort is evaluated in common design practice. In many professional workflows, thermal performance is simplified to a single indicator: indoor air temperature (T_a) [3,13–15]. This simplification does not reflect how occupants experience thermal conditions. Human thermal comfort results from a heat balance between the body and its surrounding environment and is governed by four environmental variables—air temperature, Mean Radiant Temperature, air velocity, and relative humidity—together with two personal variables: metabolic rate and clothing insulation [13].

In office spaces with large, glazed facades, Mean Radiant Temperature (MRT) often becomes the dominant source of discomfort. For example, an occupant seated near a south-facing window in West Cairo may experience thermal stress due to long-wave radiation emitted by heated glazing surfaces, even when indoor air temperature is maintained at 24 °C. This condition is more accurately described using the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices. However, calculating MRT requires dynamic thermal simulations that account for solar movement, surface temperatures, and geometry-dependent view factors. Because these simulations are computationally demanding, they are rarely used during early design stages, where design flexibility is highest, and are instead applied only at later stages for performance verification [16].

Current industry workflows for thermal comfort assessment rely on parametric tools such as Ladybug and Honeybee coupled with the EnergyPlus simulation engine. While these tools provide high accuracy, they present a significant time-related problem that limits

their usefulness during early design. First, model preparation requires substantial effort. Developing a reliable parametric setup in Grasshopper linking geometry, weather files, and thermal zones needs skills that an average architect lacks [16]. Second, building energy simulation times vary significantly based on complexity, ranging from as little as 10 s for simple office zones [17] to several hours for high-quality daylighting analyses [18]. Third, effective design exploration requires hundreds or thousands of simulations. Evaluating a design space of 1000 geometric configurations across annual conditions can require more than eight hours of continuous computation [19,20]. This cumulative delay creates a clear feedback gap between design decisions and performance results. During early design, architects need immediate responses to “what-if” questions. When performance feedback is delayed, decisions tend to rely on intuition rather than quantitative evidence. As a result, opportunities to improve thermal comfort through early-stage design choices are often missed. A faster approach that maintains simulation-level accuracy is therefore needed.

1.2. The Role of Machine Learning in the Early Design Stage

As shown in Figure 1, to bridge this feedback gap, researchers are adopting surrogate modeling and machine learning (ML) to provide near-instant predictions of thermal and energy performance [21]. By training algorithms like Random Forests and neural networks on geometric inputs (WWR, orientation, and room dimensions) and validating them through rigorous metrics like R^2 and MAE, these models enable architects to make data-driven decisions without the time-intensive overhead of traditional physics-based engines [17]. A recent study [21] shows that neural network (NN) models, which are proposed as surrogates for CFD, can reproduce indoor airflow and thermal distributions with high accuracy (relative errors < 12%) while reducing calculation time by approximately 80% compared to traditional CFD.

Further investigation highlights a paradigm shift from traditional, static simulations toward intelligent, data-driven frameworks. Table 1 summarizes 19 key studies that utilize machine learning (ML) to resolve the computational bottleneck of the early design stage. A significant portion of the studies, such as [5,22–24], focus on predicting subjective human responses. Instead of relying solely on the traditional PMV (Predicted Mean Vote) equation, these studies train ML models to predict Thermal Sensation Votes (TSVs), Comfort Scales, and Satisfaction Levels. ML models like Random Forest have demonstrated higher accuracy (70%) compared to the PMV model (34% accuracy) because they can handle non-linear relationships between personal factors (age, gender) and environmental data [23]. Studies like [5,17] use ML to predict Cooling/Heating Energy Demand and Construction Costs. These serve as “Surrogate Models.” By training an ML algorithm on synthetic data generated by EnergyPlus, architects can instantly predict the energy performance of thousands of design iterations (changing window sizes, orientation, insulation) without running time-consuming simulations for each one.

Some studies targeted specific physical behaviors; for example, ref. [21] Predict Indoor Airflow Fields to replace computationally expensive Computational Fluid Dynamics (CFDs), and [18] predict Daylight Autonomy (sDA). These models drastically reduce calculation time (from hours to seconds), enabling real-time feedback during the design process. Field data (real-world) was used primarily for thermal comfort studies [25] The trained model can capture real human behavior and complex environmental interactions, but it is often site-specific (e.g., a specific clinic in Malaysia or an office in Philadelphia), making the model hard to generalize to other climates. ASHRAE Global Thermal Comfort Database II is the notable exception, providing a global dataset for more generalized models.

Simulated data (synthetic) were used primarily for Early Design Optimization [5,17,21,26,27]. Researchers run thousands of simulations (using EnergyPlus or Radi-

ance) to create a “synthetic” dataset. This method allows for a perfectly balanced dataset covering all possible design variations (e.g., every possible Window-to-Wall Ratio). On the other hand, the model is only as good as the simulation engine; if the simulation has a “performance gap” with reality, the ML model will inherit it.

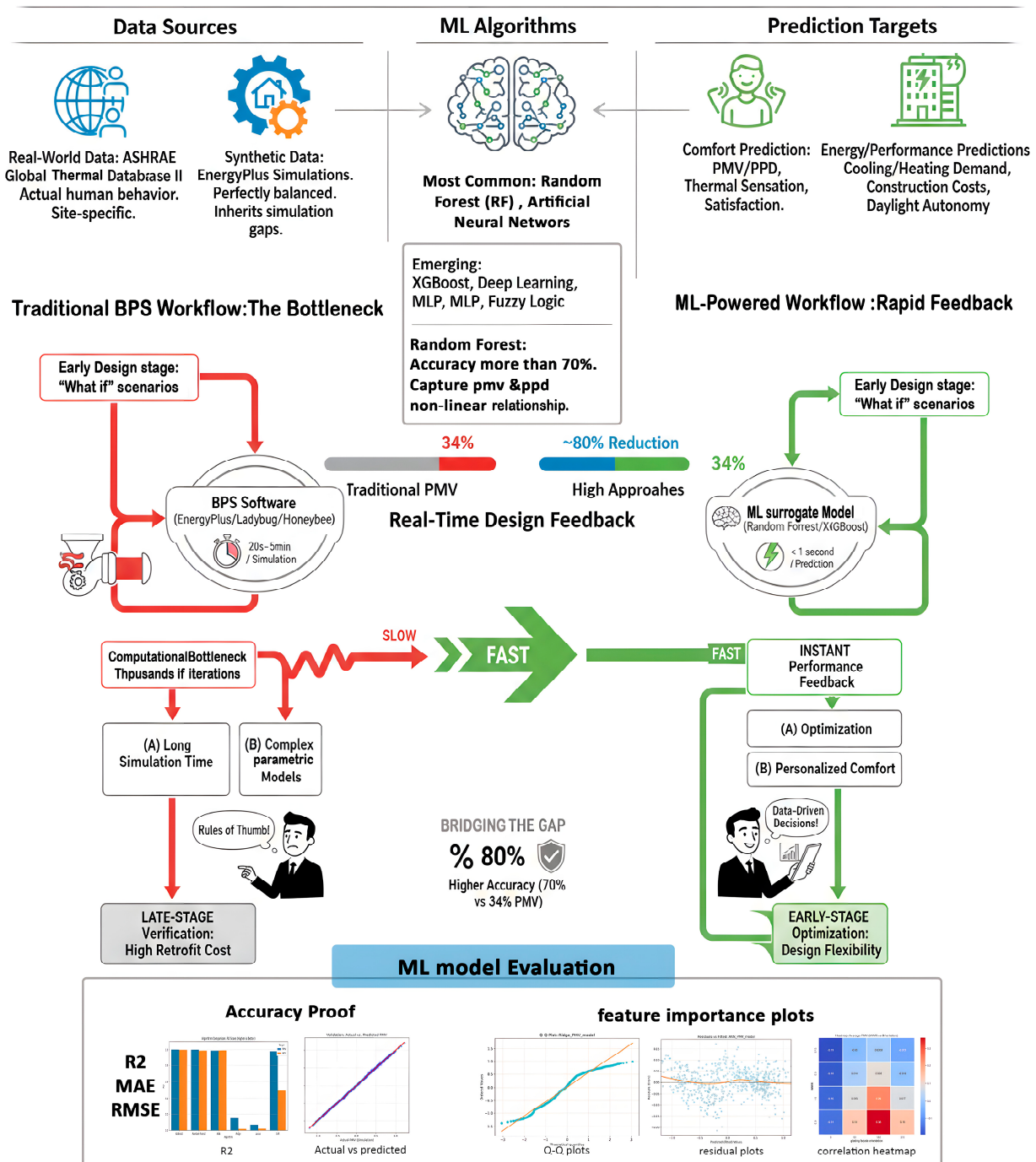


Figure 1. Summary of key insights from previous studies.

The choice of algorithm is what determines the model’s accuracy. Table 2 shows that most of the studies used Random Forest (RF) and Artificial Neural Networks (ANNs) in their model training process. Also, XGBoost was used among only two of the selected studies. Although XGBoost is a very powerful algorithm, it is still not commonly used because it is newly developed. Other algorithms were used in other studies, such as deep learning, MLP, MLR, fuzzy logic, and clustering. A significant limitation in previous re-

search is the lack of transparency; many studies do not provide access to their trained models or datasets, preventing other researchers from testing or building upon their work. Furthermore, most models fail to account for building geometry, treating the indoor environment as an abstract container while ignoring how a room’s specific dimensions and shape influence thermal behavior. In summary, machine learning in building design is evolving from theoretical experimentation to practical application. The field is shifting into two distinct paths: High-Fidelity Surrogate Modeling for rapid design optimization (replacing EnergyPlus) and Personalized Comfort Prediction (replacing PMV) for smart building operations. The primary remaining challenges identified are the “Black Box” nature of high-accuracy models, the reliance on synthetic data for design optimization, and the quality of the training data. This study addresses the identified gaps by proposing a surrogate thermal comfort prediction framework for office buildings in hot–arid climates. The main contributions of this work are as follows: (1) Development of a surrogate model: An XGBoost model is implemented in Python 3.13 to replace iterative EnergyPlus simulations during the early design phase. (2) Direct Geometry–Comfort Relationship: The study explicitly links key geometric parameters—wall width, room depth, and Window-to-Wall Ratio—to PMV and PPD, providing designers with clear and actionable guidance. (3) Climate-Specific Insights for West Cairo: The analysis focuses on the Egyptian context, examining the effect of orientation and glazing on thermal comfort and identifying the WWR as the primary source of prediction for office buildings located in West Cairo.

Table 1. Review of using machine learning models in building design, performance, and thermal comfort studies. (N/A = no available data).

Ref.	Data Available?	Input Parameters	Prediction Target	Considers Building Dimensions	Climate Zone	Limitation of the Study
[22]	No (Collected on-site)	Air temp, MRT, humidity, velocity, CO ₂ , TVOC, age, gender, clothing.	Thermal Sensation, Comfort Scale, Satisfaction Scale	No	Tropical (Malaysia)	MLP struggled to generalize; traditional AI models lack interpretability compared to fuzzy logic.
[23]	Yes (ASHRAE II is public)	Air temp, outdoor temp, RH, air velocity, clothing, metabolic rate.	Thermal Comfort Level (TSV)	No	Global/Various	Prediction performance is limited by data quality/diversity; PMV accuracy is significantly lower.
[26]	Yes (ASHRAE II is public)	Thermal comfort parameters (missing values).	Missing Thermal Comfort Data (Imputation)	No	Global/Various	Parameters related to individual preferences pose challenges for imputation.
[27]	Yes (Toolkit is software)	Task allocation, server resources, and power states.	Power Consumption/Energy Efficiency	No	N/A (Computing)	Simulator allows modeling but focuses on computing energy rather than building physics.
[5]	Yes (On request)	Typology, orientation, insulation, glazing, shading.	Construction Cost, Cooling Energy, Comfort Hours, Heating Hours	Yes (Typology/Insulation)	Extreme Hot, Tropical, Temperate (Mexico)	Inputs require coding of qualitative parameters; limited to specific housing typologies.
[28]	Yes (Zenodo)	Outdoor weather (temp, rad, wind), time, lagged indoor temp.	Indoor Air Temperature, PET	No	Temperate (Freiburg, Germany)	Models requiring “past data” perform best but cannot be used for new buildings without sensor history.
[29]	Yes (Public dataset)	Time, outdoor/indoor temp, humidity, velocity, age, floor number.	Indoor Thermal Parameters (To Determine Discomfort)	No (Floor Number Only)	Humid Subtropical (Philadelphia, USA)	Random Forest has a long modeling time; limited to a specific office context.

Table 1. Cont.

Ref.	Data Available?	Input Parameters	Prediction Target	Considers Building Dimensions	Climate Zone	Limitation of the Study
[30]	Varies	Energy, occupancy, and thermal comfort inputs.	Building Energy, Occupancy, Thermal Comfort, IAQ	Varies	Global	Most studies are experimental/simulated without post-occupancy validation.
[17]	No (Synthetic generation)	Room length, width, rotation, WWR, shading, U-values.	Cooling/Heating Demand, Comfort Indices (POR, DhC)	Yes (Length, Width, WWR)	Semi-arid/Composite (Tehran, Iran)	Constrained to single-zone calculations; specific parameter ranges.
[31]	Yes (BMKG/ERA5)	Air temp, wind speed, RH, pressure, cloud cover, irradiance.	Climate Zones (Clustering)	No	Tropical/Equatorial (Indonesia)	Identifies zones but requires a detailed building simulation to validate cooling potential.
[21]	No	Inlet temp/velocity, wall temps, obstacle temp.	Indoor Airflow Fields (Velocity, Temperature)	No (Fixed Room Size)	N/A (Indoor Physics)	Fixed domain size (2.44 m ³); non-convex training process requires early stopping.
[32]	Varies	Historical power data, meteorological data, and spatial features.	Wind Speed/Power, Solar Irradiance/Power	No	Global	Rare use of datasets from different climates; few generalizable models.
[18]	No (Generated)	Facade parameters (aperture, angle), intermediary features.	Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE)	Yes (Facade Geometry)	Subtropical (Taipei, Taiwan)	Focused only on south-facing window scenarios; uneven data distribution can reduce the model's effectiveness.
[24]	Yes (ASHRAE II is public)	Air temp, radiant temp, humidity, velocity, met, clo.	Thermal Sensation Vote (TSV)	No	Global	High accuracy (80%+) difficult to achieve with standard inputs; data imbalance.
[33]	No	Historical energy data, weather data.	Building Energy Consumption	No	Tropical Monsoon (Da Nang, Vietnam)	Requires large historical datasets; model specific to trained building types.
[34]	Varies	Urban form, building physics, systems, occupant behavior.	Urban Building Energy Performance	Yes (Urban Scale)	Global	Existing tools often lack integration with urban planning workflows.
[35]	No	Environmental variables, subjective votes.	Thermal Sensation/Perception	No	Hot Summer Cold Winter (Changsha, China)	Performance depends heavily on the diversity of the base learners.
[36]	No	Air temp, vapor pressure, wind speed, radiation.	Physiological Equivalent Temperature (PET)	No (Outdoor)	Temperate (Nis, Serbia)	Location-specific; ANN and GP had lower generalization than ELM.
[37]	No	Latitude, temp, building area, volume, passive tech.	Energy Efficiency (Heating)	Yes (Area, Volume)	Various European (Mostly Mediterranean)	Low R ² indicates the model explains only half the variance; small sample size.

Table 2. Machine learning models performance and evaluation metrics used in previous studies. (N/A = no available data).

Ref.	ML Algorithm					Evaluation Metrics				Dataset Size	Data Type	Time Resolution
	XGBoost	Random Forest	ANN	SVM	Other	R ²	RMSE	MAE	Other			
[22]	Y	Y	X	X	MLR, MLP, FUZZY LOGIC	Y	Y	Y	MBE	2278 samples	Field Data (Clinic)	Sub-hourly (1 min)
[23]	X	Y	X	X	KNN	X	X	X	AUC	107,463 entries	Field Data (ASHRAE II)	None (Point Data)

Table 2. Cont.

Ref.	ML Algorithm					Evaluation Metrics				Dataset Size	Data Type	Time Resolution
	XGBoost	Random Forest	ANN	SVM	Other	R ²	RMSE	MAE	Other			
[27]	X	X	X	X	Reinforcement Learning (Q-Learning)	X	X	X	Optimization	1000 timesteps	Simulated (EdgeAISim)	Simulation Step
[5]	X	Y	Y	Y	MLR	Y	Y	Y	MBE	Database generated	Simulated (EnergyPlus)	None (Annual/Design)
[38]	X	X	Y	X	N/A	X	X	Y	R(Pearson)	121 workplaces	Field Data (Sensors)	Hourly
[25]	X	Y	X	X	N/A	y	x	x	N/A	840,960 rows	Field Data (Office)	Sub-hourly (15 min)
[17]	X	Y	X	X	N/A	y	x	y	MSE	3384 samples	Simulated (EnergyPlus)	None (Annual/Design)
[31]	X	X	X	X	PCA, Cluster Analysis	X	X	X	N/A	8760 records/year	Historical Weather	Hourly
[21]	X	X	Y	X	N/A	X	X	X	N/A	9 training cases	Simulated (CFD)	None (Spatial/Static)
[18]	X	X	Y	X	N/A	Y	Y	X	N/A	193,500 samples	Simulated (Radiance)	None (Annual/Design)
[33]	X	Y	X	X	N/A	Y	X	Y	MAPE	1-year datasets	Field Data (Energy)	Hourly
[24]	x	Y	Y	Y	N/A	X	Y	Y	MAPE, SI	Varies (ASHRAE II)	Field Data	None (Point Data)
[36]	X	X	Y	X	ELM (Extreme Learning Algorithm)	Y	Y	X	R(Pearson)	8883 observations	Field Data	Hourly
[37]	X	Y	Y	Y	MULTIPLE REGRESSION	Y	X	X	N/A	77 buildings	Field Data (Survey)	None (Annual/Static)

2. Materials and Methods

METHODS OVERVIEW BOX: STEP 1—Parametric Energy Simulation: Tool: Grasshopper–Honeybee–EnergyPlus; inputs: 5 parameters (month, wall width, room depth, orientation, WWR); output: 3072 simulation records with PMV and PPD targets. STEP 2—ML Model Development: 6 algorithms tested; five-fold cross-validation (CV) + hyperparameter tuning; best model: XGBoost (PMV $R^2 = 0.999$; PPD $R^2 = 0.994$); SHAP interpretability + stratified feature importance. STEP 3—Deployment: Streamlit web app at <https://mlcomfortcalculator-2jmhivruday9i3qmpegnev.streamlit.app/> with real-time prediction, 3D geometry visualization, and ASHRAE comfort scale.

This study follows a simulation-driven and machine learning-supported methodology to develop an alternate model for instantaneous thermal comfort prediction in Egypt's hot-arid climate, as shown in Figure 2. The methodology is designed to isolate the influence of early-stage architectural decisions on thermal comfort while maintaining high prediction accuracy.

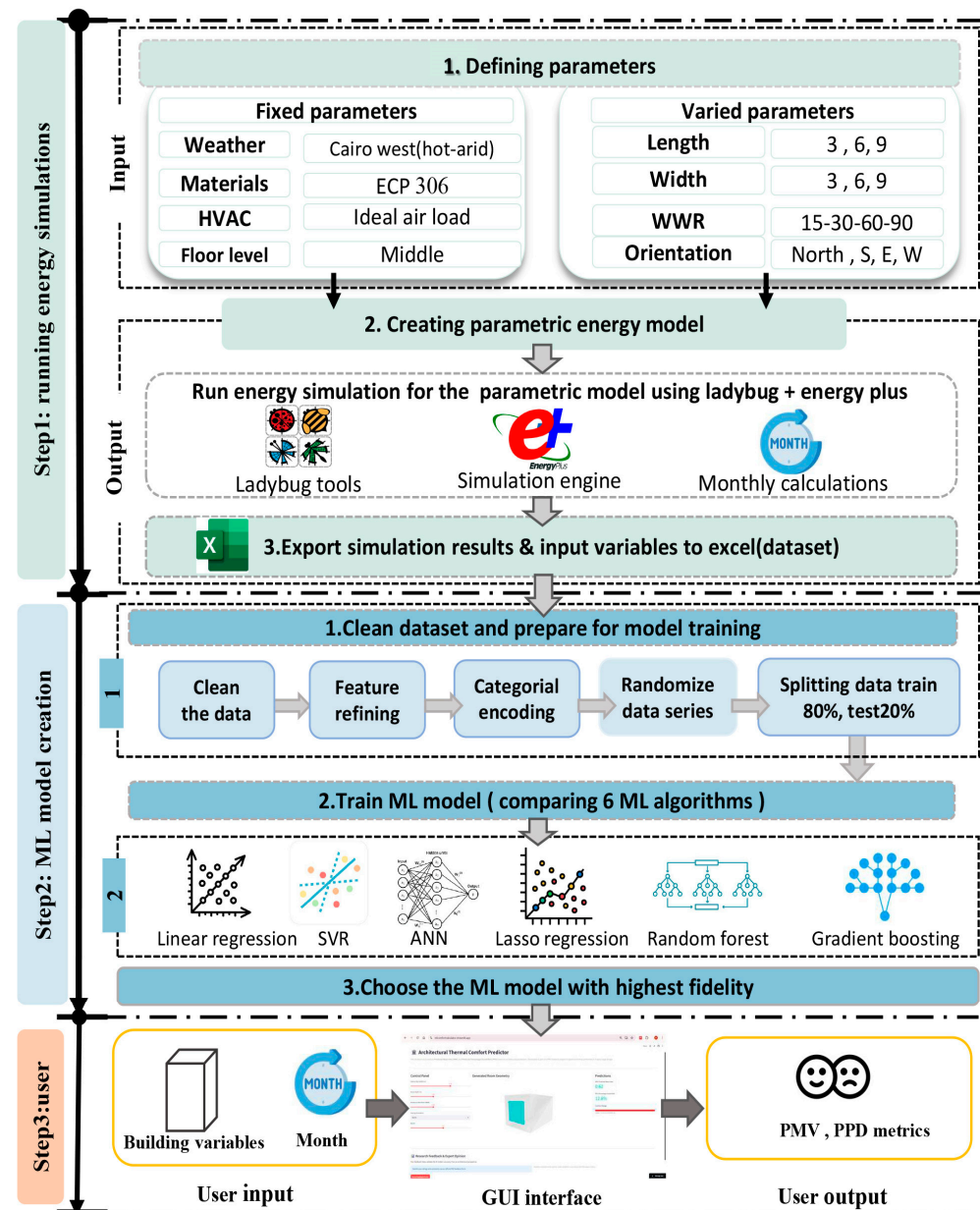


Figure 2. Methodology flow chart outlining the process of creating ML models for optimizing early design decisions through predicting PMV and PPD.

2.1. Step 1: Running Energy Simulations

The research focuses on a single office room with one exposed external facade to isolate the impact of orientation and the Window-to-Wall Ratio (WWR) on thermal comfort. Only rooms with a single exterior wall were considered to simplify thermal interactions. The parametric modeling approach was adopted, as shown in Figure 3, using the Rhinoceros 3D(Rhino 8) and Grasshopper environment to create a flexible room model that represents a hypothetical office building prototype capable of generating multiple geometric configurations. This prototype served as the foundation for dynamic thermal simulations and subsequent machine learning training. Thermal comfort simulations were conducted using the Ladybug and Honeybee plugins, which interface with the EnergyPlus simulation engine to calculate monthly thermal comfort indicators.

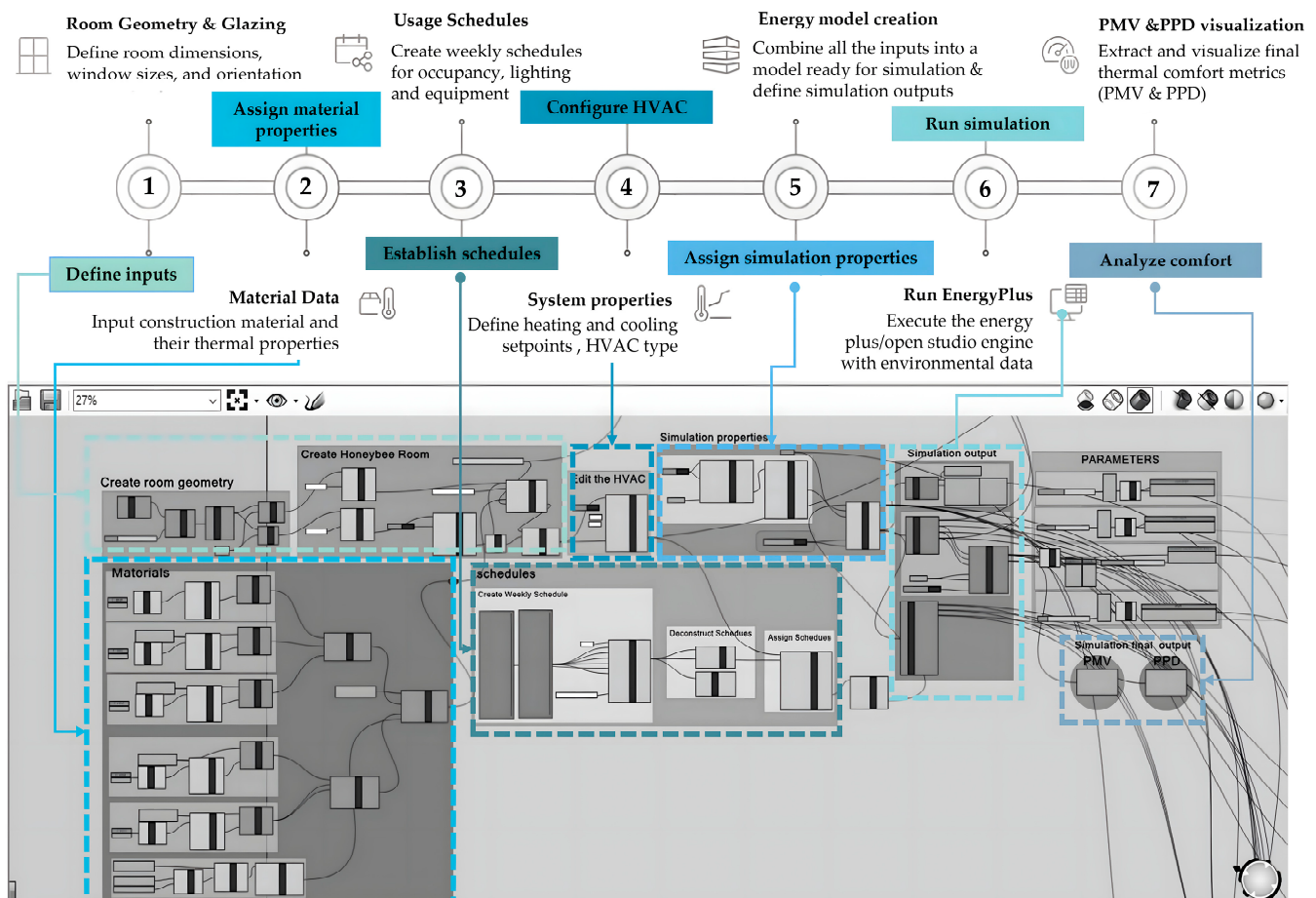


Figure 3. The parametric energy simulation workflow shows the seven main preparation steps: (1) define inputs, (2) assign materials, (3) assign schedules, (4) define HVAC system properties, (5) assign simulation properties, (6) run the energy simulation, and (7) collect results.

