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Review article

Evaluation of machine learning applications in building life cycle processes for energy efficiency: A systematic review

Gevher Nesibe Kaya [a,1], Figen Beyhan [b,2], Zeynep Yeşim İlerisoy [b,3], Jan Cudzik [c,4,*]

[a] Department of City and Regional Planning, Faculty of Fine Arts and Design, Siirt University, Siirt, Turkiye
[b] Department of Architecture, Faculty of Architecture, Gazi University, Ankara 06530, Turkiye
[c] Department of Urban Architecture and Waterside Spaces, Faculty of Architecture, Gdańsk University of Technology, Poland

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ABSTRACT

In recent years, machine learning has been increasingly applied to achieve energy efficiency in buildings. This study analyzes the utilization of machine learning across the building life cycle by reviewing literature on building energy efficiency. In this context, a systematic literature search was conducted using the Web of Science (WOS) search engine, and 868 publications were found. The publications were analyzed according to their year, subject scope, and qualification results, and 84 publications were selected. These publications were discussed under five categories: objective function and control variables, programs, simulations, machine learning, and optimization algorithms. The relationships between these categories and each phase of the building life cycle were examined. The findings suggest that machine learning can effectively optimize factors related to energy efficiency and building sustainability throughout the life cycle, and it is anticipated that interdisciplinary studies incorporating machine learning will experience exponential growth in the future.

1. Introduction

Today, energy consumption, carbon emission, and climate change are rapidly increasing due to reasons such as the increasing use of heating and cooling devices in buildings, digitalization with artificial intelligence (International Energy Agency, 2024). As a result of increasing energy consumption and carbon emissions, the European Green Deal developed by the European Union adopted a strategy aiming to reduce carbon emissions by 55 % by 2030 and achieve zero carbon emissions by 2050 (European Commission, 2019; International Energy Agency, 2023). Three main sectors, namely industry, transport, and buildings, have a significant share in global energy consumption, and efficient energy use in these sectors is important for environmental sustainability (Chou and Bui, 2014).

The building sector accounts for 36 % of global energy consumption and 39 % of carbon emissions in construction, operation, and maintenance processes (Dahiya and Laishram, 2024). Due to this high rate, the development of energy-efficient building strategies has gained importance. The Energy Performance of Building Directive (EPBD) was published to increase energy efficiency in buildings, and a legal framework was established (Hashempour, Taherkhani and Mahdikhani, 2020). Accordingly, in addition to minimizing energy consumption and carbon footprints, buildings should be able to meet building targets such as Nearly Zero Energy Building, Net Zero Energy Building (NZEB), and Positive Energy Building (PEB), which are self-sufficient in energy consumption (Soheil Fathi, Srinivasan, Fenner, and Fathi, 2020; Kaya and Beyhan, 2024; Minelli, Ciriello, Minichiello, and D'Agostino, 2024; Takva, Çalışkan, and Çakıcı, 2022).

Energy consumption and carbon footprint are significantly reduced to achieve all these goals. Energy efficiency can be achieved by addressing all processes of the building, including the Life Cycle Stages (LCS) from the design phase of the buildings (Genc, Demircan, Beyhan, and Kaplan, 2024; X. Yang, Hu, Wu, and Zhao, 2018). In addition, in the studies on building LCS, it has been determined that the highest carbon

* Corresponding author.
E-mail addresses: nesibe.kaya@siirt.edu.tr (G.N. Kaya), fbeyhan@gazi.edu.tr (F. Beyhan), zyharmankaya@gazi.edu.tr (Z.Y. İlerisoy), jan.cudzik@pg.edu.pl (J. Cudzik).
[1] ORC-ID: 0000–0001-7446–4711
[2] ORC-ID: 0000–0002-4287–1037
[3] ORC-ID: 0000–0003-1903–9119
[4] ORC-ID: 0000–0002-8162–2447

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emission (+50 %) and energy consumption (80–85 %) in the LCS of the building takes place in the operating process. Alternative improvements should be made to reduce energy consumption in this process (Sharma et al., 2011). For this reason, in studies on the subject, it is necessary to examine the targets and control variables in line with the targets in studies involving each process by considering the building of LCSs one by one. Studies on building energy efficiency usually involve comprehensive optimization processes to improve building energy calculations and designs using simulation tools.