2.1.1. Defining Fixed Parameters

To focus the analysis on the relationship between geometry and thermal comfort, the weather file and construction materials were fixed. To ensure the energy simulation reflects the actual built environment in Egypt, a detailed construction set was developed. The thermal properties assigned to each building element were derived from the Egyptian Code for Energy Efficiency in Buildings (ECP 306) [39], representing a case of conventional, non-insulated construction, as shown in Table 3. The exterior wall U-value of $2.164 \text{ W/m}^2\text{K}$ was selected to reflect real-world Egyptian construction realities, accounting for thermal bridging in mortar joints and local materials in accordance with ECP 306 reference data. Furthermore, internal partitions and floors were modeled with adiabatic boundary conditions. The weather file used for the West Cairo location is classified by Koppen as a hot-arid climate [40]. The outdoor air temperature is retrieved from the average temperature of each month, as shown in Figure 4. The outdoor climate is fixed and limited to West Cairo to isolate the sensitivity of architectural parameters on occupant comfort. Also, all simulations employed the same HVAC system configuration (ideal air load) with sensible_hr = 0.81 and latent_hr = 0.75 to mimic real HVAC settings. Personal variables are indeed part of the Fanger PMV equation. In this study, they were held constant at standard office values: metabolic rate = 1 met (seated office work, ISO 8996) [41] and clothing insulation = 1 clo, consistent with ASHRAE Standard 55 reference conditions [42].

The HVAC system was defined with a cooling setpoint of 26°C and a heating setpoint of 20°C , reflecting common comfort expectations for office environments in the

local context. By holding envelope materials and system settings constant, the effect of geometric variation on comfort performance could be evaluated without interference from secondary variables.

Table 3. Construction set used in the simulation, based on [39].

Building Element	Layer Composition (Outermost to Innermost)	Thickness (m)	Conductivity (λ) [W/m·K]	Total U–Value [W/m ² K]
Exterior Wall	1. External Cement Plaster 2. Red Clay Brick 3. Internal Cement Plaster	0.02 0.25 0.02	1.40 0.70 1.40	2.164
Floor (adiabatic)	1. Reinforced Concrete Slab 2. Sand Layer 3. Cement Mortar and Tiles	0.15 0.05 0.04	1.75 0.70 1.20	4.14
Internal Partition (adiabatic)	1. Internal Plaster 2. Red Clay Brick 3. Internal Plaster	0.02 0.12 0.02	1.40 0.70 1.40	1.64
External Glazing	Single Clear Glass (6 mm) (Standard Aluminum Frame)	0.006	-	5.8 (SHGC: 0.85)

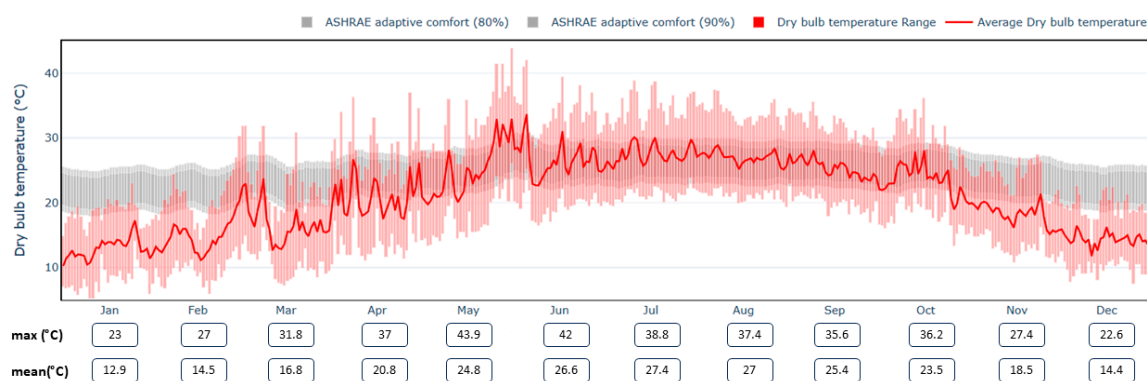
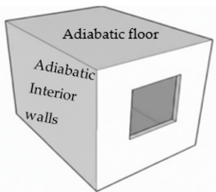


Figure 4. West Cairo weather file analysis for monthly dry bulb temperature and maximum temperatures recorded in each month based on [43].

2.1.2. Defining Varied Parameters

Five parameters were varied to generate the design space: month, exterior wall width, room depth, orientation, and Window-to-Wall Ratio. Monthly variation (1–12) was included to capture seasonal changes in solar exposure and outdoor conditions. Wall width and room depth were varied from 2 m to 9 m to represent a wide range of realistic office proportions. Orientation was tested at four primary angles (0°, 90°, 180°, and 270°), corresponding to the cardinal directions. WWR values ranged from 15% to 90%, covering both conservative and highly glazed facade scenarios, as shown in Table 4.

Table 4. Parametric model properties and parameters.

Model Properties	Parameter	Type	Values/Description
	Length	Varied	3 m, 6 m, 9 m
	Width	Varied	3 m, 6 m, 9 m
	Window-to-Wall Ratio (WWR)	Varied	15%, 30%, 60%, 90%
	Orientation	Varied	North, South, East, West
	Floor Level	Fixed	Middle
	Floor Height	Fixed	3 m

2.1.3. Workflow Validation

The simulation process was validated using the case study in [44]. The aim of the validation is to confirm that simulation inputs, parameters, and scripts produce outputs that are physically acceptable and technically correct. This process was carried out by comparing the simulation results of the electricity loads of the research parametric model and the validation paper. All key results were within an acceptable range of $\pm 10\%$, as shown in Table 5, confirming that the model and workflow are reliable in terms of creating the energy simulation database.

Table 5. Comparison of the validation model and the selected case study with respect to energy simulation results (electricity loads).

Electricity Use (kWh/m ² ·Year)	Validation Paper Result	Research Model Results	Difference	Notes
Total Electricity Use	176	169	−4%	✓ Within acceptable range.
Heating and Cooling Loads	30	27	−10%	✓ Within acceptable range.
Appliances Loads	143.5	140	−2.4%	✓ Within acceptable range.

2.1.4. Simulation Output and Dataset Creation

Through the systematic combination of the variables in Figure 5, a simulation was executed using Open Studio, an interface to EnergyPlus. Through simulation iterations, a dataset with unique geometric and climatic configurations was generated. In the Grasshopper environment, the simulation process is automated using colibri plugin, and the simulation data is exported to Excel using the TTtoolbox plugin, forming the base file of the dataset. The exported data contains simulation month, model properties (width, height, glazing ratio, etc.), and the energy performance results (monthly PMV and PPD), which are used as the target variables for machine learning prediction.

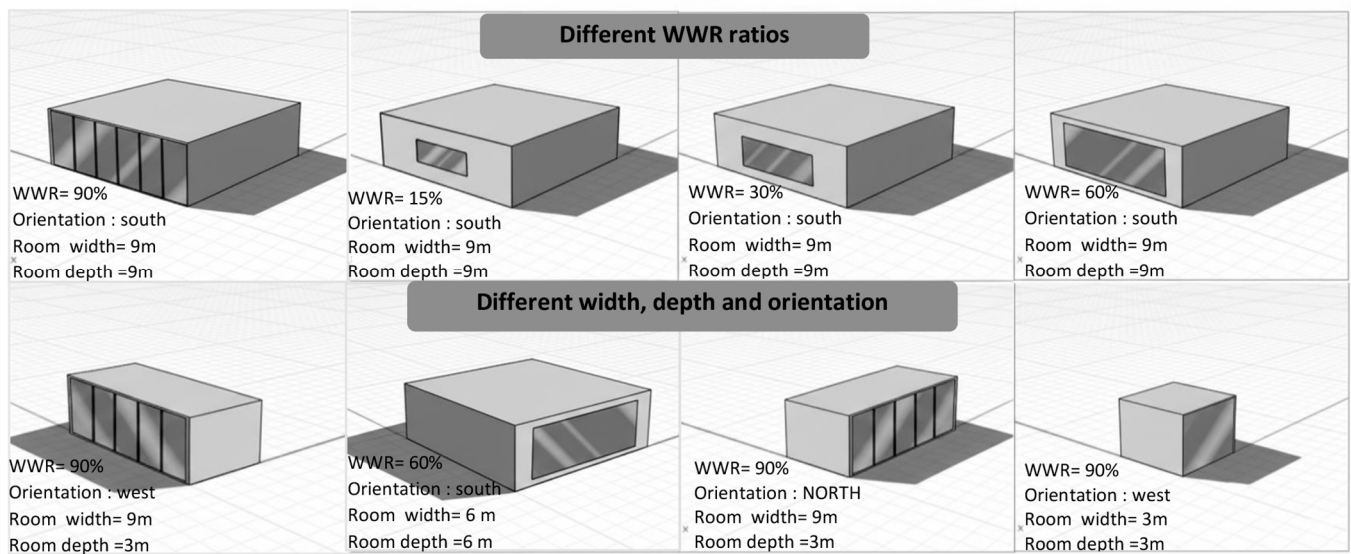


Figure 5. The parametric model design variation samples show the possibilities of different widths, depths, and Window-to-Wall Ratios.

The Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices were selected as thermal comfort indicators because they form the basis of major international standards for indoor environmental quality, specifically ASHRAE Standard 55 [41]

and ISO 7730 [45]. PMV and PPD are considered the industry standard for establishing baseline comfort in static, air-conditioned environments [46].

2.2. Step 2: Machine Learning Model Creation

The machine learning model creation follows a structured workflow to ensure accuracy and transparency. Exploratory data analysis was performed to examine data distribution and feature interactions for both subsets. Two predictive models were developed to estimate PMV and PPD using six regression algorithms selected based on prior studies: RF, XGB, ANN, Ridge, Lasso, and SVR, with predefined hyperparameters to control performance.

2.2.1. Dataset Preparation

Data preparation is the process of transforming raw data from its original format into a structured and organized form suitable for analysis [44]. In this research, dataset preparation was conducted through a structured preprocessing workflow to ensure data quality and prevent biased learning. First, a randomization process is executed; all records were randomized in Excel to remove any sequential structure in the dataset. This step prevents the ML algorithm from interpreting the data as a time-dependent series and ensures that patterns are learned based on feature relationships rather than record order. Then, data cleaning and formatting were carried out and the dataset was examined to ensure consistency and compatibility with ML algorithms. All variables were confirmed to be in numeric format, and any non-numeric entries were converted. The dataset was also checked to verify that no missing values were present.

Finally, after randomization and cleaning, the dataset was divided into 80% for training and 20% for testing. The training subset was used to develop the model, while the testing subset was reserved to evaluate its predictive performance on unseen data. This process ensures objective assessment and reliable model validation.

2.2.2. Dataset Analysis

Data analysis is the foundational stage where the researcher examines the characteristics, quality, and relationships within the dataset [46]. This process is critical because it identifies patterns that dictate which machine learning algorithms will be most effective and ensure the data is balanced for unbiased training. A distribution analysis and feature interaction analysis are conducted for both the training and testing datasets. Histogram plots are produced to visualize the distribution of individual variables and detect skewness or outliers. Finally, correlation heatmaps and scatter plots are generated to examine relationships between features and identify potential dependencies. Collectively, these visualizations provide a comprehensive understanding of the dataset, guiding model selection and ensuring robust, interpretable results.

2.2.3. Dataset Validation

A dataset validation process was conducted to confirm if thermal comfort values generated by the study reflect reality. Validation was carried out by comparing generated simulation data to real-world data. Due to the absence of monitored building data for the specific building typology studied, validation was performed against ASHRAE Global Thermal Comfort Database II [47] by comparing simulation PMV with the TSV from the ASHRAE II database.

A filtering process was conducted to keep only hot–arid climate records (Köppen BWh) with operative temperatures matching the simulation range (19.93–24.77 °C), a metabolic rate = ranges from 1.0:1.3, a clothing level from 0.7 Clo to 1 Clo and only air-conditioned office buildings to best match the simulation data constraints, yielding 23 reference records (18 winter, 5 summer) from case studies located in Australia. To eliminate sample size

bias, a 1-to-1 nearest operative temperature matching approach was applied, selecting for each ASHRAE record the single closest simulation row within the same season without replacement, resulting in 23 matched pairs with a mean temperature difference of 0.094 °C.

As shown in Table 6, winter results demonstrated acceptable PMV agreement (MBE = +0.478, $R = 0.847$, $p < 0.001$), with both datasets consistently indicating cool thermal conditions. Critically, simulation PMV showed directional agreement with real occupant Thermal Sensation Votes (TSVs) in both seasons—winter (TSV = −0.106, Sim PMV = −0.400) and summer (TSV = +0.140, Sim PMV = +0.021)—confirming that the simulation correctly characterizes occupant thermal experience. The overall Pearson correlation across all matched pairs was $R = 0.720$ ($p < 0.001$).

Table 6. Model validation summary—1-to-1 matched pairs ($n = 23$). Where R = Pearson correlation coefficient, P = probability value, std = standard deviation, and MBE = mean bias error.

Season	Metric	ASHRAE (Mean $\pm$ std)	Sim (Mean $\pm$ std)	MBE	Assessment
Winter ($n = 18$)	PMV	−0.878 $\pm$ 0.250	−0.400 $\pm$ 0.216	+0.478	Acceptable Agree
	TSV direction	−0.106 (cool)	−0.400 (cool)	—	
Summer ($n = 5$)	PMV	−0.778 $\pm$ 0.210	+0.021 $\pm$ 0.085	+0.799	Indicative (due to the small ASHRAE reference sample ($n = 5$)) Agree
	TSV direction	+0.140 (warm)	+0.021 (neutral)	—	
Overall ($n = 23$)	PMV (R)	−0.856 $\pm$ 0.241	−0.308 $\pm$ 0.262	+0.548	$R = 0.720$, $p < 0.001$ (results are valid)

This approach, while limited by the small reference sample ($n = 23$), unknown building characteristics of the ASHRAE surveyed buildings, the absence of monitored field data for the simulated typology and validation against case studies in other hemispheres, provides the best available external benchmark for the simulated thermal comfort indices. Notwithstanding these constraints, the directional consistency between simulation PMV and real occupant TSV across both seasons provides sufficient evidence to support the validity of the simulation outputs for the purposes of this study.

2.2.4. Model Training

In this study, 12 machine learning models were developed using Python 3.13 within the Visual Studio Code 1.113 environment. Visual Studio Code offers a complete set of tools and libraries, including NumPy, pandas, and scikit-learn, which support efficient development and deployment of ML models. Two independent prediction tasks were formulated: one model to estimate PMV and another to estimate PPD. Each task was trained and evaluated using the same set of selected algorithms to ensure a consistent and comparable assessment.

Based on the previous studies summarized in Table 2, the six most frequently applied machine learning algorithms in thermal comfort research were selected for training on the generated dataset. These algorithms are Random Forest, Extreme Gradient Boosting (XGBoost), Artificial Neural Network (ANN), Ridge regression, Lasso regression, and Support Vector Regression (SVR). The selection ensures methodological alignment with recent literature while allowing performance comparison across tree-based, linear, kernel-based, and neural network approaches.

The training process follows a structured workflow, as shown in Figure 6. First, the dataset generated was divided into 80% training and 20% testing subsets. The input features were identified using their column index in the data Excel sheet while PMV and PPD were treated as independent target variables. The model training workflow employs

a systematic Hyperparameter Optimization strategy using Randomized Search Cross-Validation (Randomized Search CV). The aim is to find the best parameters to train the ML model. A combination of 30 parameters is chosen based on each algorithm's search space. For XGBoost the search is for the best balance between number of trees and its learning accuracy. For algorithms sensitive to data scale such as SVR, ANN, a standard scaling process is applied inside a pipeline to prevent data leakage and to ensure accuracy. The fitted scaler was saved to be used in the future in the deployment process to make sure that the results are valid, A 5-fold cross validation method (K-fold) is used. The validation method divides the data into five parts, trains the model on four parts and tests on the fifth. The process is repeated till the model reaches its highest R^2 and lowest RMSE AND MAE. The optimized hyperparameters details, hyperparameter search space ranges and k-fold results for each algorithm are recorded in Appendix A, Table A1.

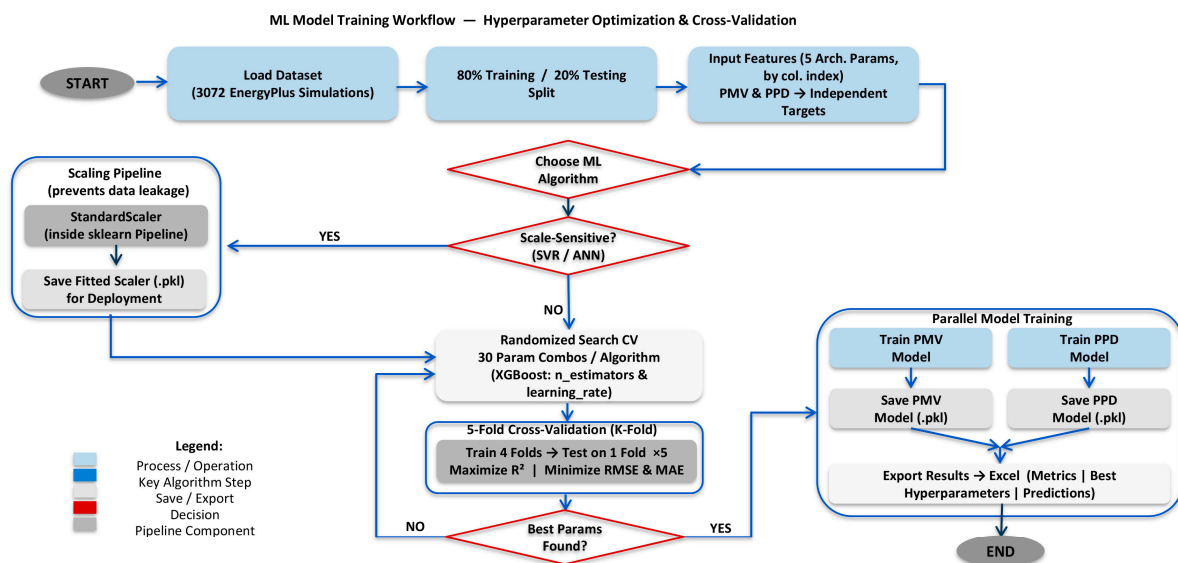


Figure 6. The ML model training workflow.

Furthermore, a learning curve analysis is conducted for the selected algorithms to evaluate the ML model learning process. The analysis helps in understanding how model performance evolves with increasing training data

2.2.5. ML Models Performance Evaluation Metrics

To verify that the machine learning surrogate serves as a reliable replacement for physics-based simulations, this study employs a rigorous validation framework using three quantitative metrics and three visual diagnostics for each trained algorithm. (A) Quantitative Metrics: Accuracy is measured through MAE (average error magnitude), RMSE (to identify significant outliers), and R^2 (to confirm the strength of the correlation between geometric inputs and comfort outcomes). Also, to enhance the quantitative robustness of the study, Quantile XGBoost Regression was employed to quantify prediction uncertainty. This method moves beyond point estimates by modeling the conditional distribution of thermal comfort indices (PMV/PPD), providing a 90% prediction interval (between the 5th and 95th percentiles).

(B) Visual Diagnostics: Actual vs. predicted plots detect systematic bias, Q-Q plots and residual plots verify the stability of errors across different room dimensions, and feature importance charts ensure the model's logic aligns with known thermal physics (e.g., the high impact of the WWR). Also, a sensitivity analysis using SHAP beeswarm plots is carried out to explain the relationships between variables, and a perturbation analysis is carried out

to evaluate the model's robustness. Each trained model was saved after training to preserve the learned parameters and to allow direct deployment without retraining. The evaluation results for all algorithms and both target variables were compiled into a comparative results table to enable objective performance benchmarking. By combining statistical precision with visual proof, this methodology transforms the "black-box" model into a transparent, trustworthy tool for early-stage architectural decision-making. The selected regression metrics listed in Table 7 are used to quantify the model's errors and correlation, as well as bias. These metrics collectively provide a detailed numerical and visual assessment of how well the model predicts the target variable across different evaluation criteria [48].

Table 7. Quantitative performance evaluation metrics are used to evaluate the predictive errors of the developed ML models [48].

Metric	Formula	
Determination Coefficient	$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$	(1)
Root Mean Squared Error	$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}$	(2)
Mean Absolute Error	$MAE = \frac{\sum_{i=1}^n y_i - \hat{y}_i }{n}$	(3)

Where n is the number of data points; y_i and $\hat{y}_i$ represent the actual and predicted values for the i th observation, respectively; and $\bar{y}$ represents the mean of the actual value.

2.3. Step 3: Model Deployment for Users

Deploying machine learning (ML) models through desktop and web-based applications improves accessibility and practical usability. Web-based deployment can be implemented using frameworks such as Streamlit [49]. Streamlit allows data-driven scripts to be transformed into interactive web applications. This approach supports real-time predictions and dynamic visualization without requiring local installation. As a result, users can access the model directly through a web browser. Deploying models as web applications expands their reach and ensures consistent user experience across different devices and platforms [45,50].

3. Results

This section presents a comprehensive evaluation of the S-TCML framework through three sequential stages. First, it establishes the statistical foundation of the study by conducting a detailed distribution and visual analysis of the generated dataset. Second, it systematically benchmarks the predictive performance of six machine learning algorithms for estimating PMV and PPD, using rigorous quantitative metrics (R^2 , MAE, and RMSE) supported by visual diagnostics to determine the most accurate model. Finally, it moves from evaluation to interpretation and application by extracting architectural insights through feature importance analysis and demonstrating the practical deployment of the best-performing model within an interactive real-time web application.

3.1. Generated Dataset Analysis

The generated dataset size is 3072 samples (rows) corresponding to the full factorial combination of 12 months $\times$ 4 orientations $\times$ 4 WWR values $\times$ 4 wall widths $\times$ 4 room depths = 3072 configurations. Each row represents an independent simulation run. The generated dataset is divided into 80% training set with 2457 rows and 20% test set with 615 rows (total: 3072 samples), as shown in Appendix A, Table A2.

The initial phase of the data analysis involved a comprehensive distribution assessment of both independent design parameters and dependent thermal comfort metrics, as detailed in Figure 7. The input parameters—month, exterior wall width, room depth, orien-

tation, and WWR—display discrete, uniform distributions with distinct peaks. Orientation is sampled at four primary cardinal points (0, 90, 180, and 270 degrees), while the WWR is tested at specific intervals ranging from 0.15 to 0.9. The exterior wall width and room depth show mirrored sampling at 2, 4, 6, and 9 m.

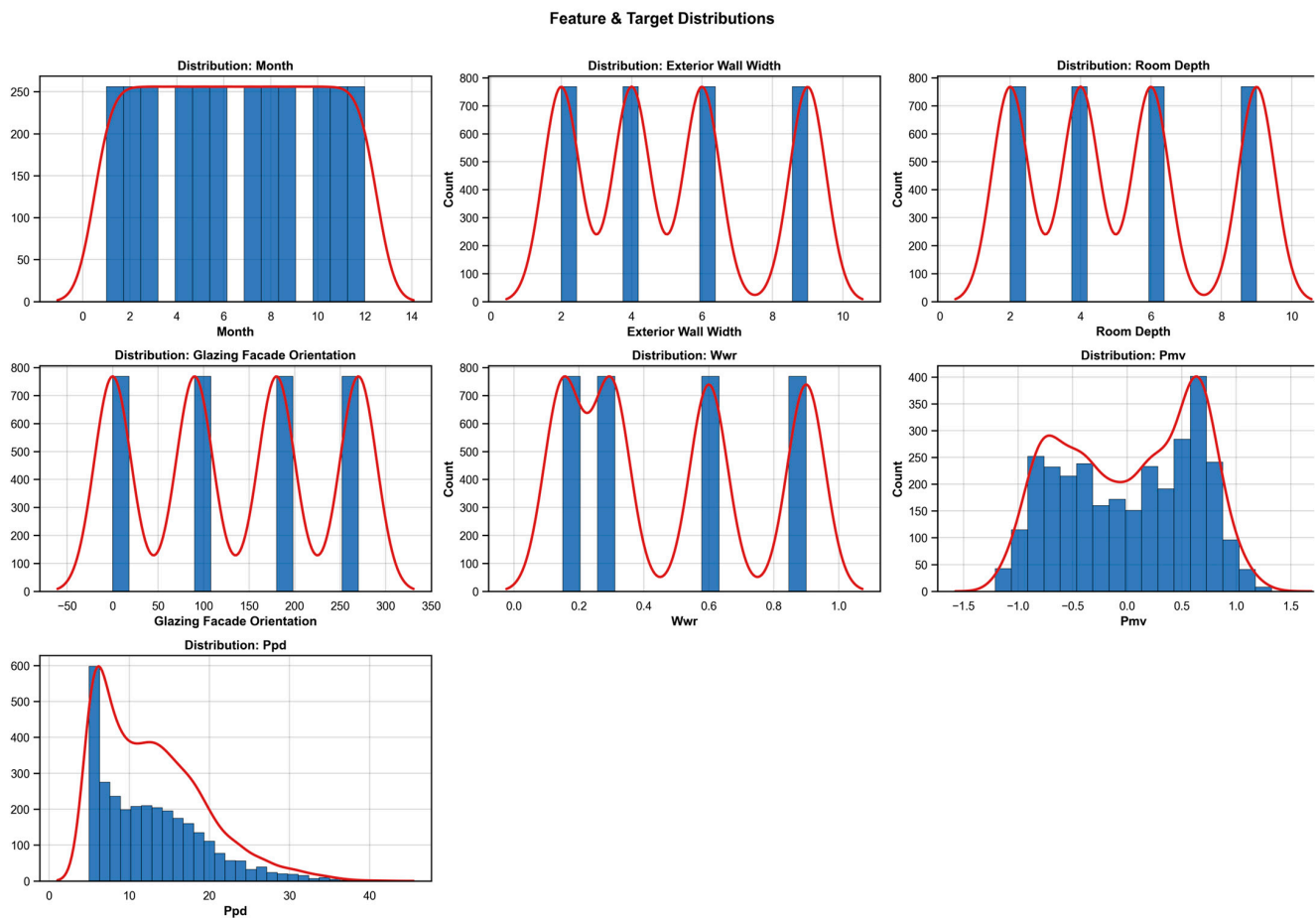


Figure 7. Distribution analysis of the main dataset. Frequency histograms (bars) and kernel density estimate (KDE) orange curves are shown for each input feature (month, wall width [m], room depth [m], glazing facade orientation [°], WWR [%]) and both target variables (PMV and PPD [%]).

The output variables for thermal comfort exhibit more continuous, natural distributions. The Predicted Mean Vote (PMV) shows a range from roughly -1.0 to $+1.2$, with a high concentration of neutral results between -0.5 and $+0.5$. The Predicted Percentage Dissatisfied (PPD) is heavily skewed toward lower values, with the majority of data points falling between 5% and 15%. A smaller tail of higher dissatisfaction reaches up to 40%, representing the most extreme design scenarios. This balanced dataset provides a robust foundation for machine learning because it represents both optimal and uncomfortable architectural configurations.