With technological advances, optimization studies carried out only through simulations are insufficient to ensure energy efficiency in buildings. The use of Machine Learning (ML), a subset of Artificial Intelligence (AI), is becoming increasingly widespread in this field (Li et al., 2025; Liu and Chen, 2025; Ahmadi, 2024; Tien et al., 2022; Ardabili et al., 2022). Machine learning methods enable a large number of parameters to be generated simultaneously with high precision and optimum results to be obtained quickly (Chou and Bui, 2014). In this context, the study aims to analyze the publications reviewed in the literature according to the identified LCSs, focusing on machine learning applications for energy efficiency in buildings. It also categorizes and classifies the software, machine learning algorithms, optimization algorithms, and objective functions used in each LCS.

Nomenclature and abbreviations

		LSM	Least Squares Method
ACO	Ant Colony Optimization	LRNN	Layered Recurrent Neural Network
AdaBoost	Adaptive Boosting	LSSVM	Least Squares Support Vector Machine
AEL	Adaptive Evolution Learning	LSTM	Long Short Term Memory
AI	Artificial intelligence	MACO	Multi-Objective Ant Colony Optimization
AIMMS	Advanced Interactive Multidimensional Modeling System	MAPS	Multi-Objective Adaptive Particle Swarm
ANFIS	Adaptive Neuro-Fuzzy Inference System	MARS	Multivariate Adaptive Regression Spline
ANN	Artificial Neural Networks	MEPSO	Multi-Objective Evolutionary Particle Swarm Optimization
aNSGA-II	Adaptive Non-Dominated Sorting Genetic Algorithm-II	MEVO	Multi-Objective Evolutionary Algorithm
BP	Back Propagation	ML	Machine Learning
BIPV	Building Integrated Photovoltaic	MLP	Multi-Layer Perceptron
BIM	Building information modelling	MLR	Multi-Linear Regression
CAD	Computer Aid Design	MOALO	Multi-objective Ant Lion Optimization
CatBoost	Category Boosting	MODA	Multi-Objective Dragonfly Algorithm
CMA-ES	Covariance Matrix Adaptation Evolution Strategy	MOEAD	Multi-objective evolutionary algorithm
CMVS	Construction Management and Visualization System	MOGA	Multi-objective genetic algorithm
CNN	Convolutional Neural Network	MOO	Multi-Objective Optimization
CO_2	Carbon dioxide	MOPSO	Multi-objective Particle Swarm Optimization
DBN	Dynamic Bayesian Network	MOSA	Multi-Objective Simulated Annealing
DCNN	Deep Convolutional Neural Network	MSOPS-II	Multi-Objective Scatter Search Optimization
DNN	Deep Neural Network	NN	Neural Networks
DT	Decision Trees	NSGA-II	Non-Dominated Shorting Genetic Algorithm-II
EFA-ANN	Electromagnetism-based Firefly Algorithm- Artificial Neural Network	NSPO	Non-Dominated Shorting Particle Swarm Optimization
EPBD	Energy Performance of Building Directive	NZEB	Net Zero Energy Building