Regarding Temporal Seasonality, this dataset is cross-sectional, not a time series. Each row represents a fully independent simulation of a specific design configuration. (width, depth, orientation, WWR) for a specific calendar month. There is no temporal sequence between rows. A month-three record for a west-facing room is completely independent from a month-four record for the same room. Randomization before splitting, therefore, carries no risk of temporal data leakage. To verify balanced seasonal representation, the monthly distribution was confirmed to be statistically uniform (each month appearing in approximately 8.3% of records) in both the training and testing subsets, as shown in distribution analysis charts in Figure 7.

The correlation matrix, Figure 8a, reveals the specific influence of design variables on these comfort metrics. The month has a moderate positive correlation with PMV (0.290), highlighting the dominant role of seasonal outdoor temperature. Room depth shows a notable negative correlation with PPD (-0.133), suggesting that deeper rooms may offer more stable thermal zones in this specific dataset. Meanwhile, glazing facade orientation (0.135) and the WWR (0.126) show low positive correlations with PMV, indicating that increased window area and specific orientations contribute to higher indoor temperatures. The near-zero correlations between input variables (e.g., month vs. WWR) validate that the parametric study was perfectly balanced and free from multicollinearity.

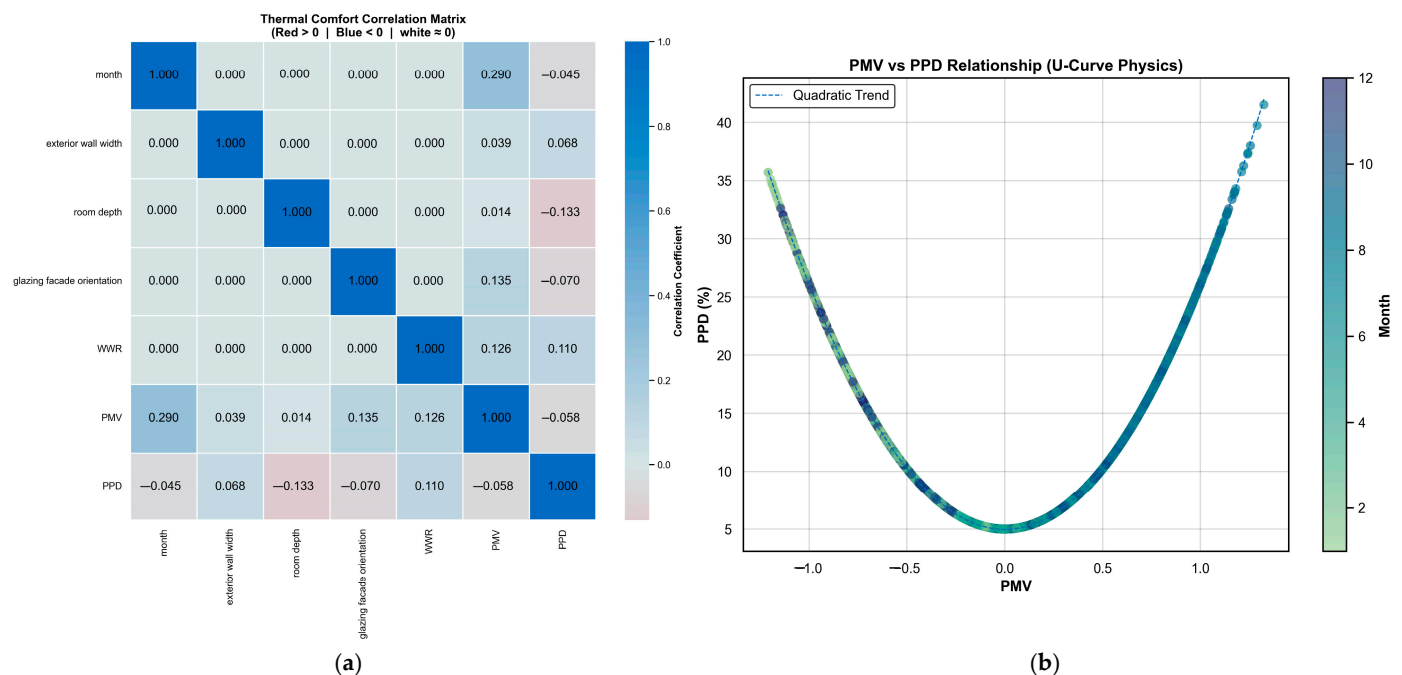


Figure 8. Feature interaction analysis of the generated dataset. (a) Pearson correlation matrix between all input features and thermal comfort indices (PMV and PPD). BLUE cells indicate positive correlations, RED cells indicate negative correlations, and light blue cells represent near-zero relationships. (b) Scatter plot illustrates the physical relationship between Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD), color-coded by month.

In the scatter plot, Figure 8b illustrates the fundamental physical relationship between the Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD), confirming the integrity of the generated simulation data. The distribution follows a perfect parabolic curve, adhering to Fanger's thermal comfort model, where the minimum PPD of 5% is achieved exactly at a neutral PMV of 0.0. As the thermal sensation deviates toward "cool" (-1.2) or "warm" ($+1.3$), the percentage of dissatisfied occupants increases symmetrically. On the cool side, a PMV of -1.0 corresponds to approximately 26% PPD, while on the warm side, the data reaches a maximum PPD of over 40% at a PMV of 1.3. The color-coding by month shows a clear seasonal divide: winter months (e.g., February and December) cluster on the negative PMV side, while summer months (June and August) dominate the positive, warmer side of the curve.

Seasonal Interaction Plots in Figure 9 illustrate the seasonal interaction between the month and the Window-to-Wall Ratio (WWR) with respect to thermal sensation. Figure 9A shows that thermal comfort follows a clear seasonal cycle. Winter has negative PMV values (around -0.75 to -0.80), meaning people feel cold. A low WWR makes winter colder because there is less solar heat gain. Spring is the only comfortable period. PMV values move close to zero for all WWR cases. Summer has positive PMV values (around $+0.75$ to

+0.85), meaning people feel hot. A high WWR increases overheating due to higher solar heat gain. Autumn gradually shifts back toward cold conditions. To conclude, the WWR increases discomfort: small windows worsen winter cold, and large windows worsen summer heat.

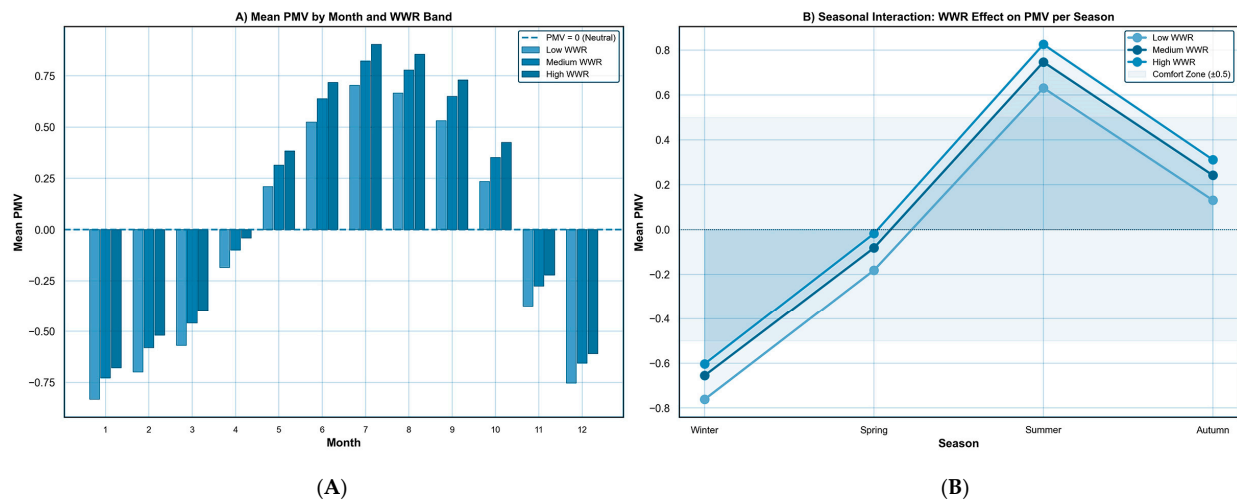


Figure 9. Seasonal interaction between month and the Window-to-Wall Ratio (WWR) on thermal sensation (PMV). (A) Mean PMV by month (1–12) for WWR = 15%, 60%, and 90% (solid, dashed, and dotted lines, respectively). (B) Mean PMV per season for each WWR level. Horizontal dashed lines mark the ASHRAE 55 comfort range (PMV $\pm$ 0.5).

Figure 9B shows that the three WWR values do not behave the same across seasons. The lines are not parallel, which means there is a real interaction between the WWR and season in affecting thermal sensation. The difference between the effect of the change in WWR values is biggest in summer and winter and smallest in spring. This means the WWR has the greatest impact during extreme weather conditions. The ASHRAE comfort range (PMV $\pm$ 0.5) is exceeded in both summer and winter for all WWR cases. This shows that the WWR, as a passive facade design alone, cannot maintain comfort all year in this building type. Overall, medium WWR gives the most balanced performance. It reduces winter cold without greatly increasing summer overheating. However, since comfort limits are still exceeded, additional solutions should be investigated.

3.2. ML Model Performance

Comparing the resulting 12 models, six for PMV and six for PPD, against six ML algorithms, quantitative analysis and visual analysis are conducted. Also, attached to Appendix A is the “Test dataset” used for model validation.

3.2.1. Training Performance Analysis (Learning Curve) for PMV and PPD Models

The training performance is evaluated through learning curve analysis across all models. The analysis plots in Figures 10 and 11 contain two curves representing models’ performance during training against two datasets; the blue curve represents the performance of the training dataset, while the red curve represents the performance of the test dataset. For the PMV model, the XGBoost, ANN, and SVR models show a much smaller gap between the two curves compared with the other algorithms, indicating that the models are not memorizing the data (overfitting). The strong alignment at a high R^2 value (around 0.99) (convergence) also indicates that these models produce reliable predictions for unseen data and successfully capture the underlying patterns governing PMV. For the PPD model, XGBoost performed the best, indicating that the rest of the algorithms failed to learn and predict PPD accurately.

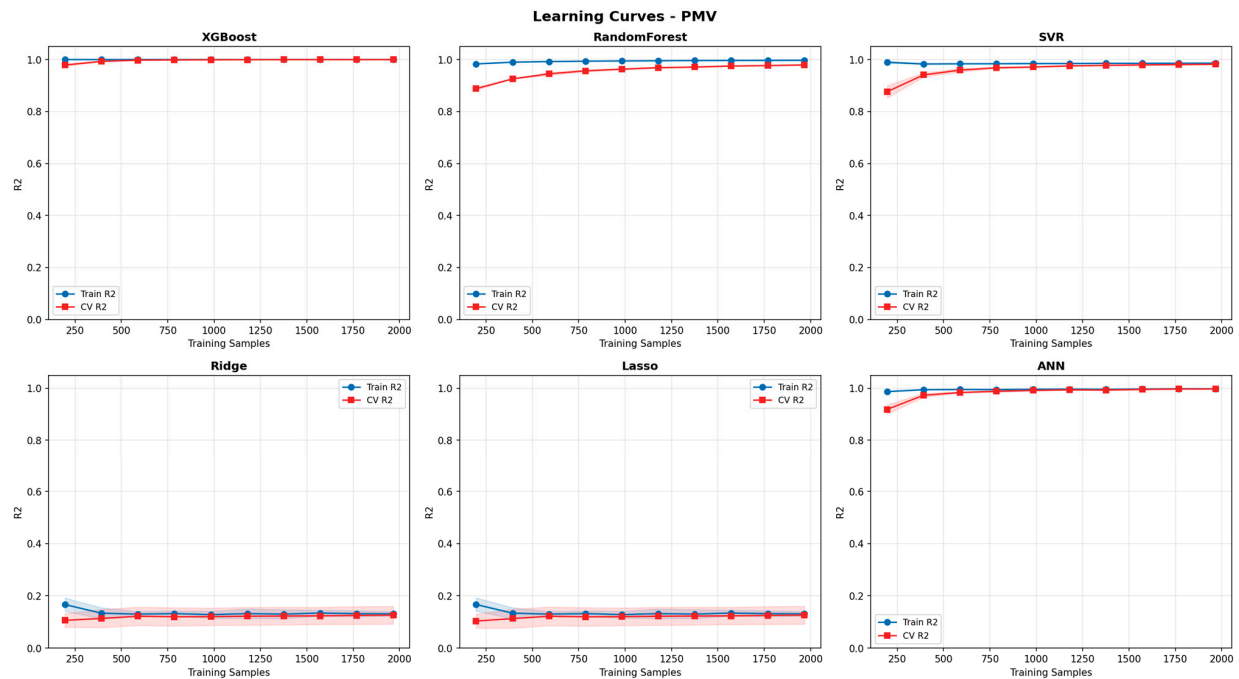


Figure 10. PMV learning curve analysis. X-axis: number of training samples; Y-axis: R^2 (dimensionless). Solid blue line: training set; dashed red line: test set. Sub-panels: XGBoost, Random Forest, ANN, SVR, Ridge, Lasso.

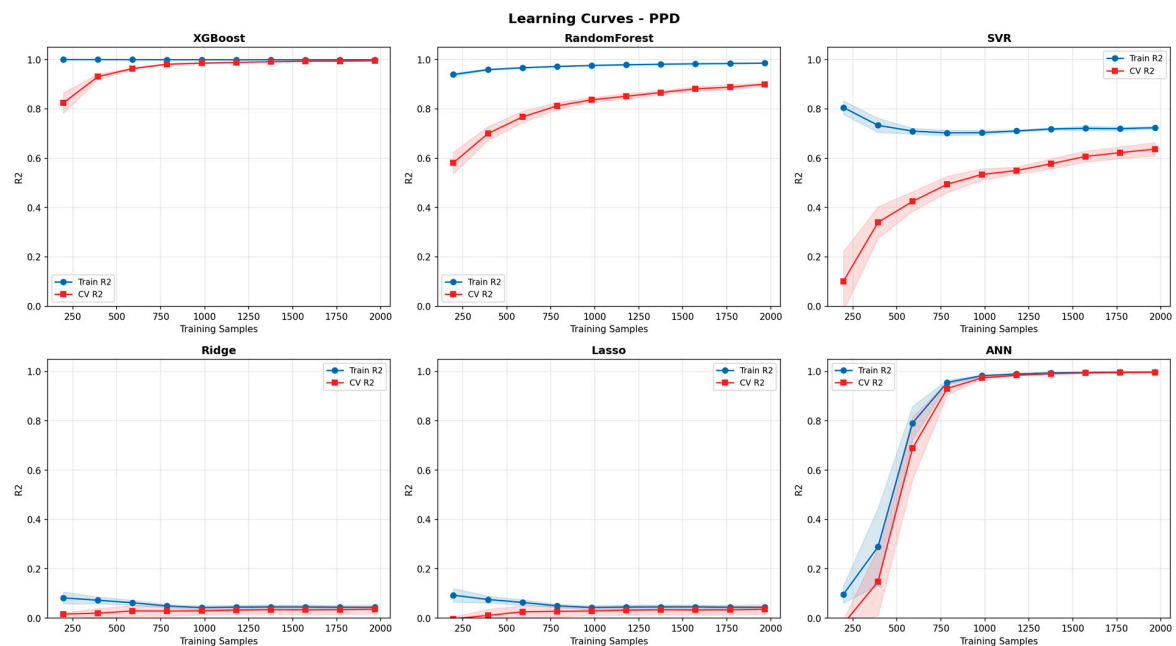


Figure 11. PPD learning curve analysis. X-axis: number of training samples; Y-axis: R^2 (dimensionless). Solid blue line: training set; dashed red line: test set. Sub-panels: XGBoost, Random Forest, ANN, SVR, Ridge, Lasso.

3.2.2. Prediction Performance Analysis for PMV and PPD Models

Model accuracy was evaluated using R^2 , MAE, and RMSE to provide a comprehensive assessment of goodness of fit and prediction error magnitude.

I PMV Prediction Performance

For PMV estimation, as shown in Figure 12a,c,e, Extreme Gradient Boosting (XGBoost) achieved the highest predictive accuracy with an R^2 of 0.999, an MAE of 0.006, and

an RMSE of 0.009. These values indicate an almost perfect agreement between predicted and simulated PMV values. The Random Forest model also demonstrated excellent performance, with an R^2 of 0.9983 and a low RMSE of 0.0246, confirming the robustness of tree-based ensemble approaches for non-linear thermal comfort prediction. The Artificial Neural Network (ANN) achieved an R^2 of 0.9905, with slightly higher error values (RMSE = 0.0574). Although less accurate than the ensemble models, the ANN model maintained strong predictive capability. Support Vector Regression (SVR) also performed well, with an R^2 of 0.9823 and RMSE of 0.0784, indicating reliable non-linear approximation but reduced precision compared to ensemble methods. In contrast, the linear regularization models, Ridge and Lasso, showed very poor performance in terms of PMV prediction. Their R^2 values (0.0686 and 0.0445, respectively) indicate that these models failed to capture the non-linear relationships within the dataset. The high RMSE values (≈ 0.57) confirm the inadequacy of purely linear approaches for modeling PMV under the studied conditions.

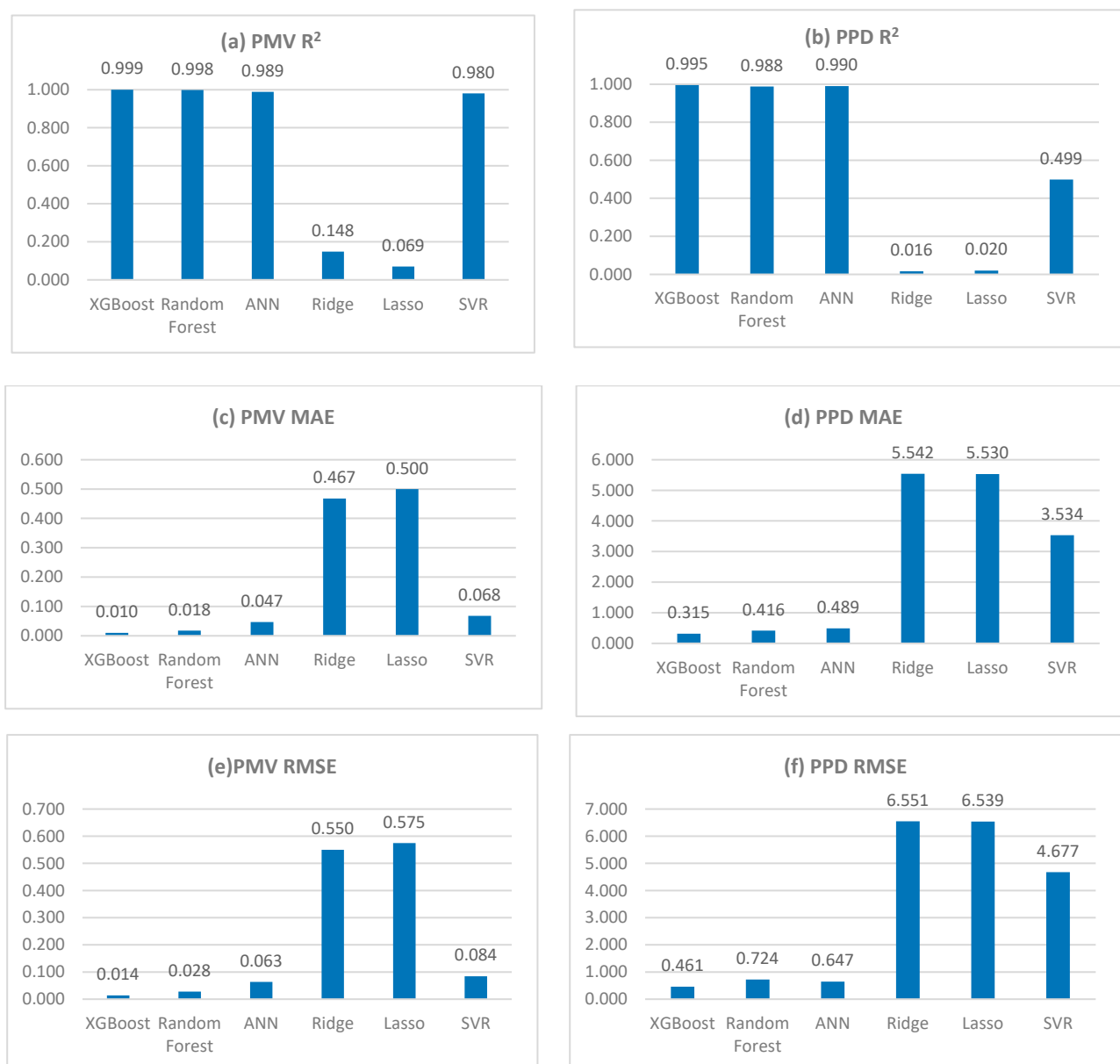


Figure 12. Quantitative analysis of the performance of tested ML models to predict PMV and PPD through comparing the values of (a) R^2 for PMV, (b) R^2 for PPD, (c) MAE for PMV, (d) MAE for PPD, (e) RMSE for PMV, and (f) RMSE for PPD.

II PPD Prediction Performance

For PPD estimation, as shown in Figure 12b,d,f, a similar performance trend was observed. XGBoost again achieved the best results, with an R^2 of 0.994, MAE of 0.299, and RMSE of 0.457. This confirms its strong generalization capability across both thermal comfort indices. The Random Forest model ranked second, achieving an R^2 of 0.9909 and RMSE of 0.600. Although slightly less precise than XGBoost, it maintained high predictive stability.

The ANN model demonstrated competitive performance, with an R^2 of 0.9936 and RMSE of 0.505. Interestingly, the ANN model slightly outperformed Random Forest in R^2 but produced higher MAE, indicating small variations in error distribution. In contrast to PMV results, SVR showed a significant reduction in performance for PPD prediction, with an R^2 of 0.4824 and RMSE of 4.53. This suggests that SVR struggled to approximate the non-linear structure of PPD, which is more complex due to its exponential relationship with PMV. Again, Ridge and Lasso performed poorly, with R^2 values close to zero (~ 0.024). The very high MAE (~ 5.17) and RMSE (~ 6.23) confirm that linear models are unsuitable for accurate PPD estimation.

III Actual vs. Predicted scatter plots

The scatter plots in Figure 13 (PMV) and Figure 14 (PPD) evaluate how closely the models' predictions align with simulated data. The XGBoost (Figures 13a and 14a) and Random Forest (Figures 13b and 14b) models demonstrate the highest accuracy, with data points tightly clustered along the diagonal identity line. The ANN model (Figures 13c and 14c) also shows strong performance, maintaining a narrow distribution around the identity line, though with slightly more variance than the ensemble models at the extreme ends of the scale. The SVR model shows a moderate "cloud" of dispersion. In the PMV chart (Figure 13d), it captures the general trend well but exhibits more variance than the tree-based models. In the PPD chart (Figure 14d), the SVR model starts to struggle at higher values (above 20% PPD), where it begins to noticeably underestimate the actual values. Finally, the Ridge (Figures 13e and 14e) and Lasso (Figures 13f and 14f) models show significant horizontal banding and wide dispersion, indicating a fundamental failure to capture the dataset's complexity.

IV Q-Q Plots

The Q-Q plots in Figures 15 and 16 verify the statistical reliability of the models by comparing residual distributions against theoretical quantiles. The XGBoost (Figures 15a and 16a) and ANN (Figures 15c and 16c) models track the reference line most consistently, suggesting their errors are normally distributed. The Random Forest model (Figures 15b and 16b) shows similar linear alignment but begins to deviate at the upper quantiles in the PPD analysis. The SVR model (Figures 15d and 16d) exhibits visible "S-curves" and significant deviations at the tails, particularly in Figure 15e, indicating that the model struggles to remain reliable when predicting outliers or extreme thermal conditions. The Ridge (Figures 15e and 16e) and Lasso (Figures 15f and 16f) models show the most dramatic departures from the diagonal, confirming that their prediction errors are highly skewed.

V Residuals vs. Fitted Plots

The charts in Figures 17 and 18 illustrate the distribution of prediction errors across the range of fitted values. The XGBoost (Figures 17a and 18a) and Random Forest (Figures 17b and 18b) models display a relatively random cloud of points centered at the zero-horizontal line, indicating homoscedasticity. The ANN model (Figures 17c and 18c) performs similarly well, though it shows a slight concentration of residuals at specific

predicted intervals. In contrast, the SVR model (Figures 17d and 18d) displays a distinct curved or “bowed” residual pattern, suggesting that it fails to capture certain non-linear relationships within the data. This issue is even more pronounced in the Ridge (Figures 17e and 18e) and Lasso (Figures 17f and 18f) models, which exhibit extreme “U-shaped” distributions, indicating high systematic bias and poor model fit.

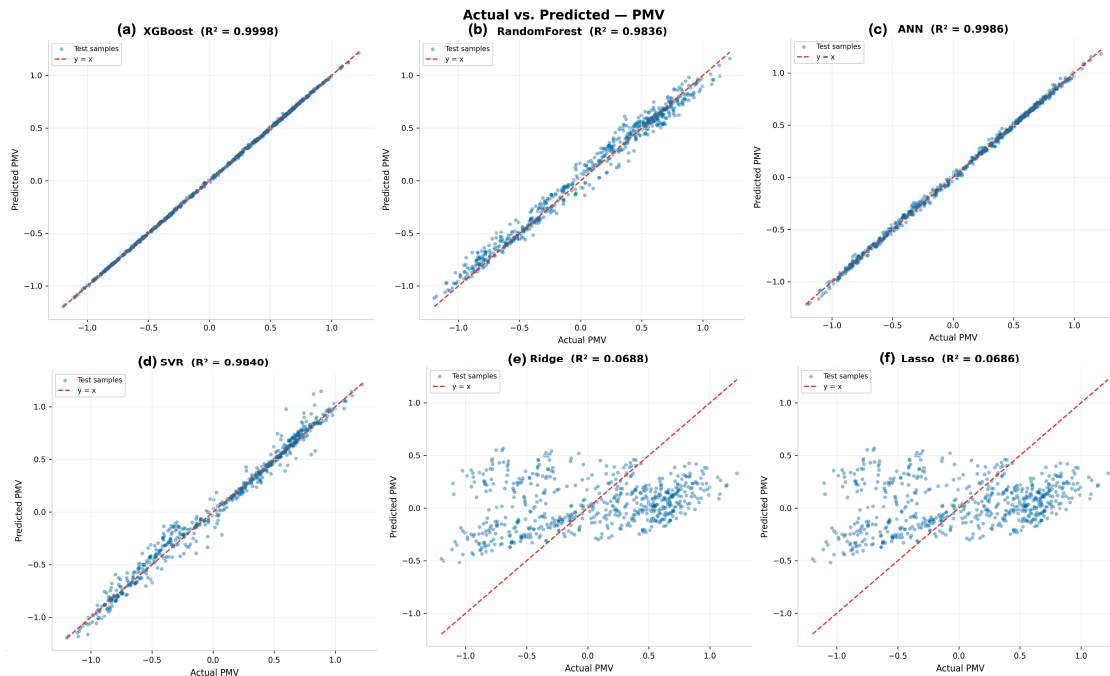


Figure 13. PMV scatter plot of actual vs. predicted values across six machine learning models. X-axis and Y-axis: PMV (dimensionless). The solid diagonal line represents perfect prediction ($y = x$). Sub-panels: (a) XGBoost, (b) Random Forest, (c) ANN, (d) SVR, (e) Ridge, (f) Lasso.

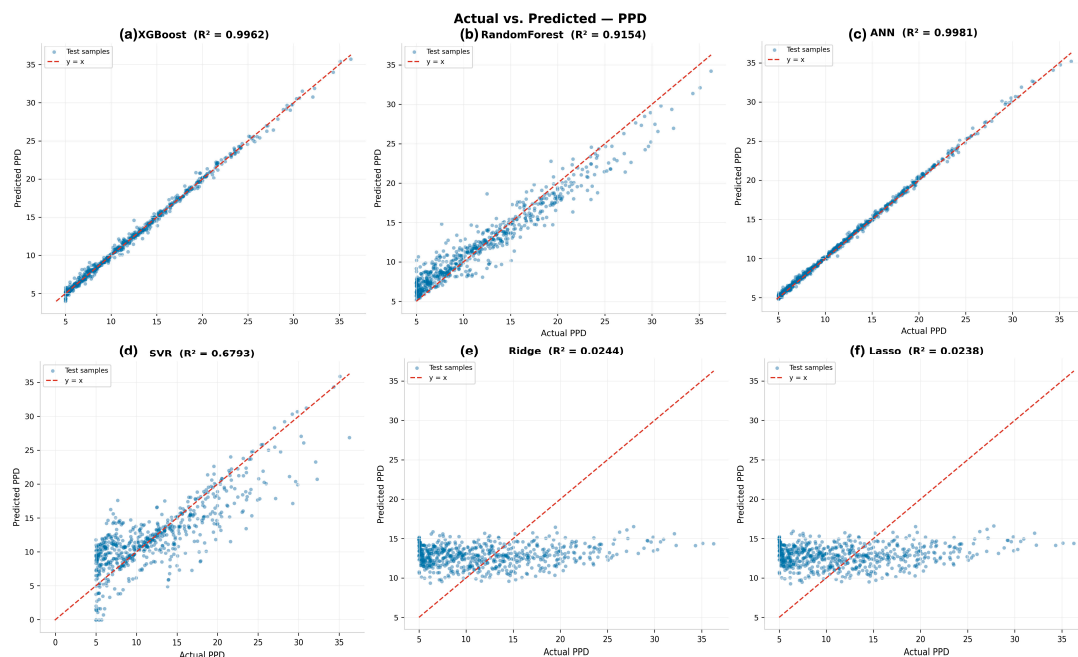


Figure 14. PPD scatter plot of actual vs. predicted values across six machine learning models. X-axis and Y-axis: PMV (dimensionless). The solid diagonal line represents perfect prediction ($y = x$). Sub-panels: (a) XGBoost, (b) Random Forest, (c) ANN, (d) SVR, (e) Ridge, (f) Lasso.

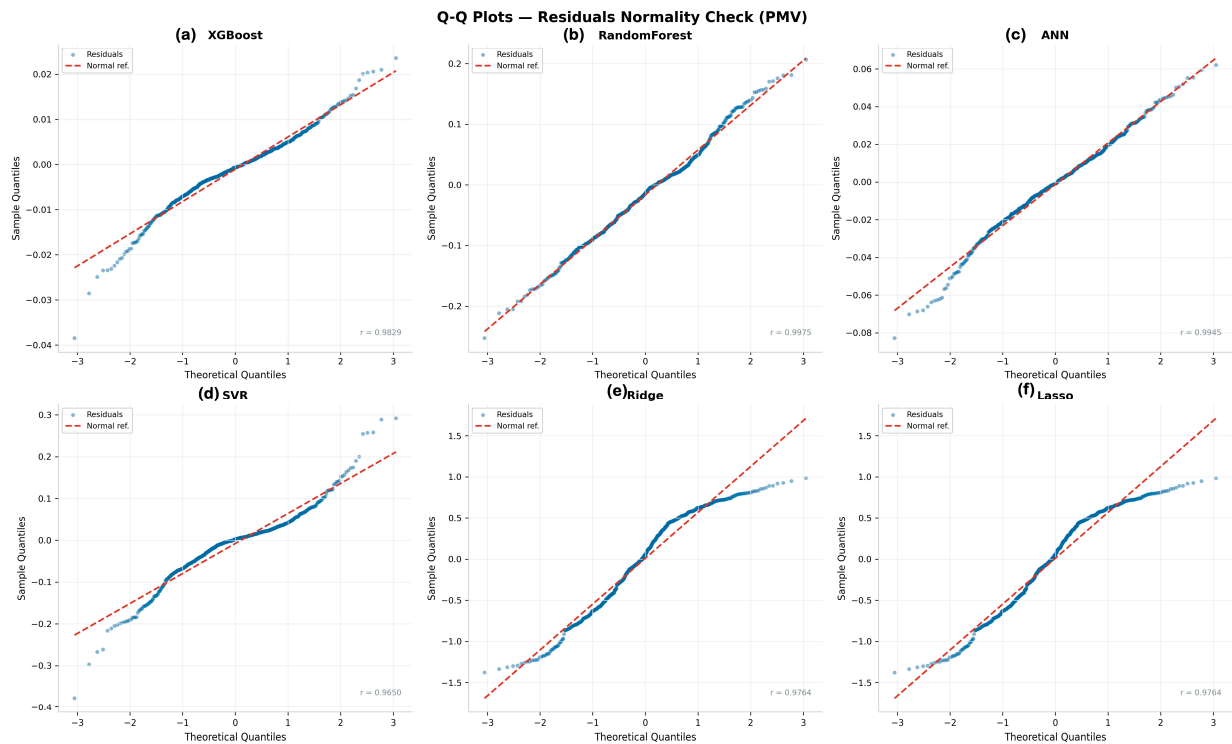


Figure 15. Q-Q plots for PMV model residuals. X-axis: theoretical standard normal quantiles; Y-axis: standardized residuals. The diagonal reference line indicates normally distributed errors. Sub-panels: (a) XGBoost, (b) Random Forest, (c) ANN, (d) SVR, (e) Ridge, (f) Lasso.

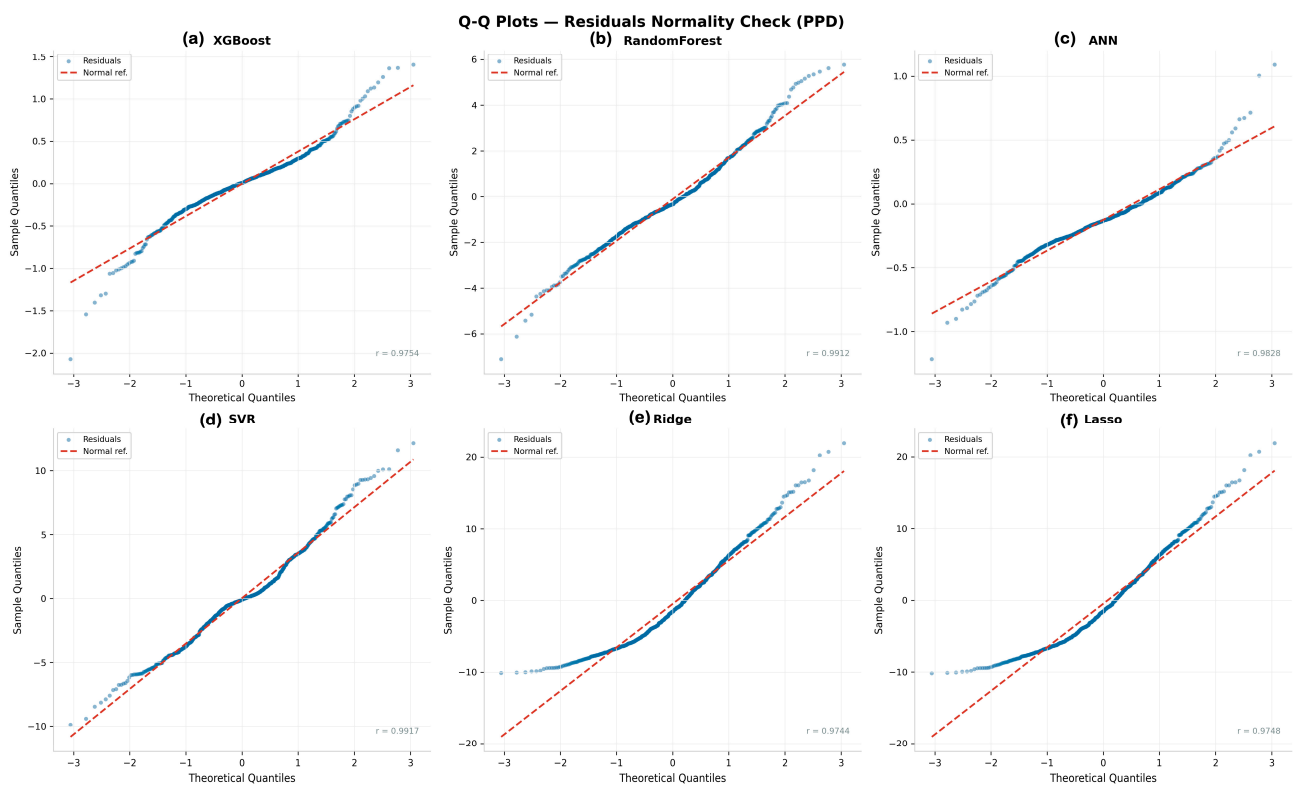


Figure 16. Q-Q plots for PPD model residuals. X-axis: theoretical standard normal quantiles; Y-axis: standardized residuals. The diagonal reference line indicates normally distributed errors. Sub-panels: (a) XGBoost, (b) Random Forest, (c) ANN, (d) SVR, (e) Ridge, (f) Lasso.

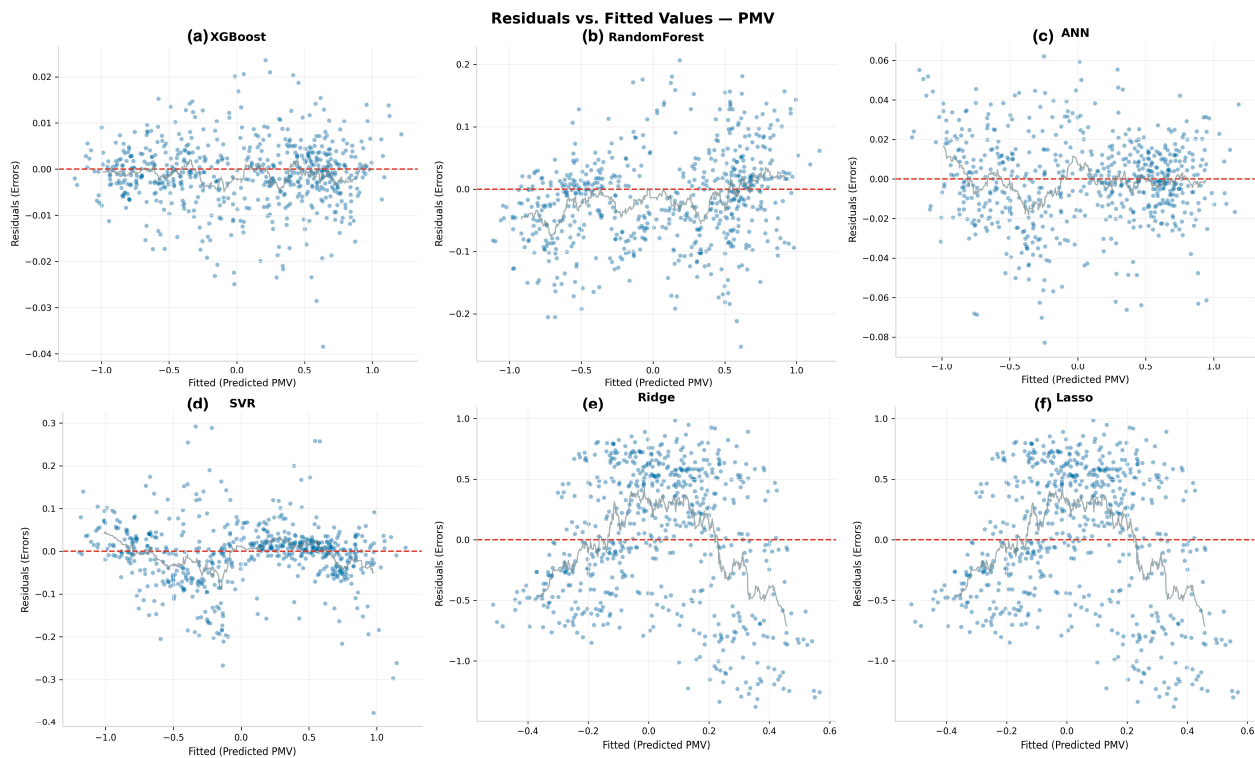


Figure 17. PMV analysis of residuals vs. fitted values. X-axis: fitted (predicted) PMV values; Y-axis: residuals (actual—predicted, PMV units). The horizontal dashed line at zero indicates unbiased predictions. Sub-panels: (a) XGBoost, (b) Random Forest, (c) ANN, (d) SVR, (e) Ridge, (f) Lasso.

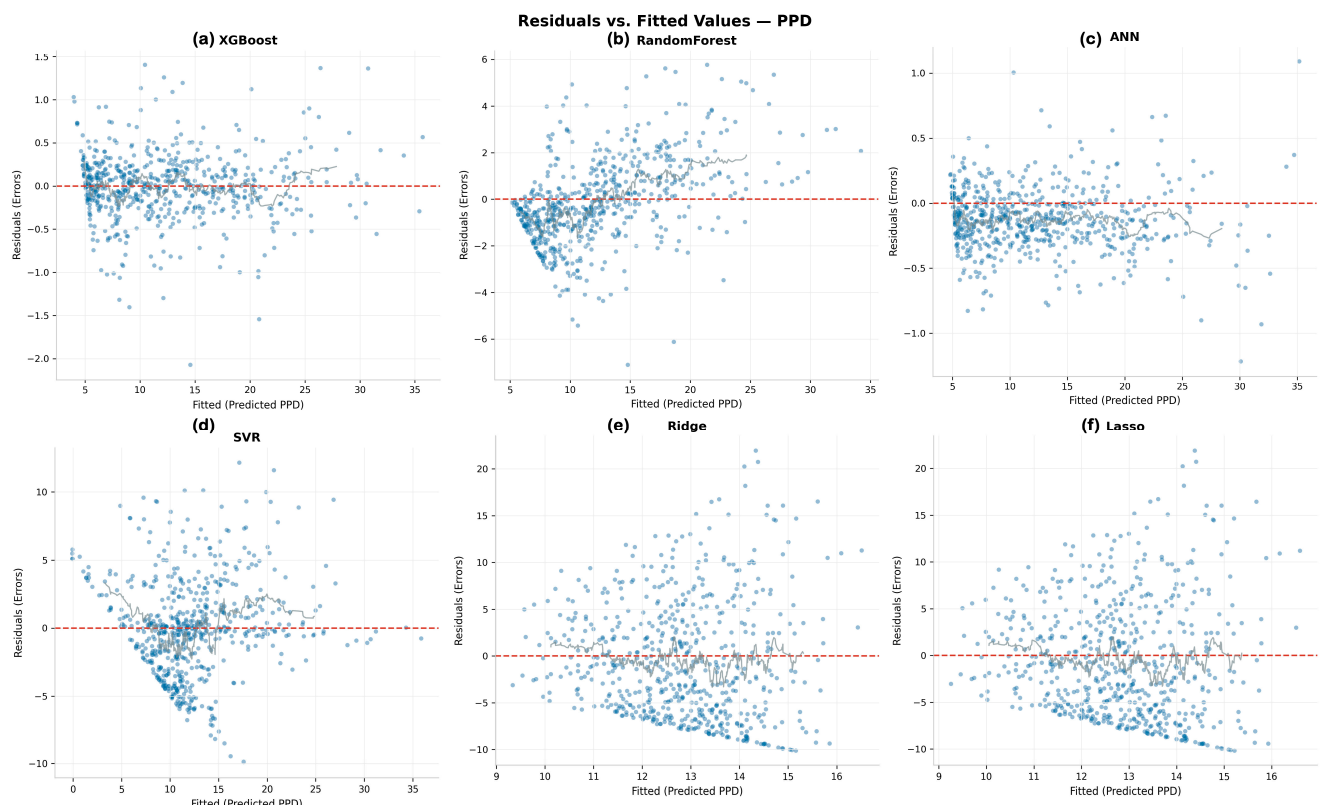


Figure 18. PPD analysis of residuals vs. fitted values. X-axis: fitted (predicted) PPD values (%); Y-axis: residuals (actual—predicted, %PPD). The horizontal dashed line at zero indicates unbiased predictions. Sub-panels: (a) XGBoost, (b) Random Forest, (c) ANN, (d) SVR, (e) Ridge, (f) Lasso.

VI Feature Importance analysis

The feature importance rankings for the top-performing models are presented in Figure 19. Across both XGBoost (Figure 19a,c) and Random Forest (Figure 19b,d), the variable “Month” is identified as the most dominant predictor, carrying the highest weight in determining both PMV and PPD outcomes. “Glazing facade orientation” emerges as the second most influential factor, followed by “WWR”. Structural features such as “Exterior wall width” and “Room depth” consistently show the lowest relative importance, suggesting they have a minimal impact on the models’ predictive performance in this specific study.

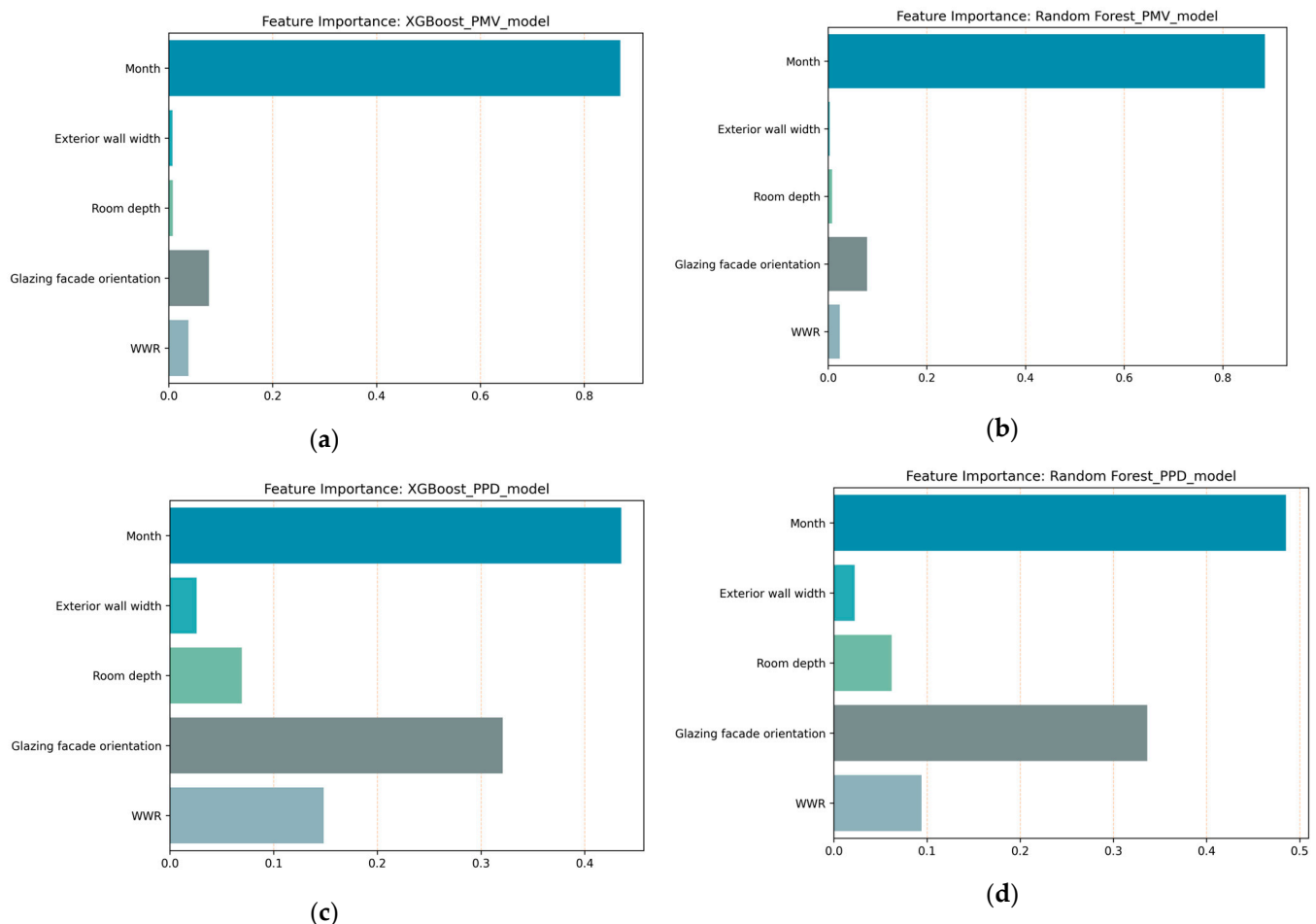


Figure 19. Relative feature importance for the top-performing models (XGBoost and Random Forest). X-axis: normalized feature importance score (range, 0–1). Sub-panels: (a) XGBoost for PMV, (b) Random Forest for PMV, (c) XGBoost for PPD, (d) Random Forest for PPD.

VII Beeswarm SHAP analysis

Beeswarm (SHAP) analysis is based on game theory and is used to calculate the contribution of each variable across all possible combinations. It analyzes the original data as it is, without modification, to explain the model behavior. The points are distributed according to how the variables interact with each other. The analysis is conducted for the top-performing model, XGBoost. The SHAP beeswarm analyses for both the PMV and PPD models reveal a hierarchical consistency in feature importance, yet they diverge significantly in their spatial implications. As expected, seasonal timing (month) and building envelope parameters (orientation and WWR) emerge as the primary drivers for both thermal sensation and occupant dissatisfaction, as shown in Figure 20.

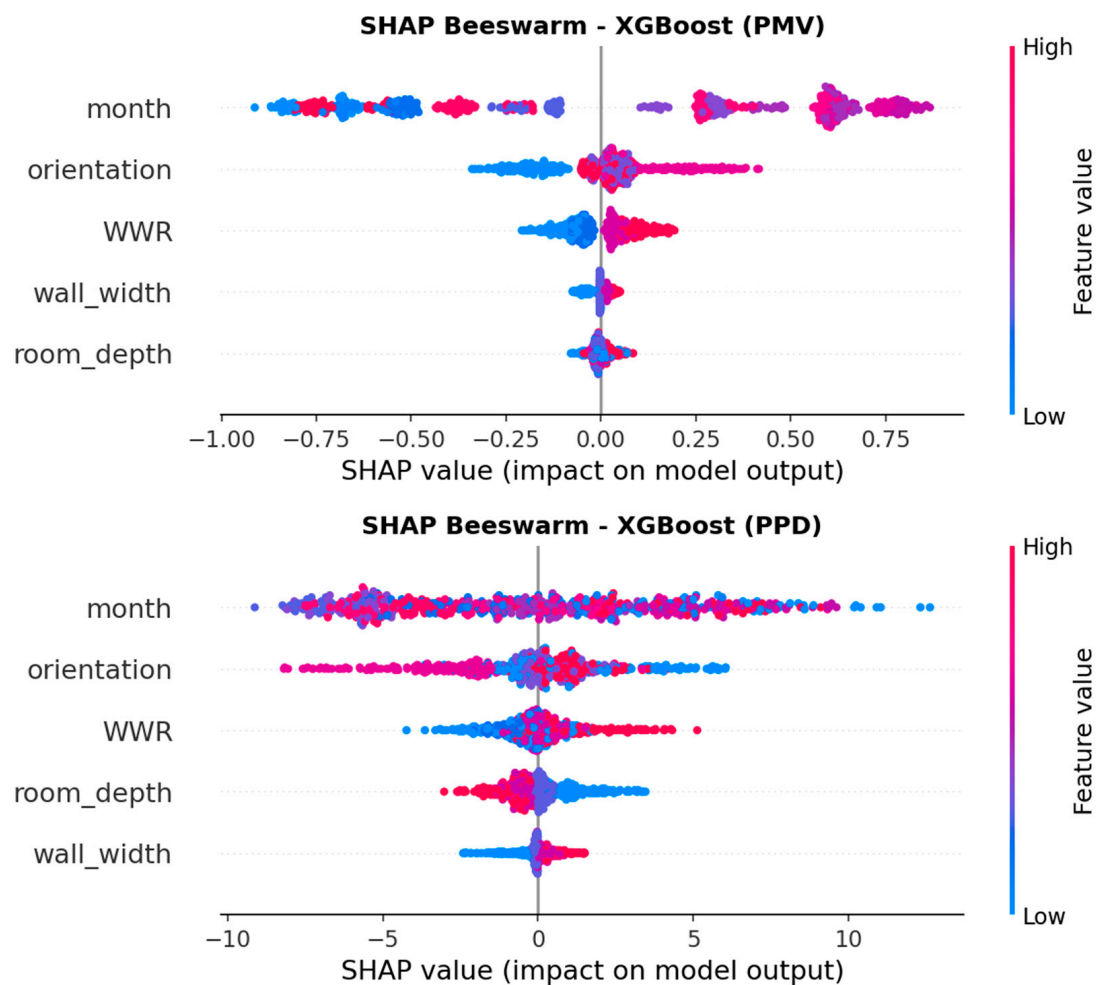


Figure 20. SHAP beeswarm analysis for the XGBoost model. Top: PMV target; bottom: PPD target. X-axis: SHAP value (impact on model output in PMV units or %PPD). Color: input feature value from low (blue) to high (red) using the “viridis” colormap. Each point represents one simulation record. Features are ranked by mean absolute SHAP value, with the highest-impact feature at the top.

1. The Glazing Conflict (WWR and Orientation)

Both models confirm a direct, positive correlation between a higher WWR and increased thermal stress. In the PMV model, high WWR values (red) consistently push results toward the “warm” side (+SHAP), while the PPD model confirms that this thermal gain translates directly into a higher percentage of dissatisfied occupants (up to +6% impact per instance).

2. The Effect of Room Depth

The most striking distinction between the two models lies in the role of room depth. While depth has a negligible effect on the overall thermal sensation (PMV), it emerges as a key mitigation factor for dissatisfaction (PPD). The PMV perspective: changing the room depth does not fundamentally alter the average temperature of the space. The PPD perspective: deeper rooms (red) show a significant negative SHAP impact (up to -2.5%), meaning they reduce the number of dissatisfied people.

This suggests that deeper spatial configurations provide a “thermal buffer zone” far from the facade. Even if the average room temperature remains high, the availability of a deeper, shielded interior zone allows for localized comfort, thereby stabilizing the overall satisfaction levels of the occupants.

VIII Perturbation analysis

The perturbation plot is based on intentionally changing one variable by a specific percentage ($\pm 5\%$, $\pm 10\%$ in this study) and observing the effect. It creates new, modified, or perturbed data to test the model's response. Only one variable is changed at a time (one-at-a-time analysis). The PMV model heatmap (Figure 21, left) shows significant sensitivity to the month (66.08%) and orientation (36.51%), which aligns perfectly with the seasonal and solar-driven nature of thermal sensation in West Cairo. In comparison, the PPD model (Figure 21, right) exhibits a more moderated sensitivity profile (with a maximum of 39.09% for the month), suggesting that the percentage of dissatisfied occupants is a more stable metric for long-term design evaluation than the immediate thermal vote.