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ETR	Extra Tree Regression	OLR	Ordinary Linear Regression
FL	Fuzzy Logic	PEB	Positive Energy Building
FNN	Feedforward Neural Network	PV	Photovoltaic
GA	Genetic algorithm	PSO	Particle Swarm Optimization
GBDT	Gradient Boost Decision Tree	Q-Learning	Quality Learning
GBR	Gradient Boost Regression	QSVM	Quantum Support Vector Machine
GenOpt	Generic Optimization Program	RBF	Radial Basis Function
GIS	Geographic Information System	RF	Random Forest
GLSSVM	Generalized Least Squares Support Vector Machine	RFR	Random Forest Regression
GPR	Gaussian Process Regression	RL	Reinforcement Regression
GSV	Google Street View	RNN	Recurrent Neural Network
GWO	Grey Wolf Optimization	SHAP	SHapley Adaptive exPlanations
HVAC	Heating, ventilation, and air conditioning	SimaPro	Simulation of Products
HypE	Hypervolume Estimation Algorithm	SPEA−2	Strength Pareto Evolutionary Algorithm−2
IES-VE	Integrated Software Virtual Environment	SVM	Support Vector Machines
IDA ICE	Indoor Climate and Energy Program	SVR	Support Vector Regression
IDBEA	Indicator-Based Evolutionary Algorithm	T-APSSA	Thermodynamic Adaptive Particle Swarm Simulated Annealing
KNN	K-Nearest Neighbor	TGP	Three Gaussian Processes
K Value	Thermal Conductivity Value	TRNSYS	Transient System Simulation Tool
LCA	Life Cycle Assessment	U Value	Thermal Transmittance Value
LCS	Life Cycle Stages	UBEM	Urban Building Energy Modelling
LEB	Low Energy Buildings	VisualSFM	Visual Structure from Motion
LIDAR	Laser Imaging Detection and Ranging	WWR	Window-to-Wall Ratio
		XGBR	Extreme Gradient Boost Regression

1.1. Background: machine learning in construction

Over the past 20 years, Life Cycle Assessment (LCA) has emerged as a widely adopted methodology for assessing and reducing buildings' environmental impact and energy use. Since no single approach can comprehensively address the diverse challenges of the construction sector, LCA is employed to meet global emission targets and optimize building system energy use (Eleftheriadis, Mumovic, and Greening, 2017). By evaluating energy consumption, emissions, and the technological performance of various materials and components, the building LCA framework offers significant advantages for enhancing design options and reducing environmental impacts (Proietti et al., 2013).

Advancements in software and information technologies have equipped researchers with powerful optimization tools to improve building life cycle performance (Gan et al., 2020). These tools facilitate using ML to optimize energy conservation and generation within building envelopes, enhancing energy efficiency across life cycle stages. While optimization studies using traditional software reduce energy consumption, they often face challenges, such as high error rates and significant time and resource demands, to achieve satisfactory results (Chou and Bui, 2014; Xu et al., 2021). Consequently, interest in data-driven building design methods has grown, with substantial progress in their application (Gan et al., 2020).

ML has emerged as a leading data-driven method. ML enables systems to learn and improve from experience without explicit programming, providing a versatile approach to solving complex problems (Hong, Wang, Luo, and Zhang, 2020). ML methods are broadly categorized into three types: Supervised, Unsupervised, and Reinforcement Learning (Turner et al., 2020). Supervised learning is particularly prominent, involving models trained to predict outcomes based on labeled data (Bhamare, Saikia, Rathod, Rakshit, and Banerjee, 2021; Reddy and Babu, 2018).

Widely used ML algorithms include Artificial Neural Networks (ANN), Fuzzy Logic (FL), Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Decision Trees (DT), and Random Forest (RF). These algorithms are highly effective for classification and regression tasks, with ANN and Random Forest achieving exceptionally reliable results. Machine learning approaches generally utilize many methods to reliably solve regression or classification problems. Supervised Learning is one of the most widely used areas of machine learning (Bhamare et al., 2021; Kabilan et al., 2021). This learning technique is a model that effectively learns how to predict from training data (Reddy and Babu, 2018). Among these, the ANN algorithm is a computational model inspired by the biological connections of brain neurons. It addresses multivariate correlations of complex problems by processing input-output relationships learned from training data. ANN's primary advantage over other AI techniques is its capability to generate multi-response functions, making it especially useful for building energy applications (Y. Lin, Zhou, Yang, and Li, 2018; May Tzuc et al., 2021).

1.2. Backgrounds: machine learning in the building envelope life cycle

With its low error rates and ability to handle multiple functions simultaneously, ML has proven effective in achieving rapid optimization results. It is widely used to enhance energy efficiency in buildings. ML-based optimization typically relies on simulation models, where numerical simulations represent building systems, and mathematical optimization models identify the most energy-efficient envelope combinations (Mousavi, Villarreal-Marroquín, Hajiaghaei-Keshteli, and Smith, 2023). While ML algorithms are valuable for designing energy-efficient buildings, certain limitations necessitate further research to broaden their applicability and guide future optimization efforts (Gan et al., 2020).