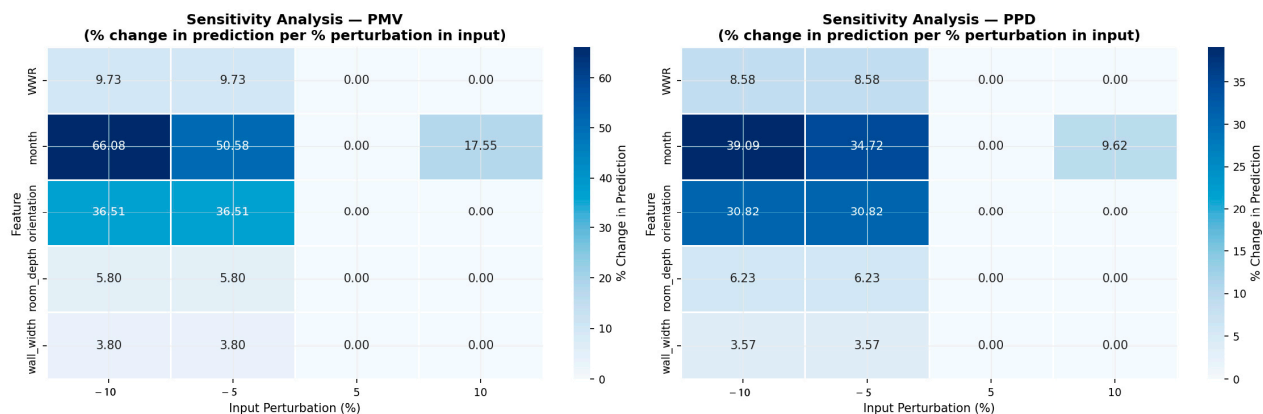


Figure 21. Perturbation sensitivity analysis for the XGBoost PMV model (left) and PPD model (right). Color scale: percentage change in predicted PMV or PPD (%) resulting from $\pm 10\%$ perturbation of each input feature.

Crucially, for both models, the structural variables—WWR, room depth, and exterior wall width—showed minimal sensitivity (mostly under 10%). This proves that XGBoost models in this study are generalizable and reliable for real-world architectural applications.

IX Dependence analysis

Figure 22 (left) shows the XGBoost PMV dependence plot for the feature “Month” interacting with room depth. The x -axis (month) represents the time of year (1 = January, 12 = December). The y -axis (SHAP value for the month) shows how much the month contributes to changing the PMV. Positive values increase PMV (warmer), while negative values decrease it (cooler). The color bar (room depth) indicates an interaction effect, showing room depth from 2.0 to 9.0 m.

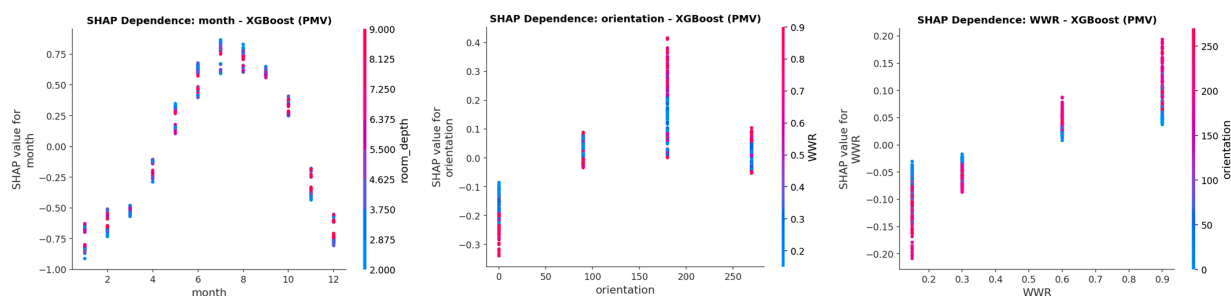


Figure 22. PMV SHAP dependence analysis. (left) Month (x -axis, 1–12) interacting with room depth (color scale, 2–9 m); (middle) glazing facade orientation (x -axis, 0–270°) interacting with WWR (color scale); (right) WWR (x -axis, 0.15–0.90) interacting with orientation (color scale). Y -axis in all panels: SHAP value for the respective feature (PMV units).

The analysis shows that there is a clear seasonal trend with a bell-shaped pattern. Summer months (June–August) strongly increase PMV, while winter months (December–February) reduce it. The spread of points within each month shows that this effect varies depending on room depth, with deeper and shallower spaces responding differently. The analysis confirms that the model is highly sensitive to the month, with this single variable shifting PMV by nearly 1.75 units (from about -0.9 in winter to $+0.85$ in summer).

Figure 22 (middle) shows the XGBoost PMV dependence plot for feature orientation interacting with the WWR. The plot explains how the direction of a building's orientation (in degrees) influences thermal comfort prediction (PMV). The plot shows that building orientation is a primary thermal driver, where south-facing (180°) rooms exert the strongest warming influence (SHAP $> +0.4$) and north-facing (0°) rooms provide a consistent cooling effect (SHAP -0.1 to -0.35). In contrast, east and west orientations remain thermally neutral. This impact is further scaled by the Window-to-Wall Ratio (WWR): at the south orientation, a high WWR amplifies heat sensation through maximum solar gain, while at the north orientation, increased glass area exacerbates cooling due to heat loss without the benefit of direct sunlight.

In Figure 22 (right), the XGBoost dependence plot illustrates how the Window-to-Wall Ratio (WWR) drives Predicted Mean Vote (PMV) across four glazing thresholds (0.15 to 0.9), revealing a distinct transition from a “cooling” zone to a “heating” zone. At low ratios (0.15–0.3), small windows generally yield negative SHAP values, contributing to a cooler environment likely due to superior opaque wall insulation. However, once glazing exceeds approximately 50%, it becomes the primary driver for a warmer thermal sensation. Orientation acts as a critical sensitivity multiplier in this relationship: at the highest WWR (0.9), south and west orientations (indicated by pink/red clusters) incur the most significant “thermal penalty,” while north and east orientations (blue clusters) show a markedly lower—though still positive—impact on PMV.

X Stratified analysis

Stratified analysis is primarily a quantitative analysis, but it is almost always presented through visual analysis to make the results interpretable. The stratified analysis of feature importance across the four seasons provides a dynamic understanding of how architectural variables influence thermal performance throughout the year. For the PMV model in Figure 23 (Top), thermal sensation in winter is almost exclusively governed by orientation, as solar heat gain becomes the primary determinant of comfort. In summer, this shifts to a “distributed importance” where WWR and month interact with orientation to manage heat admission. During the transitional spring and autumn periods, the month variable dominates, as rapid outdoor temperature fluctuations outweigh fixed architectural features.

In the PPD model in Figure 23 (bottom), which tracks occupant dissatisfaction, winter remains driven by orientation due to its role in solar exposure. However, summer highlights the necessity of architectural intervention, as room depth and WWR peak in importance. Spatial configuration, specifically the ability to retreat from the facade, is vital for minimizing discomfort. While month remains the primary driver in spring and autumn, autumn shows a unique spike in WWR significance, likely reflecting dissatisfaction caused by lower solar angles and localized overheating.

XI Taylor Diagrams

Taylor diagram analysis for trained models is presented in Figure 24. The black star marks the reference (EnergyPlus) position. The outer dashed black arc indicates normalized standard deviation = 1.0. Gray concentric arcs represent lines of constant normalized standard deviation. Gray straight spokes radiating from the origin represent

lines of constant Pearson correlation, labeled 0.0–0.99 on the outer edge. Dashed blue arcs centered on the reference star represent lines of equal Centered Root Mean Square Error (CRMSE). Each colored circle represents one trained ML model. The closer a dot is to the black star (EnergyPlus reference), the better the model. A perfect model would sit exactly on the star. For PMV models (Figure 24, left): XGBoost, ANN, and Random Forest are all clustered right on top of the reference star at correlation ≈ 1.0 and normalized standard deviation ≈ 1.0 , meaning they reproduce EnergyPlus PMV predictions almost perfectly in terms of both pattern and variability. SVR is very close to the star but slightly separated, meaning it is still a strong model. Ridge and Lasso sit far to the left at a very low normalized std (≈ 0.10), meaning they predict values that barely vary at all, essentially outputting near-constant predictions regardless of input. PPD models: XGBoost and ANN again sit on the reference star with high accuracy. Random Forest is slightly further away—still good, but with marginally more variability mismatch. SVR is noticeably separated; it struggles with PPD’s non-linear structure, consistent with its low R^2 of 0.48. Ridge and Lasso collapse again to the bottom-left corner, which indicates low accuracy.

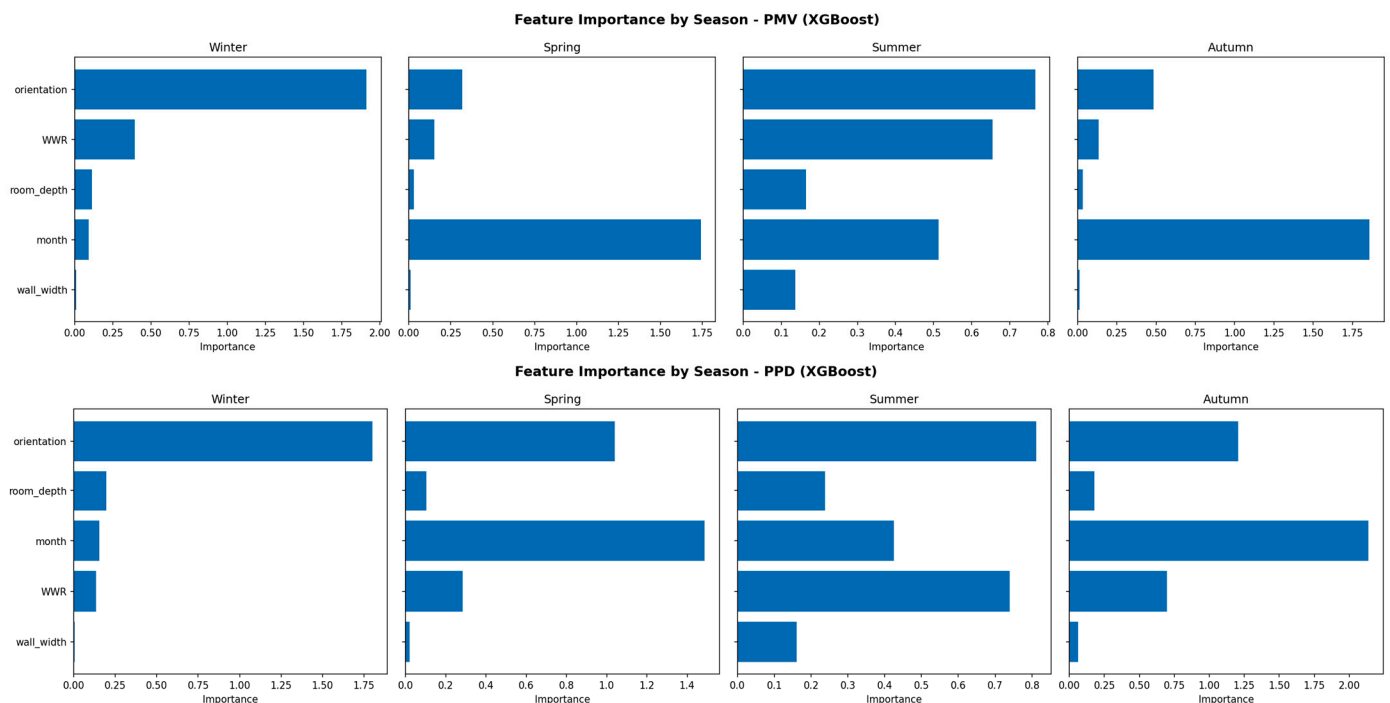


Figure 23. Stratified feature importance analysis by season for PMV (top) and PPD (bottom). X-axis: input feature; Y-axis: relative importance score (normalized, 0–1). Grouped bars represent the four seasons: winter, spring, summer, and autumn.

XII Box plots

A box centered on the dashed zero line = unbiased predictions. A narrow box = consistent small errors. A wide box = large, unpredictable errors. PMV residuals (Figure 25, left panel): XGBoost has the tightest box of all, confirming near-zero prediction error across all 615 test cases. ANN is similarly tight, and slightly wider than XGBoost. Random Forest is compact but has a few outliers below -0.2 . SVR is narrow but shows a small systematic positive bias (the box sits slightly above zero), meaning it slightly underpredicts PMV on average. Ridge and Lasso have very big boxes, spanning from -1.0 to $+1.0$ with no consistency, and random errors in every direction, confirming total model failure.

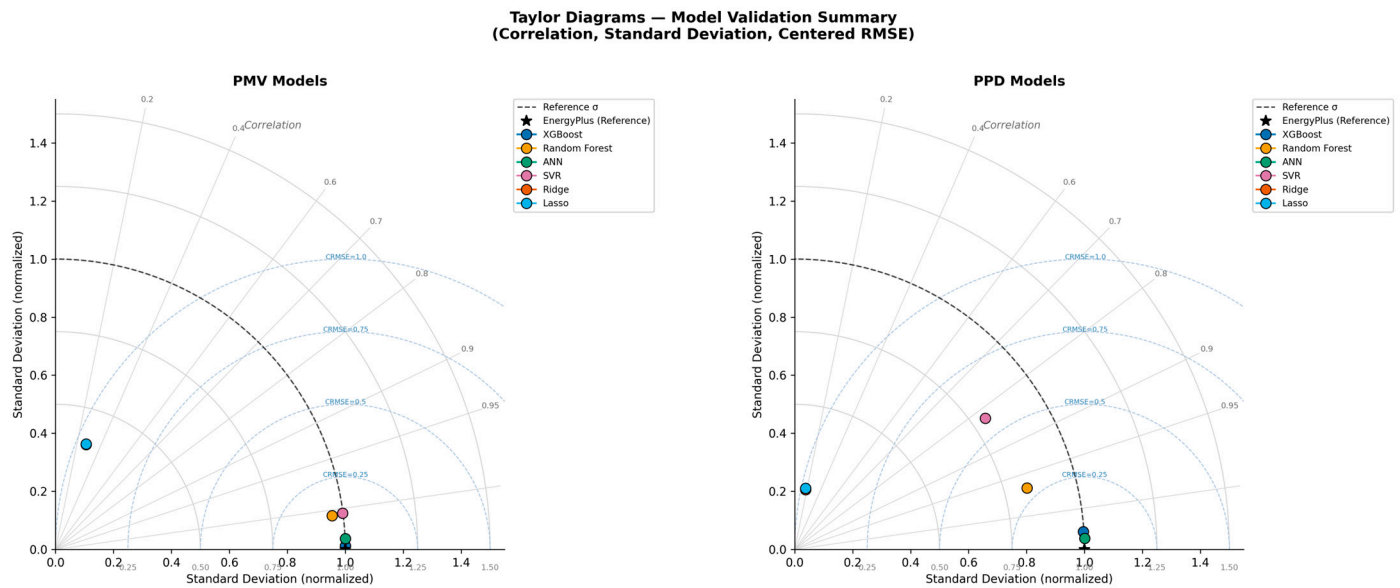


Figure 24. Taylor diagrams comparing the predictive performance of six machine learning models against EnergyPlus simulation outputs for PMV (left) and PPD (right).

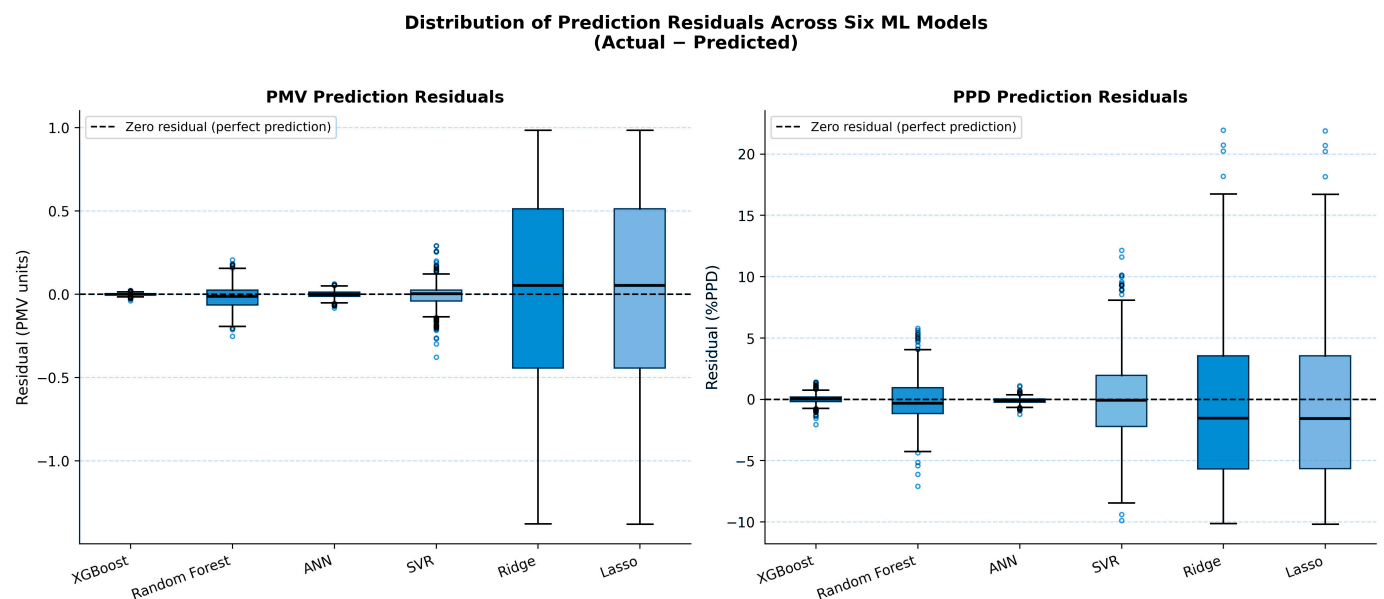


Figure 25. Box plots for distribution of prediction residuals (PMV = left, PPD = right) across six models (X-axis represents the models, Y-axis represents the residual value).

PPD residuals (Figure 25, right panel): XGBoost is extremely tight around zero and is considered the best performer by a clear margin. ANN is also very tight compared to XGBoost. Random Forest is slightly wider with a few outliers reaching $\pm 5\%$ PPD. SVR shows a noticeably larger spread, consistent with its weaker R^2 for PPD. Ridge and Lasso again show a large symmetric spread with outliers reaching $\pm 20\%$ PPD—confirming they are completely unsuitable for this task.

3.2.3. Model Validation Through Prediction Intervals Analysis

This analysis aims to validate the model's performance. The analysis is conducted by testing the model for 615 cases (test dataset) to identify a range where the confidence of the results is $\approx 90\%$. Based on the extracted results, Figure 26 (left = PMV, right = PPD), the numerical interpretation can be synthesized as follows:

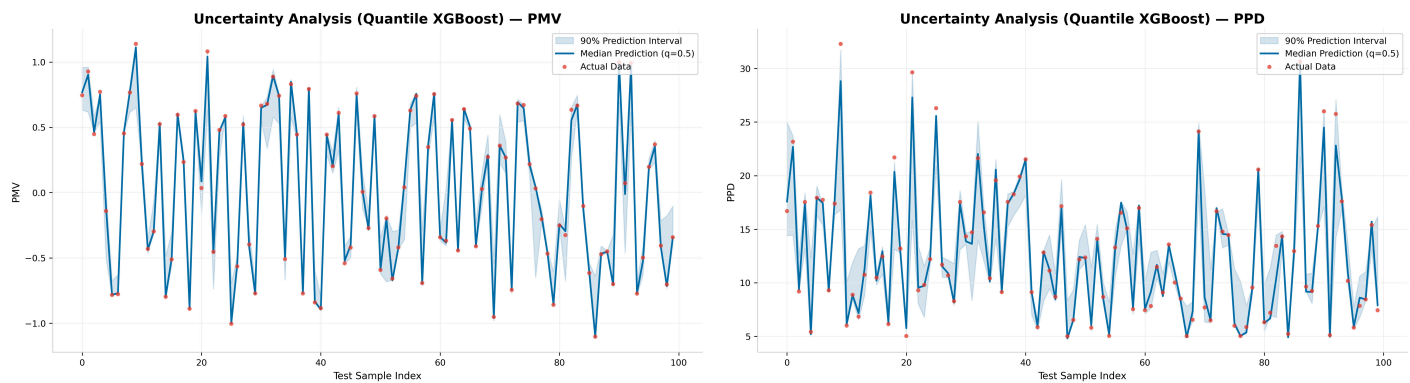


Figure 26. Prediction interval analysis for the XGBoost model, test set ($n = 614$). Right: PPD (y -axis, %); left: PMV (y -axis, dimensionless). X-axis: test sample index. Light blue shaded band: 90% prediction interval; blue line: point prediction; red dots: actual EnergyPlus simulation values.

Coverage Score: The model achieved a coverage rate of 78% for PMV and 77% for PPD. While these results fall slightly below the 90% prediction interval (PI) target, they indicate that the model captures a significant portion of the ground truth within the calculated safety zone, providing a more grounded estimation than arbitrary point values.

Average Interval Width: The average width for PMV is approximately 0.19 units and for PPD = 3.3%. This interval is sufficiently “tight” to support precise design decisions, yet “wide” enough to realistically account for expected environmental fluctuations.

Stability Zone (Narrow Bands): In samples where PPD ranges between 5–10%, the interval bands are notably narrow. This indicates high confidence from the model when the architectural configuration (orientation/WWR) successfully achieves thermal comfort. In short, optimized design solutions lead to stable and predictable thermal outcomes.

Turbulence Zone (Wide Bands): At higher PPD values (exceeding 20%), the interval width expands significantly. Physically, this suggests that as design efficiency decreases (e.g., a west-facing orientation with a high WWR in summer), the relationship between variables becomes highly non-linear and complex, increasing uncertainty. The model effectively flags these design zones as “high-risk” because the predictions fluctuate across a broad range.

Outliers (21%): A very small number of points fall outside the light blue interval (e.g., near sample 10). In quantitative research, this is entirely expected (Expected Error), since the target was 90% confidence rather than 100%.

By analyzing the outliers (resulting errors), the study found that the model failed to predict 135 of 615, with a coverage = 78% for PMV and 77% for PP. The heatmap in Figure 27 shows that the prediction failures (those that escaped outside the 90% safety range) are not randomly distributed, but are concentrated in specific architectural configurations:

North Orientation Effect: We notice the highest concentration of failures (15 cases) at the north orientation with a very high glass ratio (WWR = 0.9). Statistically, this indicates that the model finds it difficult to predict thermal comfort in northern facades with large glass areas, perhaps because of very slight differences in temperature that make the model very sensitive to any small change.

Interaction Effect: Failures are also clearly concentrated in the east and north facades at low glass ratios (0.15–0.3). This may be because the effect of the solid wall in these cases is stronger than the effect of the glass, which creates complexity in heat transfer calculations through the building mass that is hard for the model to predict with full accuracy.

West Facade: A noticeable concentration of errors (13 cases) appears at WWR = 0.3. Architecturally, western facades suffer from low-angle solar radiation in the after-

noon, which is a highly fluctuating variable, explaining the increase in “uncertainty” in these configurations.

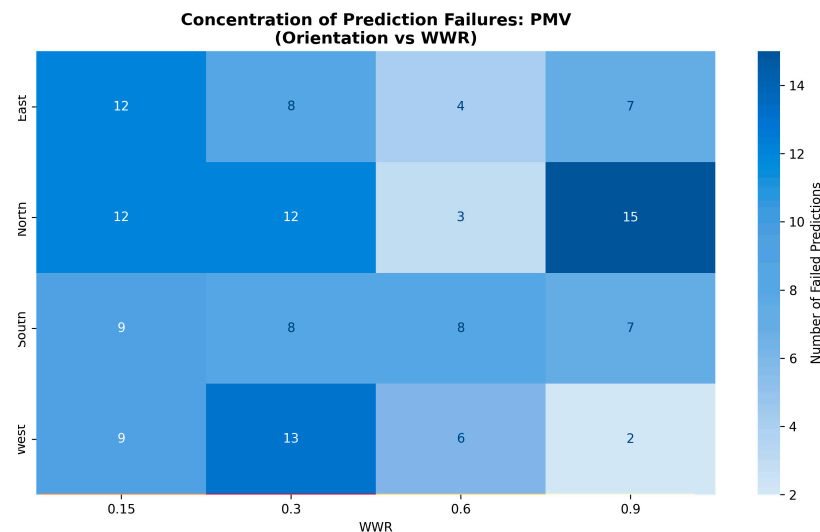


Figure 27. Prediction error heatmap for the PMV model. Color scale: number of prediction failures (cases falling outside the 90% prediction interval). X-axis: WWR (0.15–0.90); Y-axis: glazing facade orientation (cardinal directions).

Seasonal Generalization Failure: The model is trained on balanced seasonal data but fails on extreme seasons, suggesting inadequate representation of seasonal thermal dynamics.

This analysis reveals a model with systematic biases rather than random errors, making it amenable to targeted improvements through domain-specific feature engineering and stratified retraining approaches.

3.3. Model Deployment

The model is deployed as a web-based application that offers a flexible, lightweight experience suitable for remote collaborative design. It is live and accessible at <https://mlcomfortcalculator-2jmhivruday9i3qmpgegnv.streamlit.app/> (accessed on 2 March 2026) while the source code and model files can be accessed via the GitHub repository at <https://github.com/mmoeattv/mlcomfortcalculator> (accessed on 2 March 2026).

The developed Graphical User Interface (GUI) serves as a specialized decision-support tool for architects, integrating machine learning predictions with real-time architectural visualization. The interface is divided into nine core functional components, as shown in Figure 28:

(1) **Parameters:** A dynamic control panel allowing users to manipulate key architectural variables, including temporal data (month), spatial dimensions (wall width, room depth), and glazing characteristics (orientation, WWR).

(2) **Design Aims:** A reference section that displays target benchmarks (e.g., ASHRAE 55 standards), enabling immediate comparison between predicted results and international thermal comfort requirements.

(3) **Prediction Results:** High-visibility gauges providing real-time point predictions for PMV (Predicted Mean Vote) and PPD (Predicted Percentage of Dissatisfied), offering an instantaneous assessment of the indoor climate.

(4) **Error Ranges (Intervals):** A visual representation of the 90% prediction interval (PI). This component displays the uncertainty boundaries, ensuring that the user understands the statistical range within which the true value is expected to fall.

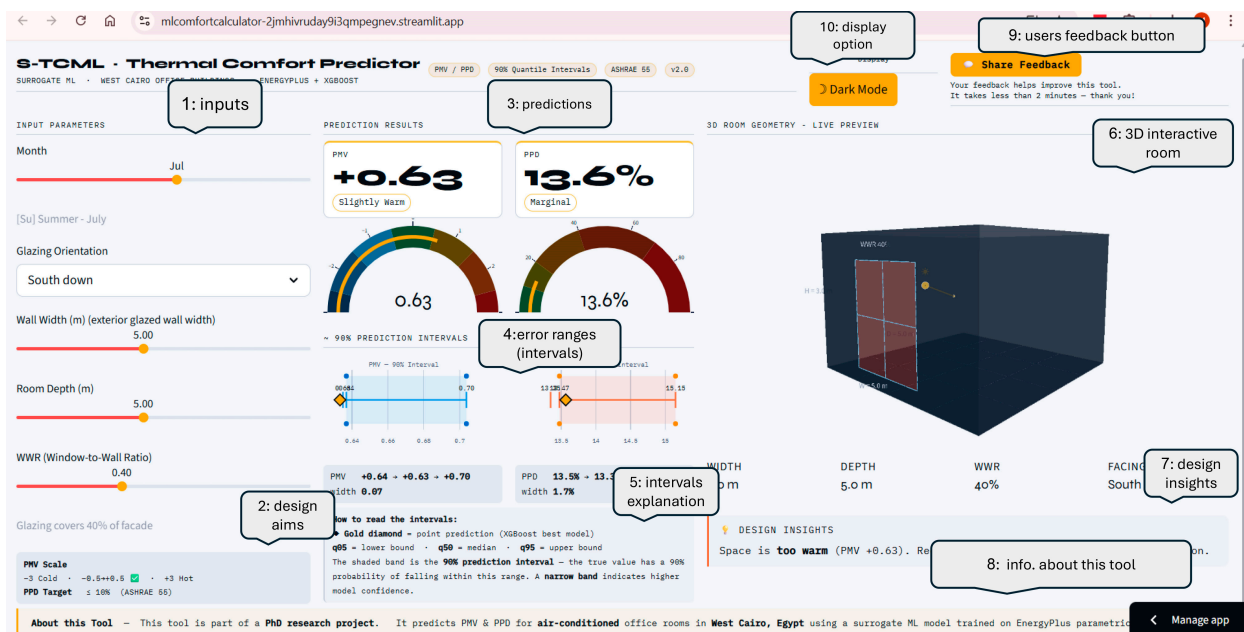


Figure 28. GUI interface for the S-TCML for Cairo office buildings.

(5) Intervals Explanation: A legend that deciphers the statistical symbols used in the interval plots (e.g., the gold diamond representing the median). It educates the user on how to interpret narrow versus wide uncertainty bands.

(6) 3D Interactive Room: A live WebGL-based 3D previews that updates synchronously with input changes. This allows architects to visualize the physical proportions of the space and the Window-to-Wall Ratio in real-time.

(7) Design Insights: An intelligent feedback module that translates numerical data into actionable design advice (e.g., “Space is too warm; suggest reducing WWR or changing orientation”), bridging the gap between raw data and architectural practice.

(8) Information Tooltip: Background information regarding the research context, specifying the study area (West Cairo, Egypt) and the underlying surrogate models trained on EnergyPlus parametric simulations.

(9) User Feedback Mechanism: An integrated feedback loop designed for usability testing, allowing practitioners to provide qualitative data that aids in the iterative refinement of the S-TCML framework.

(10) Display option: A mode toggle button for the users to choose light mode or dark mode display.

4. Discussion

This section contextualizes the S-TCML results within the broader literature on surrogate modeling for thermal comfort and addresses key limitations of the present framework.

EnergyPlus provides data at hourly intervals, but in this study, an average monthly simulation is conducted. Therefore, the output is a monthly average of thermal comfort, not a constant or fixed value. This reflects the dynamic nature of the environment throughout the month.

The model performance and feature importance results did not reveal unexpected relationships—they confirmed well-established thermal physics. Seasonal variation drives indoor comfort more than any geometric parameter. South-facing rooms are warmer than north-facing ones at 30°N latitude, large glazing areas cause overheating, and deeper rooms shield occupants from facade radiant heat. These are principles that any building physics textbook would state. The significance of the model reproducing them is not

in the findings themselves, but in what the reproduction proves: the XGBoost model has successfully learned the real physical relationships between architectural inputs and thermal comfort outcomes from simulation data alone, without being programmed with any thermal formula. A model that recovers known physics from data can be trusted to predict unknown configurations correctly—and it does so with near-zero error in milliseconds.

The WWR does not behave linearly: below approximately 50%, solid wall insulation outweighs solar gain, and glazing provides a net cooling benefit; above 50%, the relationship reverses, and overheating accelerates. This threshold cannot be identified by simplified linear tools, and it gives designers a specific, quantified target range of 30–50% WWR for this climate. Furthermore, room depth reduces PPD (occupant dissatisfaction) without noticeable changes in the results of the PMV model for the same inputs, because deeper spaces create a zone shielded from facade radiant heat where some occupants are more comfortable even when the room average is unchanged. This split between PMV and PPD as two models is invisible to single-indicator temperature tools and only becomes apparent when both indices are evaluated together.

The study found that S-TCML delivers PMV and PPD predictions in milliseconds, compared to the minutes or hours required by EnergyPlus for equivalent configurations—a 99.9% reduction in computational time. This means that an architect can evaluate hundreds of geometric alternatives in the time it would previously take to run a single simulation, fundamentally changing the role of performance feedback in early-stage design. Across the 12 models trained in this study, the best-performing model (XGBoost for PMV and PPD) is selected for deployment, as it consistently outperformed all alternatives across every evaluation metric and visual diagnostic.

Linear models completely failed. This is because the relationship between building geometry and thermal comfort is fundamentally non-linear.

The model also provides a confidence range, not just a single prediction. The study found that the 90% prediction interval had an average width of 0.19 PMV units and 3.3%PPD—both within the ASHRAE 55 acceptable tolerance of ± 0.5 PMV. This means that a designer can trust the prediction within a known margin. Additionally, the model was found to be less confident for north-facing rooms with very high WWR (Figure 25), giving designers a clear signal about which configurations carry more uncertainty. None of the studies reviewed in Table 2 provide this kind of uncertainty information.

The study used monthly average PMV and PPD values rather than hourly outputs. This was a deliberate choice to cover the full range of geometric configurations across all seasons efficiently. The consequence is that the model smooths out daily peaks—it cannot predict the worst hour of the hottest day, which limits its use for air-conditioning system sizing. However, for the intended purpose of comparing geometric options at the early design stage, monthly averages are sufficient and meaningful. Moving to an hourly resolution is the most important next step for the future development of this framework.

Although PPD is mathematically derived from PMV (where $PMV \pm 0.5$ corresponds to $PPD = 10\%$), both were modeled as independent targets to evaluate the ML's ability to autonomously 'learn' this non-linear physical relationship. The results confirmed that the models successfully mirrored Fanger's logic. However, for future optimization, predicting PMV and analytically deriving PPD is recommended to reduce computational overhead while maintaining physical integrity.

A significant limitation of prior ML studies in this field is the lack of transparency. Most studies reviewed in Table 1 do not share their trained models, datasets, or source code, preventing other researchers from testing, reproducing, or building on their work. This study directly addresses that gap: the validated XGBoost model was deployed as a free, publicly accessible web application using Streamlit, and both the dataset and source

code are shared openly via GitHub. This means any architect or researcher can use the tool immediately, without owning simulation software or writing a single line of code.

The deployed application transforms complex building physics into a practical design tool. By entering room dimensions, orientation, and WWR, a designer receives instant PMV and PPD predictions with a calibrated uncertainty range, a real-time 3D room visualization, and automatic ASHRAE Standard 55 compliance feedback. This moves the S-TCML framework from theoretical experimentation to practical application—making evidence-based thermal comfort evaluation accessible at the earliest and most consequential stage of the design process.

5. Conclusions

This study developed and validated a surrogate machine learning framework that predicts indoor thermal comfort (PMV and PPD) from early-stage architectural decisions for office buildings in the hot–arid climate of West Cairo, Egypt. The framework replaces time-consuming EnergyPlus simulations with millisecond predictions, achieving a 99.9% reduction in computational time without sacrificing accuracy. The main findings are as follows:

- (a) On the relationship between building geometry and thermal comfort:
 - The time of year (month) is the strongest driver of indoor thermal comfort in this climate, confirming that no geometric decision alone can guarantee year-round comfort in West Cairo—mechanical conditioning is always required, and the design goal should be to reduce its load.
 - By analyzing prediction results, the surrogate model found that south-facing offices are consistently the warmest and north-facing the coolest, following the solar geometry expected at Cairo’s latitude. Orientation is, therefore, the most actionable single geometric variable available to the designer, which validates that the model captures the physical relationship between thermal comfort variables.
 - A Window-to-Wall Ratio between 30% and 50% offers the best thermal balance. Below this range, solid wall insulation outperforms glazing; above it, solar heat gain dominates and discomfort increases sharply.
 - Deeper rooms reduce occupant dissatisfaction (PPD) because interior occupants are shielded from radiant heat near the facade. Room depth is, therefore, a low-cost design strategy to improve comfort satisfaction.
- (b) On machine learning model performance:
 - XGBoost was the best-performing algorithm across all metrics and both targets, outperforming Random Forest and ANN—the two most commonly used algorithms in comparable studies—particularly at extreme thermal conditions, where design decisions matter most.
 - Linear models (Ridge and Lasso) completely failed to predict thermal comfort from geometric inputs, providing direct evidence that the geometry–comfort relationship is non-linear and cannot be captured by simplified linear tools.
 - The model provides a calibrated 90% prediction interval with an average width of 0.19 PMV units and 3.3%PPD—both within the ASHRAE 55 acceptable range
- (c) On practical deployment
 - The validated XGBoost model was deployed as a free, publicly accessible web application (S-TCML) that allows architects to input room geometry and receive instant PMV and PPD predictions with uncertainty ranges, without requiring any simulation software or coding skills.

- The dataset and source code are shared publicly, addressing the transparency gap identified in prior ML studies and enabling other researchers to build on this work.

The S-TCML framework demonstrates that transparent, geometry-aware surrogate models can successfully replace iterative physics-based simulations during early-stage architectural design, turning a process that previously took hours into one that takes milliseconds—and making evidence-based thermal comfort evaluation accessible to every practitioner from the very first design decision.

6. Limitations and Future Work

While the model is accurate for the West Cairo context, its current application is limited to air-conditioned office spaces with a single exposed facade. A significant limitation stems from the use of monthly simulation intervals rather than hourly data.

The monthly simulations in EnergyPlus utilize average temperatures, which effectively smooths out the data and eliminates peak hot days.

Future research could expand this framework to include predicting multiple glazing facades and multi-zone interactions to account for internal heat transfer between adjacent rooms. Also, future research could (1) extend the dataset to include double-facade configurations (e.g., north–south, east–west exposed walls), (2) introduce floor position as an additional parameter (ground floor with slab boundary vs. top floor with roof exposure), and (3) retrain and fine-tune the model on these expanded configurations. Additionally, a transition to hourly datasets is highly recommended to enable the prediction of specific design days, thereby providing a more accurate and robust assessment of architectural performance under peak climatic stress.

Synthetic Data Dependency: The model is trained on EnergyPlus-generated data; real-world field validation is planned.

Due to fixed metabolic rate and clothing level predictions for populations with significantly different metabolic rates (e.g., standing/active work) or clothing norms, the model would require retraining with adjusted personal variable assumptions. This design choice prioritizes early-stage applicability where occupant diversity cannot be known, while the limitation is now transparently reported.

While the developed surrogate model demonstrates high accuracy in predicting thermal comfort within the specific context of Cairo’s hot–arid climate, currently, the model utilizes seasonal indexing as a proxy for climatic conditions to isolate the sensitivity of architectural parameters. This approach, while effective for site-specific design optimization, limits the model’s direct applicability to diverse climatic zones without retraining.

Also, it is recommended that the month index be replaced with CDD/HDD derived from a full EPW file, which is identified as a priority enhancement for future work, as it would simultaneously address both the temporal resolution limitation and improve climate transferability of the framework.

Future research is encouraged to measure PPD using Fanger’s equation, as it is a simpler method.

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Abbreviations

The following abbreviations are used in this manuscript:

AEC	Architecture, Engineering, and Construction
ANN	Artificial Neural Network
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BIM	Building Information Modeling
BPS	Building Performance Simulation
CBE	Center for the Built Environment
CFD	Computational Fluid Dynamics
clo	Unit of clothing insulation (1 clo = 0.155 m ² ·°C/W)
CV	Cross-Validation
ECP 306	Egyptian Code for Energy Efficiency in Buildings (Decree 306)
EnergyPlus	U.S. DOE open-source building energy simulation engine
GUI	Graphical User Interface
HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
ISO	International Organization for Standardization
KDE	Kernel Density Estimate
Lasso	Least Absolute Shrinkage and Selection Operator
MAE	Mean Absolute Error
MENA	Middle East and North Africa
met	Metabolic Equivalent of Task (1 met = 58.2 W/m ²)
ML	Machine Learning
MLR	Multiple Linear Regression
MOEA	Multi-Objective Evolutionary Algorithm
MRT	Mean Radiant Temperature
PI	Prediction Interval
PMV	Predicted Mean Vote (Fanger, ISO 7730)
PPD	Predicted Percentage of Dissatisfied (Fanger, ISO 7730)
R ²	Coefficient of Determination
RF	Random Forest
RMSE	Root Mean Square Error
S-TCML	Surrogate Thermal Comfort Machine Learning (this study's framework)
sDA	Spatial Daylight Autonomy
SHAP	SHapley Additive exPlanations

SHGC	Solar Heat Gain Coefficient
SVR	Support Vector Regression
TCDB II	ASHRAE Global Thermal Comfort Database II
TSV	Thermal Sensation Vote
U-value	Thermal Transmittance [W/m^2K]
WebGL	Web Graphics Library
WWR	Window-to-Wall Ratio
XGBoost	Extreme Gradient Boosting

Appendix A

Table A1. Hyperparameter tuning search space ranges and results and cross-validation performance.

Identifiers		Hyperparameter Details			Cross-Validation Performance				
Target	Model	Hyperparameter	Search Space	Best Value	Best CV R ²	CV R ² Mean	CV R ² Std	CV RMSE Mean	CV MAE Mean
PMV	XGBoost	n_estimators	[100, 200, 300, 500]	500	0.999762	0.999773	0.000031	0.009182	0.006632
		max_depth	[3, 5, 7, 9]	5					
		learning_rate	[0.01, 0.05, 0.1, 0.2]	0.1					
		subsample	[0.6, 0.8, 1.0]	0.8					
		colsample_bytree	[0.6, 0.8, 1.0]	1.0					
	min_child_weight	[1, 3, 5]	3						
	Random Forest	n_estimators	[100, 200, 300, 500]	500	0.979047	0.979047	0.001717	0.088284	0.067875
		max_depth	[None, 10, 20, 30]	None					
		min_samples_split	[2, 5, 10]	2					
		min_samples_leaf	[1, 2, 4]	1					
		max_features	['sqrt', 'log2', 0.5]	0.5					
	SVR	C	[0.1, 1, 10, 100]	100	0.981862	0.981862	0.002070	0.082061	0.055089
		gamma	['scale', 'auto', 0.01, 0.1]	0.1					
	kernel	['rbf', 'linear', 'poly']	rbf						
	epsilon	[0.01, 0.1, 0.2]	0.01						
Ridge	alpha	[0.001, 0.01, 0.1, 1, 10, 100, 1000]	10	0.126036	0.126036	0.034012	0.570748	0.490618	
Lasso	alpha	[0.0001, 0.001, 0.01, 0.1, 1, 10]	0.0001	0.126011	0.126011	0.034204	0.570755	0.490480	
ANN	hidden_layer_sizes	[(64,), (128,), (64, 64), (128, 64), (128, 64, 32)]	(64, 64)	0.996755	0.996755	0.001307	0.034192	0.025304	
	activation	['relu', 'tanh']	relu						
	alpha	[0.0001, 0.001, 0.01]	0.01						
	learning_rate_init	[0.001, 0.01]	0.01						
PPD	XGBoost	n_estimators	[100, 200, 300, 500]	500	0.994878	0.995169	0.000767	0.457942	0.299592
		max_depth	[3, 5, 7, 9]	5					
		learning_rate	[0.01, 0.05, 0.1, 0.2]	0.1					
		subsample	[0.6, 0.8, 1.0]	0.8					
		colsample_bytree	[0.6, 0.8, 1.0]	1.0					
		min_child_weight	[1, 3, 5]	3					
	Random Forest	n_estimators	[100, 200, 300, 500]	500	0.900458	0.900458	0.006850	2.082922	1.545660
		max_depth	[None, 10, 20, 30]	None					
		min_samples_split	[2, 5, 10]	2					
		min_samples_leaf	[1, 2, 4]	1					
		max_features	['sqrt', 'log2', 0.5]	0.5					
	SVR	C	[0.1, 1, 10, 100]	100	0.636748	0.636748	0.026852	3.978053	2.973582
		gamma	['scale', 'auto', 0.01, 0.1]	scale					
	kernel	['rbf', 'linear', 'poly']	rbf						
	epsilon	[0.01, 0.1, 0.2]	0.2						
Ridge	alpha	[0.001, 0.01, 0.1, 1, 10, 100, 1000]	100	0.035749	0.035749	0.018583	6.488451	5.330505	
Lasso	alpha	[0.0001, 0.001, 0.01, 0.1, 1, 10]	0.01	0.035538	0.035538	0.019351	6.489101	5.333022	
ANN	hidden_layer_sizes	[(64,), (128,), (64, 64), (128, 64), (128, 64, 32)]	(128, 64, 32)	0.996890	0.996890	0.001017	0.363694	0.226318	
	activation	['relu', 'tanh']	tanh						
	alpha	[0.0001, 0.001, 0.01]	0.001						
	learning_rate_init	[0.001, 0.01]	0.001						

Table A2. Test dataset used to validate ML model prediction accuracy.

Month	Exterior Wall Width	Room Depth	Glazing Facade Orientation	WWR	Indoor Operative Temp	Indoor Air Temp	Indoor Mean Rad Temp	Indoor Relative Humidity	PMV	PPD
7	6	2	180	0.6	25.7915	24.13513	27.44787	60.29764	0.745064	16.68876
7	2	4	90	0.9	26.52467	24.40398	28.64535	58.28824	0.92724	23.1584
6	6	4	180	0.3	24.92273	23.98399	25.86148	51.62386	0.44757	9.179787
7	2	2	0	0.9	25.89803	24.16987	27.62619	59.97942	0.771167	17.53008
12	2	6	180	0.9	22.9807	21.54438	24.41701	44.62262	−0.14072	5.410286
12	4	4	270	0.6	20.445	20.00246	20.88754	47.69714	−0.78316	17.92632
12	9	6	270	0.3	20.4585	20.13639	20.78061	47.71022	−0.77732	17.73255
6	4	4	0	0.15	24.95069	24.18108	25.7203	50.9823	0.453182	9.286003
7	4	9	270	0.3	25.93212	24.79438	27.06986	56.80394	0.766595	17.3806
7	9	2	270	0.6	27.27621	24.11198	30.44044	60.22146	1.138407	32.29435
10	4	4	90	0.3	24.04158	23.11538	24.96777	53.4384	0.218908	5.994063
3	2	4	90	0.9	22.14514	21.0135	23.27678	33.91004	−0.43104	8.874743
11	6	6	90	0.9	22.2379	21.28165	23.19415	50.04637	−0.29705	6.833458
6	2	2	90	0.15	25.22865	24.01406	26.44323	51.21182	0.524121	10.74577
12	9	6	270	0.15	20.37497	20.16014	20.58979	47.71086	−0.79752	18.40908
11	4	6	0	0.15	21.3698	21.2501	21.4895	50.61327	−0.51153	10.47081
9	2	4	90	0.6	25.27939	23.89806	26.66072	58.95333	0.595974	12.44633
5	6	6	270	0.15	24.38648	23.37272	25.40024	43.13884	0.234197	6.138092
3	9	2	0	0.15	20.28292	20.42057	20.14527	36.35742	−0.88923	21.69491
8	4	9	0	0.3	25.31331	24.67227	25.95435	59.40397	0.624646	13.18743
11	2	9	180	0.6	23.55439	22.41814	24.69064	46.96959	0.035012	5.025377
7	6	4	90	0.9	27.09964	24.405	29.79427	58.33347	1.080685	29.63733
1	2	2	180	0.3	21.99527	20.91707	23.07346	36.41695	−0.45356	9.293176
5	4	6	90	0.9	25.34547	23.38074	27.31021	42.65286	0.479633	9.804916
9	2	9	270	0.6	25.26186	24.16273	26.361	57.60367	0.586062	12.19843
2	4	2	0	0.9	19.68052	20.07076	19.29027	42.49939	−1.00407	26.29143
3	4	4	270	0.3	21.61208	20.7819	22.44227	34.41513	−0.56461	11.67647
8	2	2	0	0.3	24.87297	24.01026	25.73567	62.59072	0.521579	10.6897
11	6	4	270	0.6	21.83439	20.87378	22.795	51.45272	−0.39675	8.27944
3	9	4	0	0.3	20.76014	20.69642	20.82386	35.42162	−0.77151	17.54146
7	6	9	180	0.15	25.52972	24.86333	26.19612	57.18337	0.666465	14.33231
10	9	9	180	0.6	25.85253	24.05066	27.65441	50.18108	0.679508	14.70487
9	9	4	270	0.9	26.381	23.61395	29.14804	59.81791	0.887431	21.62715
6	9	9	90	0.6	26.0779	24.40209	27.7537	49.84776	0.741269	16.56885
1	6	9	180	0.3	21.76404	20.87956	22.64852	36.93738	−0.50889	10.41394
9	9	6	270	0.9	26.17762	23.79714	28.55809	59.0517	0.830655	19.55565
9	6	6	0	0.6	24.68345	23.90723	25.45968	59.30224	0.444591	9.123954
12	6	4	90	0.3	20.46664	20.29805	20.63522	47.78926	−0.77184	17.55224
8	9	9	270	0.3	25.97013	24.63701	27.30326	59.16948	0.792843	18.25081
12	6	2	90	0.3	20.19455	20.11882	20.27028	48.05123	−0.84067	19.91117
1	9	4	270	0.3	20.25817	19.95273	20.56361	38.86589	−0.88457	21.51968
5	9	9	90	0.6	25.21488	23.65879	26.77098	42.06898	0.444205	9.116735
10	6	9	0	0.15	23.97388	23.6059	24.34186	52.28354	0.202126	5.847233
10	4	9	180	0.6	25.59188	24.06689	27.11688	50.10066	0.610839	12.82609
3	4	2	90	0.3	21.70024	20.89368	22.50679	34.43851	−0.54104	11.12603
2	4	6	180	0.3	22.03796	21.0356	23.04033	39.5896	−0.42054	8.687157
7	9	4	0	0.6	25.87215	24.42066	27.32363	58.73419	0.759343	17.14538
4	4	2	180	0.9	23.73685	21.73221	25.74148	37.3318	0.006004	5.000746
11	6	9	90	0.6	22.35316	21.64299	23.06334	48.65914	−0.27108	6.525926
6	9	6	0	0.6	25.46641	24.1667	26.76612	50.79829	0.58522	12.17755
2	2	2	90	0.9	21.34626	20.50488	22.18765	41.03203	−0.59236	12.35532
1	2	2	180	0.6	23.00249	21.33731	24.66766	35.82556	−0.19687	5.803687
12	4	9	90	0.9	20.92766	20.52924	21.32609	47.08412	−0.65789	14.09124
11	4	4	90	0.15	21.74971	21.34677	22.15264	49.88924	−0.41972	8.672677
3	6	2	180	0.9	23.99373	21.51166	26.47581	33.03532	0.040555	5.034049
6	4	4	90	0.3	25.63614	24.18116	27.09112	50.65485	0.628591	13.2922
6	9	9	270	0.6	26.0736	24.23259	27.9146	50.15579	0.740099	16.53203
12	6	9	270	0.9	20.80258	20.23811	21.36705	47.38539	−0.69219	15.07408
10	4	6	270	0.9	24.55162	22.90032	26.20292	53.69525	0.348564	7.527827
8	6	9	90	0.3	25.82502	24.72407	26.92597	58.84527	0.754048	16.97503
11	4	9	270	0.15	22.06151	21.64393	22.47909	48.99371	−0.34218	7.435625
11	2	2	90	0.9	21.95058	20.89276	23.0084	51.31149	−0.36804	7.819666
6	2	9	90	0.3	25.37044	24.5385	26.20237	49.48606	0.555857	11.46926
3	6	9	270	0.6	22.101	21.062	23.13999	33.72695	−0.4429	9.092345
9	4	9	90	0.6	25.46632	24.29468	26.63796	57.26421	0.639109	13.57481
6	2	6	0	0.6	25.10149	24.18072	26.02225	50.69113	0.489834	10.01309
11	2	6	270	0.6	21.78546	21.12466	22.44627	50.50548	−0.41074	8.516227
4	6	2	180	0.9	23.82163	21.7258	25.91746	37.35809	0.028013	5.016245
5	9	9	180	0.9	24.5367	23.31777	25.75564	43.17291	0.272455	6.541541
12	2	4	0	0.6	19.74184	19.9088	19.57488	49.08845	−0.9515	24.12251
10	2	2	270	0.9	24.5826	22.42568	26.73952	55.1807	0.359551	7.690492
5	6	2	0	0.9	24.52927	22.92735	26.13119	43.50738	0.268036	6.491802
1	9	9	270	0.9	20.82005	20.1567	21.4834	38.51266	−0.74451	16.6713
7	2	6	0	0.9	25.58863	24.4895	26.68776	58.14093	0.6819	14.77402
8	6	9	180	0.15	25.49569	24.72704	26.26434	59.10814	0.670634	14.45059
5	9	2	270	0.15	24.32238	22.85196	25.79281	44.04955	0.217517	5.981443
1	4	2	180	0.9	23.89403	21.52172	26.26634	35.5654	0.032556	5.021941
4	6	2	180	0.3	22.91093	21.71516	24.10671	37.72862	−0.20339	5.857861
3	9	6	180	0.15	22.00156	21.20522	22.7979	33.65131	−0.46694	9.552158
1	2	6	270	0.3	20.36072	20.10247	20.61897	38.57513	−0.85882	20.56646
11	2	4	180	0.15	22.42397	21.5981	23.24984	49.07085	−0.25116	6.309346
1	6	9	180	0.6	22.48753	21.20391	23.77115	36.49812	−0.32512	7.197824

Table A2. Cont.

Month	Exterior Wall Width	Room Depth	Glazing Facade Orientation	WWR	Indoor Operative Temp	Indoor Air Temp	Indoor Mean Rad Temp	Indoor Relative Humidity	PMV	PPD
5	4	2	90	0.9	25.93532	23.0437	28.82694	42.96013	0.634129	13.44039
8	2	4	180	0.6	25.45869	24.18194	26.73544	61.18532	0.666138	14.32306
4	4	9	180	0.6	23.31945	22.35763	24.28128	36.17648	−0.1029	5.21929
2	4	9	270	0.9	21.26334	20.45184	22.07485	40.75579	−0.61563	12.95045
12	6	2	0	0.6	19.13003	19.64568	18.61438	49.63409	−1.10267	30.63618
3	4	6	270	0.6	21.99045	20.89414	23.08677	33.96349	−0.47103	9.632868
11	6	4	270	0.3	21.62007	20.96711	22.27302	51.24536	−0.45025	9.230397
12	4	9	270	0.9	20.77235	20.24893	21.29577	47.33863	−0.69981	15.29934
7	6	4	270	0.6	26.77412	24.32875	29.21948	58.91256	0.997179	26.00102
2	6	4	180	0.9	23.9605	21.65313	26.26787	38.66884	0.072208	5.107957
8	9	2	90	0.6	26.68157	24.05161	29.31154	61.8807	0.991239	25.75221
1	4	6	90	0.9	20.68734	20.33865	21.03603	38.79389	−0.77314	17.59497
2	9	2	180	0.15	21.73118	20.69987	22.76249	40.31915	−0.49755	10.1736
5	4	9	0	0.15	24.24296	23.72825	24.75767	42.49442	0.197383	5.807869
5	2	6	270	0.9	24.93235	23.12869	26.73601	42.72218	0.369386	7.840477
11	2	4	270	0.9	21.79976	20.82964	22.76989	51.44854	−0.40629	8.439957
11	2	2	0	0.15	20.58725	20.61956	20.55493	52.94709	−0.70298	15.39384
11	9	4	270	0.9	22.05346	20.79385	23.31306	51.65827	−0.34151	7.426041
8	2	6	90	0.9	25.96897	24.33894	27.59899	60.07461	0.793895	18.2863
10	2	9	180	0.3	24.739	23.87028	25.60773	50.61706	0.390263	8.172504
5	6	4	270	0.3	24.662	23.10153	26.22247	43.40811	0.303886	6.919134
10	2	4	90	0.15	23.80919	23.22264	24.39574	53.11182	0.159045	5.524213
4	4	6	90	0.3	23.45813	22.52792	24.38834	35.71494	−0.06897	5.098476
9	2	2	180	0.3	25.40146	23.89015	26.91276	58.81006	0.626505	13.23672
1	2	2	0	0.6	19.33691	19.78757	18.88625	39.7385	−1.10969	30.95841
6	4	9	0	0.15	25.17097	24.5529	25.78903	49.81455	0.507178	10.37735
1	6	4	270	0.15	20.08002	19.93112	20.22892	39.05424	−0.92766	23.17497
11	2	2	270	0.9	21.81701	20.60117	23.03284	52.02259	−0.40233	8.3729
2	4	9	270	0.3	21.00411	20.54405	21.46418	40.71614	−0.67924	14.69703
12	2	9	180	0.6	22.27535	21.32669	23.22401	44.76339	−0.32217	7.158008
8	6	4	180	0.3	25.46816	24.24616	26.69016	61.07695	0.669107	14.40717
2	2	2	180	0.15	21.52375	20.70979	22.33771	40.28628	−0.54977	11.32699
6	6	6	270	0.9	26.50932	23.95063	29.06801	50.84401	0.85689	20.49626
2	2	2	90	0.6	21.15117	20.50483	21.7975	41.11868	−0.6406	13.61518
12	6	6	0	0.6	19.83165	19.97744	19.68586	49.07365	−0.92823	23.19739
1	4	2	90	0.15	19.98397	20.09057	19.87736	39.45414	−0.94629	23.91367
9	9	6	90	0.9	25.95132	23.97657	27.92606	58.56655	0.77033	17.50265
11	6	6	0	0.15	21.35536	21.23325	21.47747	50.68482	−0.51498	10.54538
6	2	4	0	0.15	24.82945	24.19226	25.46663	50.9265	0.421679	8.707266
6	2	9	180	0.3	24.94131	24.40003	25.48259	50.25326	0.448814	9.203203
6	9	9	180	0.15	25.12564	24.44843	25.80284	50.26826	0.497325	10.16883
9	2	4	270	0.3	24.98538	23.83229	26.13846	59.22802	0.520432	10.6645
3	6	6	90	0.9	22.36209	21.11538	23.60879	33.81497	−0.37567	7.938426
11	4	9	90	0.9	22.31004	21.52241	23.09767	49.05599	−0.28134	6.644018
7	6	9	180	0.9	25.80509	24.59063	27.01956	57.72574	0.73698	16.43411
4	9	6	180	0.3	23.17573	22.24325	24.1082	36.6009	−0.13779	5.393373
10	2	4	90	0.9	24.22808	22.86505	25.59112	54.21167	0.268056	6.49202
4	2	6	0	0.9	22.55934	21.99137	23.1273	37.24751	−0.29255	6.778171
10	4	2	270	0.6	24.42854	22.47876	26.37833	55.20937	0.320527	7.135965
9	2	2	0	0.15	24.08025	23.57995	24.58054	60.98226	0.295565	6.815118
8	4	6	270	0.9	26.54014	24.203	28.87727	60.83725	0.948123	23.9871
7	4	6	0	0.15	25.42567	24.7508	26.10054	57.57325	0.64037	13.609
9	4	4	0	0.9	24.61498	23.62165	25.60831	60.36336	0.429031	8.838506
11	2	6	90	0.3	21.98037	21.55097	22.40976	49.04754	−0.36385	7.755597
6	6	9	90	0.3	25.67732	24.52525	26.8294	49.57141	0.636093	13.49327
10	6	9	270	0.9	24.6653	23.1568	26.1738	52.87119	0.37625	7.947585
1	6	2	180	0.15	21.41462	20.56562	22.26362	37.02696	−0.59995	12.54693
3	2	4	90	0.3	21.69208	21.09662	22.28753	34.01109	−0.54354	11.18336
5	6	9	270	0.3	24.68952	23.53822	25.84082	42.53557	0.309966	6.996992
3	4	2	90	0.15	21.40878	20.88062	21.93695	34.73291	−0.6123	12.86393
10	2	9	270	0.15	24.14327	23.63917	24.64737	51.69569	0.241489	6.210245
4	4	4	270	0.3	23.16888	21.96203	24.37573	37.10998	−0.13911	5.400922
7	4	6	180	0.9	25.73801	24.41963	27.05639	58.53299	0.722621	15.98872
3	4	2	0	0.15	20.35	20.45058	20.24942	36.17889	−0.87341	21.10329
9	2	2	90	0.15	24.79058	23.80594	25.77521	59.69296	0.473107	9.674088
8	2	6	180	0.6	25.40721	24.34964	26.46478	60.32603	0.649446	13.85724
12	9	2	180	0.6	23.40234	21.29449	25.51019	44.53942	−0.03649	5.027568
7	6	4	180	0.15	25.31932	24.506	26.13265	58.74505	0.617216	12.99197
8	9	9	270	0.9	26.65732	24.39755	28.9171	59.84884	0.974887	25.07431
7	9	4	180	0.6	25.76937	24.34229	27.19644	59.11925	0.734001	16.34097
9	9	2	0	0.6	24.48363	23.44563	25.52162	61.29653	0.398485	8.308371
6	2	4	180	0.15	24.63882	24.05778	25.21986	51.49716	0.374727	7.923642
2	6	4	180	0.15	21.58798	20.73293	22.44304	40.35865	−0.53286	10.9406
8	6	2	270	0.9	27.51389	23.80998	31.21781	63.19276	1.220906	36.27533
2	9	2	0	0.9	19.53525	20.03708	19.03342	42.70659	−1.03882	27.78254
11	9	2	270	0.3	21.38843	20.63013	22.14674	52.31609	−0.50764	10.38723
9	4	4	270	0.15	24.94846	23.90177	25.99515	59.16908	0.511854	10.47779
12	4	4	90	0.15	20.36172	20.2823	20.44113	47.86259	−0.79757	18.41066
4	6	4	0	0.15	22.37583	22.05375	22.69792	37.52405	−0.33604	7.348648
7	4	4	270	0.9	27.10572	24.25893	29.95251	59.12125	1.086244	29.88832
8	9	4	0	0.15	25.07446	24.33517	25.81376	61.15694	0.569606	11.79625

Table A2. Cont.

Month	Exterior Wall Width	Room Depth	Glazing Facade Orientation	WWR	Indoor Operative Temp	Indoor Air Temp	Indoor Mean Rad Temp	Indoor Relative Humidity	PMV	PPD
12	9	4	90	0.9	20.66091	20.27527	21.04656	47.8054	−0.72408	16.03347
3	4	2	0	0.3	20.48404	20.51297	20.4551	35.6435	−0.84085	19.9178
4	6	4	0	0.6	22.49741	21.87646	23.11835	37.64148	−0.30691	6.957639
12	9	4	0	0.9	19.4375	19.8187	19.05631	49.58455	−1.02462	27.16748
12	4	6	0	0.15	19.89935	19.97502	19.82367	48.96006	−0.91036	22.5012
5	4	6	270	0.6	24.95776	23.19983	26.71569	42.88615	0.37806	7.97617
6	2	4	180	0.9	25.02932	23.82525	26.23339	51.82574	0.474002	9.691914
4	4	9	0	0.9	22.81926	22.22074	23.41779	36.72098	−0.2277	6.075683
8	2	6	270	0.9	26.11271	24.20711	28.01831	60.79575	0.83485	19.70413
2	4	9	180	0.6	22.63744	21.37867	23.89621	38.93584	−0.26873	6.499574
3	9	2	180	0.3	22.53195	21.10799	23.9559	33.70043	−0.33333	7.310785
12	4	2	180	0.15	21.41022	20.54715	22.27329	45.87025	−0.54486	11.21353
10	2	4	180	0.9	26.43608	24.18251	28.68964	50.39343	0.837006	19.78074
6	4	6	90	0.9	26.2671	24.14789	28.38631	50.58896	0.79336	18.26823
11	4	2	180	0.6	24.59749	22.1072	27.08778	48.78346	0.313321	7.040635
1	6	6	180	0.3	21.85813	20.86422	22.85203	37.00089	−0.48497	9.913292
1	9	4	90	0.3	20.35599	20.24626	20.46572	39.1074	−0.85449	20.40917
6	2	2	0	0.6	25.24915	23.81577	26.68253	51.70765	0.53004	10.8774
8	4	2	0	0.6	25.25085	23.93111	26.57059	62.83411	0.619644	13.05556
12	4	9	90	0.15	20.85031	20.64459	21.05603	46.51677	−0.67867	14.6807
9	6	6	0	0.9	24.72798	23.80241	25.65354	59.61779	0.456285	9.345316
12	4	6	270	0.3	20.44503	20.15738	20.73269	47.61965	−0.78083	17.84891
3	4	2	270	0.3	21.56347	20.5829	22.54404	34.68048	−0.57738	11.98465
8	4	9	90	0.15	25.60539	24.79931	26.41147	58.67399	0.697068	15.21812
5	2	9	0	0.15	24.15034	23.74004	24.56064	42.44361	0.173475	5.623783
6	9	4	0	0.6	25.49543	24.01644	26.97442	51.23613	0.593816	12.392
4	2	9	0	0.6	22.77766	22.36482	23.19049	36.42199	−0.23856	6.18095
6	6	4	270	0.9	26.80808	23.79965	29.81652	51.23461	0.93775	23.57328
10	4	2	180	0.15	24.5751	23.12926	26.02095	53.29417	0.355574	7.631015
8	9	6	180	0.6	25.84497	24.33791	27.35203	60.42292	0.764173	17.30181
12	4	9	180	0.9	23.0036	21.51285	24.49434	44.68205	−0.1349	5.376996
11	2	6	180	0.9	24.23872	22.49898	25.97846	47.58936	0.216831	5.975252
8	6	2	0	0.9	25.54102	23.88384	27.1982	62.99749	0.69558	15.1741
9	9	4	0	0.9	24.70016	23.61856	25.78175	60.42405	0.451414	9.252396
9	9	9	90	0.15	25.34695	24.51787	26.17602	56.68673	0.607907	12.75043
10	9	6	90	0.15	24.20976	23.48153	24.93799	52.23335	0.25972	6.400407
10	6	6	90	0.15	24.16942	23.48388	24.85496	52.21391	0.249274	6.289745
10	6	6	0	0.6	23.54531	23.01623	24.07438	54.13407	0.095404	5.188492
6	6	4	270	0.15	25.29898	24.01463	26.58333	51.28603	0.542996	11.1708
4	6	6	270	0.15	23.1159	22.29104	23.94076	36.54759	−0.15285	5.484107
9	4	9	270	0.9	25.73896	24.02946	27.44845	58.06725	0.711597	15.65283
8	2	2	0	0.6	25.10841	23.93553	26.28129	62.7822	0.582339	12.1064
1	9	4	270	0.6	20.51906	19.98507	21.05305	38.65292	−0.82085	19.21147
3	4	2	180	0.6	23.29794	21.38638	25.2095	33.25675	−0.13793	5.394147
5	4	2	270	0.9	26.02842	22.7502	29.30665	43.03079	0.656142	14.04265
3	6	6	0	0.9	21.03295	20.80005	21.26586	34.81326	−0.70643	15.49717
10	9	4	270	0.6	24.5232	22.77566	26.27075	54.32065	0.343676	7.457106
3	6	9	90	0.15	22.00771	21.50922	22.50621	33.28108	−0.46447	9.503845
11	2	4	0	0.9	20.98264	20.81012	21.15515	52.03332	−0.60712	12.73011
5	9	9	90	0.15	24.78864	23.88752	25.68976	41.6156	0.332969	7.305736
11	6	4	180	0.9	25.07022	22.38475	27.7557	48.16525	0.436391	8.972236
7	9	9	90	0.6	26.44282	24.76738	28.11826	56.71365	0.89934	22.07849
2	6	9	90	0.15	21.21492	20.87309	21.55675	40.3138	−0.62442	13.18152
7	6	6	270	0.3	26.07702	24.60141	27.55263	57.69321	0.808087	18.76962
12	4	4	270	0.3	20.25624	19.99211	20.52037	47.87023	−0.82895	19.49543
7	9	6	0	0.3	25.63942	24.67657	26.60226	57.69628	0.695298	15.16578
8	6	9	270	0.15	25.69211	24.71702	26.6672	59.01792	0.720697	15.92972
4	9	6	180	0.9	23.61732	22.00253	25.23212	36.95282	−0.02483	5.012767
8	4	6	270	0.15	25.53287	24.50339	26.56234	59.91545	0.682076	14.77911
5	9	6	180	0.9	24.52648	23.12359	25.92937	43.59926	0.270485	6.519262
1	4	2	0	0.15	19.02171	19.5253	18.51812	41.29637	−1.1814	34.34362
3	4	2	180	0.9	23.89813	21.5233	26.27296	33.03228	0.016466	5.005613
4	4	6	0	0.9	22.6487	21.98224	23.31516	37.29703	−0.26975	6.510943
11	2	6	180	0.15	22.48724	21.78222	23.19225	48.29849	−0.23731	6.168634
2	2	9	90	0.15	21.16909	20.91261	21.42558	40.18861	−0.63605	13.49209
11	6	6	0	0.9	21.16929	20.97271	21.36587	51.52788	−0.56081	11.58619
10	2	6	180	0.3	24.74505	23.69443	25.79568	51.28422	0.393986	8.233661
9	6	9	0	0.9	24.84218	24.02714	25.65723	58.71252	0.483437	9.882022
9	6	2	270	0.6	26.07005	23.43842	28.70169	60.68012	0.808398	18.78028
6	4	6	90	0.3	25.588	24.34935	26.82665	50.11327	0.614374	12.91783
3	2	2	180	0.15	21.69038	20.90362	22.47715	34.07964	−0.54574	11.2339
4	9	4	90	0.6	23.91947	22.18593	25.65301	36.48433	0.051529	5.054971
12	9	9	90	0.6	20.94512	20.56665	21.3236	46.97589	−0.65358	13.97137
3	6	6	180	0.6	22.9493	21.47793	24.42068	33.07273	−0.22769	6.07561
12	4	4	0	0.9	19.59036	19.87689	19.30384	49.25871	−0.98813	25.62262
11	2	6	0	0.15	21.3914	21.28297	21.49984	50.45102	−0.5066	10.36489
3	9	4	90	0.9	22.45202	21.00047	23.90356	34.05184	−0.35241	7.584105
11	9	2	90	0.9	22.11615	20.89115	23.34115	51.36704	−0.32586	7.20786
2	2	9	0	0.6	20.54174	20.47022	20.61325	41.4568	−0.7903	18.16516
12	9	2	90	0.3	20.18039	20.11031	20.25048	48.13089	−0.84382	20.024
11	6	4	0	0.3	20.99307	20.91809	21.06805	51.85047	−0.60354	12.63847

Table A2. Cont.

Month	Exterior Wall Width	Room Depth	Glazing Facade Orientation	WWR	Indoor Operative Temp	Indoor Air Temp	Indoor Mean Rad Temp	Indoor Relative Humidity	PMV	PPD
8	2	9	180	0.6	25.42031	24.54604	26.29458	59.40715	0.649629	13.86226
5	2	4	90	0.6	24.87665	23.31159	26.4417	42.77255	0.357426	7.658629
10	2	6	180	0.6	25.50899	24.02418	26.99381	50.28279	0.589963	12.29549
8	9	2	90	0.9	27.21429	24.0061	30.42248	62.04968	1.134448	32.10855
12	6	9	180	0.3	21.90044	20.99054	22.81033	45.27454	−0.41853	8.651753
8	9	6	180	0.3	25.56893	24.43552	26.70235	60.14471	0.691875	15.06493
10	2	6	90	0.6	24.1153	23.20328	25.02733	52.96669	0.235916	6.154907
5	9	4	90	0.3	24.90387	23.40554	26.4022	42.76214	0.365563	7.781694
12	6	9	90	0.3	20.90019	20.62476	21.17562	46.69196	−0.66553	14.30578
5	9	9	180	0.6	24.4407	23.42326	25.45815	42.99277	0.247737	6.27384
9	9	9	270	0.15	25.32112	24.39253	26.24971	57.11697	0.602157	12.60313
7	4	9	0	0.3	25.57614	24.84842	26.30386	56.93559	0.676132	14.60773
12	6	9	0	0.6	20.14071	20.16011	20.12132	48.44254	−0.85069	20.27133
9	4	6	90	0.15	25.09962	24.3013	25.89795	57.53979	0.546343	11.24779
4	9	2	270	0.6	24.00393	21.59247	26.41539	37.71068	0.076285	5.120497
9	2	6	0	0.6	24.52223	23.91676	25.1277	59.18644	0.40243	8.374587
1	9	4	0	0.6	19.41898	19.8229	19.01506	40.35698	−1.08534	29.84733
12	6	9	90	0.9	20.94949	20.52437	21.37461	47.14299	−0.65217	13.9324
11	2	2	270	0.15	21.09915	20.68505	21.51324	52.26039	−0.57918	12.0287
3	6	4	180	0.3	22.34167	21.18695	23.4964	33.63129	−0.38134	8.02836
5	4	6	0	0.9	24.36356	23.25647	25.47064	43.32277	0.282105	6.079525
6	2	4	0	0.9	25.29717	23.94649	26.64786	51.32535	0.541707	11.14129
10	9	6	0	0.3	23.61236	23.18043	24.04429	53.70769	0.112539	5.262322
12	2	2	270	0.3	20.03421	19.82913	20.2393	47.8357	−0.88691	21.60745
8	4	4	90	0.15	25.50188	24.43034	26.57342	60.20654	0.674818	14.57005
4	4	4	180	0.6	23.21838	21.89877	24.53798	37.23388	−0.12629	5.330385
3	4	4	0	0.3	20.80438	20.72207	20.8867	35.29287	−0.76104	17.20035
3	4	2	270	0.9	22.50755	20.59448	24.42063	34.17206	−0.34322	7.450593
9	2	6	180	0.3	25.12577	24.1778	26.07374	57.59368	0.551002	11.35575
7	6	6	180	0.6	25.68208	24.50333	26.86083	58.28479	0.707691	15.53506
6	6	4	180	0.9	25.33481	23.81367	26.85595	51.91506	0.553941	11.42434
12	4	9	0	0.6	20.18072	20.18579	20.17565	48.32192	−0.84111	19.92695
10	2	6	90	0.3	24.03994	23.38387	24.69601	52.41129	0.215768	5.965689
3	2	2	180	0.9	23.66663	21.55428	25.77898	32.97023	−0.04351	5.039188
4	6	6	180	0.3	23.12287	22.24689	23.99885	36.58933	−0.15129	5.474266
4	4	9	270	0.15	23.27345	22.60159	23.94531	35.73982	−0.11501	5.273953
4	2	4	0	0.3	22.35535	21.99733	22.71337	37.47236	−0.3423	7.437404
6	9	2	90	0.15	25.53632	24.00943	27.0632	51.28414	0.604757	12.66956
1	4	2	270	0.15	19.84802	19.79139	19.90465	38.99397	−0.98723	25.58486
5	4	9	180	0.6	24.30261	23.4347	25.17051	42.93205	0.21191	5.931398
8	9	9	180	0.9	26.00596	24.44642	27.5655	59.75696	0.803191	18.60191
9	6	4	270	0.6	25.81696	23.70025	27.93366	59.59322	0.737886	16.46251
11	9	9	270	0.6	22.17981	21.35028	23.00935	49.74843	−0.31252	7.030153
2	6	2	0	0.9	19.60459	20.05557	19.15362	42.6029	−1.02223	27.06491
11	2	2	270	0.3	21.29655	20.67393	21.91916	52.08984	−0.53125	10.9045
4	2	4	90	0.3	23.20967	22.31066	24.10869	36.25786	−0.13082	5.354541
8	2	9	270	0.6	25.7553	24.52116	26.98944	59.4078	0.736272	16.41195
1	9	6	180	0.3	21.91723	20.85845	22.976	37.02079	−0.47001	9.612603
9	6	6	270	0.9	26.04224	23.79804	28.28644	59.02562	0.794668	18.3124
1	4	4	180	0.6	22.84532	21.27705	24.4136	36.26447	−0.23473	6.143338
6	2	4	270	0.3	25.30079	23.98653	26.61506	51.06235	0.541243	11.13067
9	2	9	0	0.9	24.65776	24.03902	25.27651	58.5665	0.435043	8.94756
5	6	2	270	0.9	26.17142	22.74479	29.59805	43.09188	0.692145	15.07289
10	4	4	90	0.15	23.92066	23.21524	24.62609	53.1703	0.187814	5.731328
5	9	6	270	0.3	24.72993	23.29683	26.16304	43.09904	0.321628	7.150726
7	2	9	270	0.15	25.57268	24.86955	26.2758	56.72496	0.673926	14.54452
8	4	2	90	0.15	25.511	24.17173	26.85027	61.53235	0.682316	14.78604
5	9	4	270	0.15	24.36889	23.14605	25.59173	43.6772	0.230653	6.103837
3	6	9	180	0.15	22.10132	21.41853	22.78412	33.24864	−0.44217	9.07891
5	4	6	0	0.6	24.24819	23.33574	25.16064	43.24987	0.198965	5.820896
11	4	6	180	0.9	24.60429	22.47033	26.73826	47.67285	0.312041	7.023922
4	6	4	180	0.6	23.30825	21.89379	24.72271	37.25224	−0.10321	5.220626
5	6	2	90	0.15	24.50787	23.20634	25.8094	43.23324	0.264005	6.447138
1	6	4	90	0.15	20.24346	20.22161	20.26531	39.25269	−0.8817	21.41183
6	4	2	270	0.15	25.25422	23.74936	26.75908	51.99094	0.53247	10.93187
10	6	4	90	0.3	24.10488	23.11261	25.09715	53.46258	0.235282	6.148695
7	4	4	0	0.15	25.34645	24.58781	26.10509	58.353	0.622793	13.13847
4	2	2	270	0.6	23.58376	21.61886	25.54866	37.57121	−0.03299	5.022525
8	9	6	180	0.9	26.09822	24.26865	27.9278	60.64016	0.831002	19.56793
2	4	4	0	0.15	19.93957	20.09546	19.78369	43.10323	−0.93649	23.52348
10	2	9	180	0.15	24.47126	23.80237	25.14015	50.95487	0.322794	7.166411
1	9	6	180	0.6	22.80581	21.232	24.37962	36.45111	−0.24404	6.236037
11	6	4	180	0.6	24.3489	22.19978	26.49802	48.34342	0.246719	6.263374
5	4	9	90	0.6	24.99267	23.66596	26.31938	42.02468	0.38616	8.105782
2	4	4	0	0.6	20.04175	20.18742	19.89608	42.51412	−0.9135	22.62267
2	9	4	270	0.15	20.54499	20.20628	20.88369	41.86483	−0.79116	18.19427
3	4	4	180	0.3	22.26468	21.19175	23.3376	33.62004	−0.40087	8.348313
9	6	2	270	0.9	26.63051	23.3807	29.88032	60.77175	0.957432	24.36206
1	4	9	90	0.15	20.65235	20.47584	20.82887	38.26974	−0.78311	17.92479
6	2	4	90	0.3	25.39976	24.1891	26.61042	50.61097	0.566739	11.7274

Table A2. Cont.

Month	Exterior Wall Width	Room Depth	Glazing Facade Orientation	WWR	Indoor Operative Temp	Indoor Air Temp	Indoor Mean Rad Temp	Indoor Relative Humidity	PMV	PPD
3	6	2	270	0.3	21.60017	20.57284	22.6275	34.72269	−0.56799	11.75735
3	6	4	0	0.6	20.83871	20.7027	20.97473	35.09715	−0.75407	16.97566
11	9	6	90	0.6	22.19955	21.38009	23.01901	49.66788	−0.30756	6.965995
11	6	4	0	0.6	20.96383	20.84589	21.08177	52.05688	−0.61091	12.82786
9	2	6	90	0.6	25.22692	24.08437	26.36948	58.11314	0.579463	12.03574
9	4	4	0	0.3	24.44165	23.82458	25.05872	59.812	0.384597	8.080557
12	9	6	90	0.9	20.7986	20.37795	21.21924	47.58623	−0.68945	14.99379
11	6	9	270	0.15	22.08866	21.63154	22.54577	49.04953	−0.3352	7.336939
10	4	2	270	0.3	23.92421	22.56966	25.27876	55.19898	0.191623	5.76134
6	6	9	270	0.15	25.40557	24.43871	26.37244	49.91252	0.566761	11.72793
9	4	9	0	0.9	24.78483	24.03148	25.53818	58.66148	0.468339	9.57965
1	4	9	270	0.15	20.48604	20.24205	20.73003	38.37885	−0.82701	19.42708
6	6	6	270	0.15	25.33471	24.22045	26.44898	50.62272	0.550437	11.3426
10	4	6	0	0.9	23.49925	22.90214	24.09637	54.43407	0.083637	5.144848
11	9	6	90	0.9	22.28382	21.27939	23.28825	50.0655	−0.28535	6.691408
8	4	4	90	0.9	26.55276	24.18895	28.91658	60.88027	0.951558	24.12505
3	4	2	180	0.3	22.41448	21.11349	23.71547	33.69678	−0.36317	7.745171
12	9	9	90	0.9	20.9616	20.51653	21.40668	47.18404	−0.64903	13.84586
8	6	6	90	0.6	26.175	24.42193	27.92806	59.84921	0.847862	20.16934
11	2	9	180	0.9	24.00948	22.58638	25.43258	46.92564	0.154074	5.491923
10	6	4	270	0.3	24.08039	22.91517	25.2456	54.0432	0.229676	6.094483
9	9	6	0	0.9	24.76958	23.80114	25.73803	59.64888	0.467241	9.558047
6	2	4	180	0.6	24.88535	23.90249	25.86821	51.65656	0.436739	8.978617
1	2	2	270	0.15	19.86671	19.80576	19.92765	38.92156	−0.98286	25.40334
2	9	2	90	0.3	20.89202	20.46791	21.31613	41.59134	−0.7027	15.38562
6	4	6	270	0.15	25.25175	24.22946	26.27404	50.57387	0.528661	10.84658
6	2	6	0	0.9	25.21798	24.09312	26.34283	50.88657	0.520098	10.65716
4	2	4	270	0.15	22.77826	22.06082	23.49571	37.06366	−0.23762	6.171687
11	9	6	0	0.15	21.34399	21.22106	21.46691	50.73564	−0.51771	10.60483
10	9	9	180	0.15	24.7821	23.77808	25.78612	51.08615	0.403458	8.39196
10	2	2	180	0.6	26.29579	23.90896	28.68262	51.31929	0.803365	18.60786
8	6	6	90	0.15	25.61848	24.60907	26.62788	59.45119	0.702807	15.38875
10	9	2	0	0.3	23.00602	22.55945	23.45259	55.95182	−0.03746	5.029042
1	4	6	90	0.15	20.44571	20.34299	20.54842	38.81915	−0.83269	19.62768
7	9	9	90	0.9	26.73909	24.68369	28.79449	56.95836	0.978183	25.21011
10	2	2	0	0.9	23.14197	22.42017	23.86378	56.02746	−0.00531	5.000583
6	6	2	90	0.6	26.57281	23.87955	29.26607	51.4204	0.877373	21.25045
2	4	4	270	0.3	20.73679	20.24533	21.22825	41.55534	−0.74493	16.68433
7	9	6	90	0.3	26.15244	24.71623	27.58865	57.18381	0.825889	19.38786
11	6	4	270	0.9	22.00894	20.80165	23.21622	51.60962	−0.35295	7.59213
9	9	6	180	0.15	25.26224	24.19472	26.32976	57.83427	0.588638	12.26244
9	6	9	90	0.9	25.75112	24.17965	27.32258	57.68943	0.714623	15.74451
4	4	4	180	0.9	23.49575	21.85167	25.13984	37.23941	−0.05561	5.064035
6	6	4	0	0.15	25.00671	24.17769	25.83573	51.00263	0.467752	9.568101
5	4	4	90	0.3	24.73345	23.40966	26.05724	42.72212	0.321107	7.143737
7	9	6	270	0.6	26.69481	24.4875	28.90213	58.0441	0.971859	24.94989
5	6	9	0	0.9	24.46785	23.42962	25.50608	42.9844	0.254753	6.347214
10	2	4	0	0.3	23.2877	22.93191	23.64349	54.49729	0.030974	5.019861
5	2	6	0	0.6	24.09387	23.34361	24.84413	43.182	0.158975	5.523753
12	2	9	0	0.6	20.24675	20.22942	20.26408	48.07572	−0.82556	19.37638
12	2	2	180	0.15	21.30165	20.55378	22.04953	45.84554	−0.5721	11.85649
4	9	2	90	0.3	23.46376	22.02391	24.9036	36.95987	−0.06403	5.084871
7	2	2	90	0.9	27.05003	24.23576	29.8643	59.35055	1.072779	29.28226
3	2	6	270	0.3	21.59547	20.98498	22.20597	34.01369	−0.56904	11.78262
11	9	4	180	0.3	23.41399	21.8396	24.98838	48.76617	0.002877	5.000171
4	9	9	0	0.15	22.97965	22.59715	23.36214	36.09688	−0.18697	5.724716
6	4	9	180	0.6	25.12908	24.26	25.99815	50.58063	0.497453	10.17152
1	4	6	180	0.9	23.20716	21.4766	24.93772	36.14676	−0.14089	5.411262
10	6	9	180	0.15	24.71482	23.78177	25.64788	51.06506	0.385988	8.102998
9	2	6	0	0.3	24.52594	24.06166	24.99023	58.79597	0.403504	8.392745
6	9	2	180	0.6	25.22999	23.66864	26.79134	52.36792	0.527746	10.8262
9	4	4	0	0.15	24.39791	23.90363	24.89219	59.67484	0.374074	7.913416
11	9	9	0	0.6	21.56052	21.32456	21.79648	50.23826	−0.46508	9.515642
10	4	2	0	0.3	23.00453	22.56697	23.4421	55.87272	−0.03825	5.030282
12	4	9	0	0.9	20.12272	20.15817	20.08727	48.50525	−0.85476	20.41874
11	2	4	0	0.6	21.01932	20.88056	21.15808	51.83496	−0.59789	12.4947
6	2	4	0	0.3	24.93294	24.12622	25.73966	51.00965	0.447852	9.185089
3	4	9	180	0.6	22.72148	21.56668	23.87628	32.86968	−0.28632	6.702944
5	9	2	90	0.15	24.55705	23.20626	25.90783	43.24044	0.276772	6.590932
12	4	2	0	0.3	19.15296	19.56872	18.7372	50.12168	−1.09577	30.32096
8	6	9	180	0.3	25.57724	24.65158	26.50289	59.22988	0.691178	15.04447
4	2	6	180	0.9	23.17652	22.0229	24.33013	36.86819	−0.13818	5.395556
3	2	6	180	0.15	21.78738	21.2322	22.34256	33.57225	−0.52098	10.67661
9	4	9	270	0.3	25.30837	24.30787	26.30887	57.24529	0.598176	12.50198
3	4	9	90	0.9	22.28866	21.2804	23.29691	33.41059	−0.39528	8.255127
7	9	6	90	0.15	25.90198	24.78047	27.0235	57.10769	0.760959	17.19761
3	6	4	90	0.9	22.3987	21.00292	23.79449	34.01737	−0.36614	7.790581
10	6	9	180	0.3	25.06023	23.85094	26.26952	50.72338	0.473855	9.688993
11	6	9	180	0.3	23.25118	22.13455	24.36782	47.37612	−0.04398	5.040047
2	4	9	90	0.6	21.37676	20.80649	21.94702	40.38935	−0.58454	12.16066
9	4	6	180	0.15	25.11714	24.20203	26.03224	57.79873	0.550896	11.35328
8	9	6	0	0.6	25.40538	24.33726	26.47349	60.66688	0.651443	13.91232

Table A2. Cont.

Month	Exterior Wall Width	Room Depth	Glazing Facade Orientation	WWR	Indoor Operative Temp	Indoor Air Temp	Indoor Mean Rad Temp	Indoor Relative Humidity	PMV	PPD
6	6	4	0	0.6	25.42319	24.01661	26.82977	51.21806	0.574835	11.92276
5	9	2	90	0.3	24.97548	23.16765	26.78332	43.1374	0.384187	8.073954
5	4	2	0	0.9	24.46384	22.92434	26.00333	43.47906	0.250837	6.306009
11	4	4	0	0.6	20.98884	20.85994	21.11774	51.97505	−0.60495	12.67456
11	6	9	90	0.15	22.34264	21.90562	22.77967	47.9746	−0.27387	6.557631
9	6	6	90	0.15	25.16609	24.29774	26.03444	57.56114	0.563634	11.65321
10	9	6	90	0.9	24.63688	23.07051	26.20325	53.46741	0.371871	7.879025
8	6	9	270	0.9	26.50892	24.39999	28.61786	59.82875	0.935424	23.48108
2	2	9	0	0.9	20.49676	20.42807	20.56545	41.58785	−0.80126	18.536
7	2	2	180	0.9	25.78883	24.0864	27.49126	60.38862	0.744114	16.65869
2	2	4	180	0.9	23.51175	21.69674	25.32677	38.58786	−0.04379	5.039689
3	9	4	270	0.6	22.13861	20.73769	23.53953	34.24016	−0.43344	8.918289
6	9	9	180	0.3	25.17363	24.37473	25.97253	50.37463	0.509303	10.42289
5	4	4	0	0.15	23.89433	23.29636	24.4923	43.69109	0.111095	5.255629
6	9	9	0	0.3	25.3485	24.47284	26.22416	49.95121	0.552842	11.39864
3	9	4	180	0.15	21.91775	21.04779	22.78771	33.9359	−0.48789	9.97314
6	4	2	180	0.3	24.80251	23.73658	25.86843	52.31407	0.417537	8.634342
4	4	4	90	0.9	24.04857	22.11119	25.98595	36.53887	0.084628	5.148301
3	4	4	180	0.6	23.01157	21.44481	24.57834	33.13768	−0.21162	5.928854
10	4	2	90	0.6	24.27679	22.66717	25.88641	54.97488	0.282717	6.660239
8	2	2	180	0.6	25.65133	23.96114	27.34151	62.55132	0.722579	15.98745
7	6	2	180	0.9	26.0878	24.0842	28.0914	60.44789	0.82314	19.29153
2	6	4	90	0.15	20.85159	20.58222	21.12095	41.46238	−0.71178	15.65844
9	4	2	270	0.3	25.28266	23.51865	27.04667	60.58776	0.601932	12.59738
7	6	6	90	0.6	26.47319	24.61246	28.33391	57.43672	0.910471	22.50557
6	9	6	90	0.3	25.77536	24.34083	27.20989	50.15405	0.663492	14.24841
2	6	9	180	0.6	22.75402	21.37213	24.13592	38.94028	−0.2391	6.186326
9	4	9	0	0.15	24.84847	24.40291	25.29404	57.58884	0.48415	9.896545
3	4	6	0	0.3	21.04517	20.90156	21.18878	34.89078	−0.70156	15.35139
2	9	6	270	0.15	20.73667	20.37113	21.10221	41.37631	−0.74414	16.65939
7	4	9	270	0.6	26.25769	24.68047	27.83491	57.04929	0.851761	20.31011
1	9	9	180	0.6	22.57588	21.19935	23.95241	36.51655	−0.30258	6.902576
2	6	2	90	0.9	21.40415	20.49043	22.31787	41.19748	−0.57699	11.97537
2	4	4	180	0.6	23.14189	21.43396	24.84982	39.02335	−0.13866	5.39836
12	4	2	180	0.9	23.94017	21.51535	26.365	44.20059	0.102823	5.218963
3	6	2	90	0.9	22.46774	20.86937	24.06611	34.15252	−0.34912	7.535881
12	2	9	180	0.15	21.3336	20.8495	21.8177	45.35631	−0.5624	11.62391
10	2	4	270	0.3	23.83859	22.93509	24.74208	53.8965	0.166922	5.577485
12	2	2	270	0.15	19.82656	19.76028	19.89284	48.25657	−0.93669	23.53112
10	9	2	90	0.6	24.41122	22.67499	26.14744	54.97223	0.317653	7.097674
5	4	2	180	0.15	23.68965	22.89922	24.48008	44.31706	0.057581	5.068644
1	2	6	180	0.9	22.91834	21.49789	24.33878	36.12342	−0.21479	5.956897
5	6	6	180	0.15	24.06868	23.41027	24.72709	43.26275	0.154094	5.49205
8	2	6	270	0.15	25.34521	24.51394	26.17648	59.86193	0.633161	13.41441
6	9	2	180	0.9	25.50177	23.61853	27.38502	52.41809	0.598355	12.50651
8	9	9	270	0.15	25.76249	24.71351	26.81147	59.03878	0.73912	16.50126
1	2	4	0	0.15	19.56348	19.76064	19.36631	40.53007	−1.05008	28.27493
8	4	2	0	0.15	24.82538	24.05304	25.59772	62.57302	0.510148	10.44103
11	4	9	270	0.9	22.12176	21.24952	22.994	50.01611	−0.32713	7.225288
7	2	9	0	0.9	25.56285	24.65598	26.46972	57.32317	0.671919	14.48722
5	6	6	180	0.3	24.14987	23.33196	24.96778	43.35068	0.174438	5.630734
8	4	4	270	0.6	26.34817	24.11262	28.58372	61.47305	0.900589	22.12615
9	4	9	180	0.15	25.2357	24.44426	26.02714	56.84175	0.578859	12.02095
11	9	6	180	0.9	24.91115	22.45075	27.37154	47.72816	0.392419	8.207848
8	6	9	0	0.3	25.37212	24.66913	26.07511	59.43175	0.640016	13.5994
11	2	4	270	0.3	21.51341	20.99848	22.02833	51.09895	−0.47733	9.758547
4	9	9	180	0.3	23.35323	22.52076	24.1857	35.93805	−0.09419	5.183714
12	2	2	90	0.6	20.41339	20.1807	20.64609	47.46475	−0.78919	18.12794
7	4	9	90	0.6	26.19772	24.77322	27.62222	56.67133	0.834628	19.69625
12	2	9	180	0.3	21.67724	21.01957	22.3349	45.13623	−0.47508	9.713412
10	2	6	0	0.9	23.42498	22.90967	23.94028	54.341	0.064211	5.085364
7	4	4	90	0.3	26.02945	24.56972	27.48917	57.88736	0.796586	18.37729
3	9	2	0	0.6	20.52069	20.524	20.51739	35.35852	−0.83347	19.65518
12	9	9	180	0.9	23.2458	21.49706	24.99454	44.73654	−0.07267	5.109338
8	9	6	90	0.15	25.68312	24.6072	26.75904	59.47386	0.71978	15.90166
6	2	9	0	0.15	25.05387	24.56288	25.54486	49.75502	0.47667	9.745273
6	4	2	90	0.3	25.79538	23.95664	27.63413	51.30095	0.671909	14.48691
3	9	2	0	0.9	20.54592	20.52841	20.56344	35.15725	−0.82847	19.47843
8	9	2	90	0.3	26.02993	24.12406	27.93581	61.66623	0.818329	19.12369
4	4	4	270	0.15	22.90223	22.03855	23.76591	37.1342	−0.20596	5.87971
5	9	9	270	0.9	25.43148	23.29489	27.56807	42.64936	0.501234	10.25106
9	6	4	180	0.15	25.12559	23.9772	26.27398	58.7165	0.555755	11.46688
7	9	4	270	0.3	26.24676	24.42247	28.07104	58.65194	0.857099	20.50387
4	6	9	90	0.6	23.84114	22.61851	25.06376	35.37732	0.027596	5.015764
6	6	4	0	0.9	25.65585	23.94212	27.36957	51.38697	0.635767	13.48448
5	4	2	90	0.3	24.82589	23.16691	26.48487	43.11012	0.345025	7.476517
2	2	6	0	0.6	20.32303	20.32343	20.32264	42.03434	−0.84301	19.99486
10	4	9	180	0.15	24.63261	23.78637	25.47885	51.03865	0.364667	7.768003
1	9	6	90	0.15	20.43038	20.32298	20.53778	38.93308	−0.83606	19.74715
10	2	9	90	0.6	24.24461	23.48688	25.00234	51.93259	0.266461	6.47426
4	4	2	270	0.15	22.75961	21.69648	23.82274	37.90596	−0.24089	6.204233
3	9	4	180	0.6	23.19841	21.42924	24.96758	33.17621	−0.16362	5.554847

Table A2. Cont.

Month	Exterior Wall Width	Room Depth	Glazing Facade Orientation	WWR	Indoor Operative Temp	Indoor Air Temp	Indoor Mean Rad Temp	Indoor Relative Humidity	PMV	PPD
11	2	4	180	0.3	23.0072	21.86584	24.14855	48.67672	−0.10139	5.212897
11	2	4	180	0.9	24.52788	22.43081	26.62494	48.06686	0.29443	6.801145
5	6	2	270	0.6	25.55527	22.78851	28.32202	43.26027	0.53328	10.95008
7	4	2	0	0.3	25.472	24.29795	26.64604	59.6656	0.659901	14.14758
6	2	2	0	0.3	24.93283	23.89227	25.97339	51.65534	0.448833	9.203568
4	6	2	0	0.3	22.1397	21.6833	22.5961	38.20376	−0.39566	8.261293
2	6	2	180	0.15	21.69305	20.70146	22.68464	40.30889	−0.5072	10.37774
11	9	6	90	0.15	22.04335	21.58775	22.49895	49.0161	−0.3476	7.513752
2	4	4	270	0.6	21.03395	20.25178	21.81613	41.31039	−0.67235	14.49949
8	4	9	90	0.9	26.16601	24.51506	27.81696	59.27839	0.842698	19.98388
3	6	4	180	0.6	23.11623	21.43523	24.79724	33.15668	−0.18477	5.707736
4	9	2	90	0.15	23.102	22.06563	24.13837	36.9866	−0.15587	5.503472
10	6	6	90	0.9	24.55395	23.0702	26.0377	53.45268	0.350262	7.552631
6	2	6	270	0.3	25.26446	24.17874	26.35018	50.48181	0.530376	10.88491
4	6	2	180	0.15	22.63392	21.76514	23.50271	37.76509	−0.27292	6.546827
6	6	2	90	0.15	25.47938	24.00924	26.94952	51.27625	0.589827	12.29208
8	2	2	270	0.9	26.93205	23.81366	30.05044	63.1288	1.063753	28.8796
1	2	2	180	0.15	21.27057	20.57177	21.96938	37.00333	−0.63609	13.49309
11	6	6	90	0.15	22.02604	21.59556	22.45652	48.98688	−0.352	7.578161
5	9	6	180	0.3	24.19729	23.32781	25.06677	43.36791	0.186676	5.722473
2	2	9	90	0.3	21.22053	20.88437	21.55669	40.15725	−0.62388	13.16708
7	6	2	270	0.15	25.83922	24.22337	27.45507	59.95416	0.7566	17.05698
6	9	4	180	0.3	24.96635	23.97936	25.95335	51.65281	0.458996	9.39748
2	4	6	0	0.15	20.22451	20.26642	20.1826	42.37991	−0.86605	20.8312
2	6	4	270	0.3	20.75196	20.2304	21.27353	41.6127	−0.74102	16.56115
7	6	2	180	0.15	25.21792	24.24991	26.18594	60.02753	0.595794	12.44177
2	9	4	0	0.6	19.94131	20.1542	19.72843	42.71375	−0.93747	23.56214
9	9	2	90	0.6	25.89862	23.66281	28.13444	60.09787	0.76262	17.2514
8	6	4	90	0.15	25.58167	24.42883	26.73451	60.24107	0.695828	15.18144
7	2	6	0	0.6	25.47745	24.57579	26.3791	57.88195	0.652661	13.94601
8	9	4	180	0.15	25.32956	24.30134	26.35777	60.99255	0.633588	13.42586
4	4	6	90	0.15	23.30573	22.60693	24.00453	35.63992	−0.10746	5.239172
11	4	6	270	0.3	21.80268	21.23987	22.3655	50.24462	−0.40604	8.435829
10	6	4	270	0.15	23.86875	23.00267	24.73484	53.952	0.176332	5.644523
12	9	9	0	0.15	20.22424	20.1931	20.25538	48.10262	−0.83163	19.59
8	2	9	0	0.15	25.19148	24.75386	25.6291	59.23693	0.593643	12.38764
10	4	2	90	0.15	23.6957	22.84927	24.54213	54.54151	0.133491	5.369171
12	6	4	270	0.6	20.45109	19.98725	20.91494	47.77154	−0.78146	17.86992
11	6	6	0	0.3	21.32394	21.18163	21.46625	50.82532	−0.52287	10.71815
8	4	2	180	0.9	26.26598	23.91542	28.61654	62.7503	0.885104	21.53961
5	2	9	270	0.3	24.40847	23.57532	25.24163	42.3699	0.236752	6.16312
1	6	4	90	0.9	20.5831	20.26436	20.90184	38.91956	−0.79927	18.4684
7	4	4	90	0.15	25.7553	24.63445	26.87614	57.78424	0.72534	16.0724
6	9	6	90	0.9	26.57522	24.14536	29.00507	50.62685	0.875283	21.17273
5	4	4	180	0.3	23.98886	23.13642	24.8413	43.76325	0.133473	5.369071
1	9	2	270	0.9	20.5772	19.9105	21.24389	38.29786	−0.80968	18.82426
5	4	6	90	0.15	24.54599	23.673	25.41898	42.16502	0.27187	6.534908
9	6	2	0	0.15	24.15448	23.57458	24.73437	61.06571	0.315067	7.063528
3	9	4	0	0.9	20.8282	20.67458	20.98182	35.06612	−0.75725	17.07794
1	4	2	270	0.6	20.40104	19.91052	20.89155	38.36031	−0.85296	20.35366
1	6	6	90	0.3	20.53222	20.35242	20.71201	38.80478	−0.81127	18.87927
8	2	9	270	0.9	25.94905	24.41385	27.48426	59.7555	0.787604	18.07477
6	4	2	180	0.6	25.11561	23.66956	26.56167	52.33967	0.497764	10.17802
11	4	6	180	0.6	23.9897	22.28762	25.69177	47.7656	0.150702	5.470603
6	9	6	180	0.9	25.36157	23.96567	26.75747	51.47893	0.559997	11.56687
3	2	9	180	0.3	22.11151	21.45884	22.76418	33.06403	−0.44041	9.046254
6	2	2	270	0.9	26.75446	23.61469	29.89423	51.64013	0.924278	23.04224
7	4	9	0	0.6	25.68089	24.73957	26.62221	57.12642	0.702685	15.3851
6	4	2	270	0.3	25.73429	23.71589	27.75269	51.82294	0.656283	14.04658
3	6	6	270	0.9	22.33164	20.83333	23.82996	33.94701	−0.3854	8.093441
1	6	6	180	0.15	21.31064	20.62236	21.99892	37.43199	−0.62267	13.13515
1	6	2	0	0.15	18.95432	19.50092	18.40773	41.45084	−1.19725	35.11302
11	4	4	180	0.9	24.90495	22.39936	27.41053	48.13338	0.393019	8.21773
12	6	4	270	0.9	20.5815	19.98146	21.18154	47.66639	−0.74987	16.84143
2	2	4	0	0.6	20.13407	20.21577	20.05237	42.33559	−0.88942	21.70211
1	6	4	0	0.6	19.47724	19.84109	19.1134	40.24698	−1.0715	29.22512
4	6	4	90	0.3	23.44749	22.2971	24.59788	36.31387	−0.06988	5.101101
2	9	4	270	0.3	20.76081	20.21719	21.30444	41.6716	−0.73866	16.48674
6	6	2	270	0.15	25.32761	23.74047	26.91476	52.04984	0.551918	11.37709
5	6	4	270	0.6	25.24862	23.01317	27.48407	43.16775	0.454129	9.304068
7	4	9	0	0.9	25.77749	24.64843	26.90655	57.39325	0.728208	16.16097
11	4	9	180	0.15	22.75734	21.99011	23.52457	47.60688	−0.17028	5.600958
5	2	4	0	0.15	23.80495	23.30715	24.30274	43.61323	0.087857	5.159838
5	2	6	180	0.6	24.05119	23.22797	24.8744	43.39113	0.147965	5.453648
11	2	2	90	0.6	21.78095	20.94385	22.61804	51.19095	−0.41065	8.514646
4	2	9	180	0.9	23.20228	22.25168	24.15289	36.33369	−0.13283	5.365504
11	4	4	180	0.6	24.20881	22.21004	26.20757	48.31308	0.210234	5.9167
5	6	4	180	0.3	24.04661	23.13079	24.96244	43.79686	0.148447	5.456615
7	2	6	270	0.9	26.36089	24.4122	28.30957	58.2508	0.883774	21.48972
1	9	2	180	0.3	22.25241	20.90128	23.60354	36.46791	−0.38832	8.140786
3	4	9	270	0.3	21.84221	21.17305	23.71241	40.26697	−0.50697	10.37287
9	4	6	0	0.3	24.61448	24.05402	25.17493	58.87773	0.426703	8.796707

Table A2. Cont.

Month	Exterior Wall Width	Room Depth	Glazing Facade Orientation	WWR	Indoor Operative Temp	Indoor Air Temp	Indoor Mean Rad Temp	Indoor Relative Humidity	PMV	PPD
9	6	9	90	0.3	25.39262	24.43463	26.35061	56.8576	0.61946	13.05074
11	4	9	0	0.15	21.76063	21.57297	21.94828	49.48488	−0.41548	8.598446
10	4	6	90	0.15	24.11952	23.48829	24.75076	52.18697	0.236371	6.159373
12	6	6	0	0.9	19.78291	19.97415	19.59168	49.11651	−0.93997	23.6616
5	4	4	180	0.15	23.86028	23.19241	24.52815	43.80025	0.101676	5.214099
9	6	9	0	0.6	24.8425	24.14702	25.53798	58.32629	0.483013	9.873392
7	4	6	180	0.6	25.59461	24.50764	26.68158	58.25657	0.684764	14.85709
3	4	4	270	0.6	22.01081	20.75611	23.26551	34.15586	−0.46609	9.53537
5	2	2	90	0.9	25.61845	23.04592	28.19098	42.83512	0.549338	11.31708
11	6	9	270	0.9	22.18768	21.23853	23.13683	50.07342	−0.3103	7.001348
12	4	9	180	0.15	21.43159	20.82326	22.03992	45.48164	−0.53754	11.04624
2	9	4	90	0.6	21.2957	20.58919	22.0022	41.23996	−0.60248	12.61128
8	4	6	0	0.6	25.2744	24.34168	26.20711	60.60877	0.61708	12.98839
3	2	6	90	0.6	21.96266	21.19439	22.73092	33.63713	−0.47695	9.750853
5	9	4	0	0.3	24.11071	23.24963	24.97179	43.6344	0.165361	5.566727
8	9	6	270	0.6	26.45913	24.29085	28.6274	60.5285	0.925818	23.10257
11	9	9	270	0.9	22.2429	21.2324	23.2534	50.10392	−0.29625	6.823542
8	2	4	0	0.3	24.95279	24.27547	25.63011	61.15905	0.536864	11.03103
2	6	6	0	0.3	20.22292	20.27619	20.16966	42.30631	−0.86673	20.85644
4	2	2	180	0.3	22.71318	21.72265	23.70372	37.68939	−0.25385	6.337698
2	4	9	180	0.15	21.5355	20.89207	22.17893	39.85331	−0.54709	11.26495
5	4	2	0	0.3	23.92433	23.01631	24.83235	43.92021	0.116385	5.280568
7	6	2	0	0.3	25.53521	24.29948	26.77094	59.66893	0.676419	14.61597
10	6	9	90	0.9	24.59019	23.32284	25.85754	52.50857	0.35691	7.650931
9	6	2	90	0.9	26.25844	23.60198	28.91491	60.24517	0.857922	20.53385
12	4	9	90	0.6	20.92284	20.58765	21.25804	46.85087	−0.65954	14.1375
2	2	4	90	0.6	21.17053	20.60592	21.73515	41.05051	−0.63471	13.45599
7	2	6	180	0.9	25.50451	24.4242	26.58482	58.47495	0.661384	14.18915
1	4	9	270	0.3	20.55864	20.22894	20.88834	38.35144	−0.80941	18.81491
12	9	6	0	0.9	19.72319	19.94845	19.49794	49.2633	−0.9542	24.23145
8	4	9	270	0.15	25.60702	24.72195	26.49209	59.00649	0.698582	15.263
9	9	2	90	0.15	25.0341	23.80386	26.26435	59.7524	0.536558	11.02409
11	4	4	270	0.6	21.78721	20.88463	22.68979	51.38738	−0.40886	8.483896
10	9	4	0	0.15	23.344	22.99568	23.69231	54.50606	0.046611	5.044979
1	2	4	270	0.3	20.23825	19.9906	20.4859	38.71463	−0.88986	21.71859
1	6	9	0	0.9	19.94772	20.05521	19.84024	39.7637	−0.95383	24.21672
5	4	2	0	0.15	23.71438	23.02381	24.40496	44.19635	0.064863	5.087109
6	6	4	180	0.15	24.79327	24.03948	25.54706	51.5741	0.414748	8.585652
10	2	2	0	0.3	22.98809	22.57855	23.39763	55.76912	−0.04291	5.03812
6	9	4	270	0.3	25.75912	23.95945	27.55879	51.23072	0.661881	14.20312
10	6	4	0	0.15	23.33975	23.002	23.6775	54.46064	0.045327	5.042533
3	6	9	0	0.6	21.27814	21.02679	21.52948	34.45874	−0.64485	13.73107
6	6	9	90	0.6	25.9679	24.40366	27.53215	49.82923	0.71227	15.67319
1	9	6	0	0.15	19.67992	19.84492	19.51492	40.35534	−1.02127	27.02366

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