This study explores life cycle stages defined by ISO 14040, including design, construction, operation (maintenance and control), and retrofitting, in the context of ML-driven energy efficiency within the building envelope. Wong et al. (2010) employed EnergyPlus software to optimize daylighting in office buildings in subtropical climates, creating an ANN-based model to calculate cooling and heating energy consumption (Wong, Wan, and Lam, 2010). Similarly, Chen and Yang (2017) compared three ML algorithms, SVM, Multi-Linear Regression (MLR), and Multivariate Adaptive Regression Spline (MARS), to optimize residential building designs. The study found that SVM achieved the best prediction performance and nearly zero HVAC energy demand in Los Angeles (X. Chen and Yang, 2017). Lin and Tsay (2021) used Rhino-Grasshopper, Dodo, and Ladybug simulations combined with the ANN algorithm to evaluate facade daylight performance, enabling designers to make informed decisions during the early design phase (C. H. Lin and Tsay, 2021). In another design-stage optimization study, Himmetoğlu et al. (2022) used EnergyPlus and DesignBuilder simulations alongside ANN and genetic algorithms to reduce energy consumption, CO_2 emissions, and life cycle costs in hospital buildings (Himmetoğlu, Delice, Kızılkaya Aydoğan, and Uzal, 2022).

Addressing both the design and construction stages, Bui et al. (2020) identified insulation thickness and window-to-wall ratio (WWR) as key variables affecting heating and cooling loads using the EFA-ANN model for residential buildings (Bui, Nguyen, Ngo, and Nguyen-Xuan, 2020). Liu et al. (2021) concluded that parameters such as window and wall U-values and WWR significantly influence energy consumption using BP-ANN, RF, DT, and SVM algorithms in DesignBuilder and Revit simulations (Y. Liu, Chen, Zhang, and Feng, 2021).

Paudel et al. (2017) utilized TRNSYS simulations and an SVM algorithm to predict heating loads in Low Energy Buildings (LEB) for the operation stage. The study highlighted that using relevant data significantly improves prediction accuracy (Paudel et al., 2017). Bhamare et al. (2021) employed ANN, XGBR, RFR, ETR, Gradient Boost Regression (GBR), and CatBoost algorithms to evaluate building thermal performance, identifying ANN as the most effective (Bhamare et al., 2021). Kabilan et al. (2021) optimized photovoltaic (PV) power generation using ANN and Bayesian optimization, achieving improved prediction accuracy through linear regression adjustments (Kabilan et al., 2021).

In studies spanning design, construction, and operation stages, Naji et al. (2016) employed genetic programming, ANFIS, ANN, and SVM algorithms to calculate residential building energy consumption. Insulation material parameters, particularly U and K values, were critical factors in energy performance predictions, with ANFIS showing the highest accuracy (Naji et al., 2016).

For retrofitting, Ilbeigi et al. (2020) optimized energy consumption and costs in office buildings using ANN-BP and MLP algorithms with genetic and Levenberg-Marquardt optimization techniques. The study achieved a 35 % reduction in energy consumption by prioritizing user ratio and U-values (Ilbeigi, Ghomeishi, and Dehghanbanadaki, 2020). Si et al. (2019) combined ANN with optimization algorithms like MOSA and NSGA-II to improve energy efficiency and comfort in a tourist center (Si et al., 2019). Von Platten et al. (2020) analyzed facade changes in 514 Swedish residential buildings using SVM and logistic regression to identify retrofitting opportunities and enhance building databases (von Platten et al., 2020).

Recent literature reviews have explored ML applications in energy efficiency. (Shan and Junghans, 2023) examined multi-objective optimization (MOO) for facade design, while Mousavi et al. investigated ML tools for NZEB and PEB. (Hong et al., 2020) reviewed ML applications across building life cycle stages, and (Chalal, Benachir, White, and Shrahily, 2016) focused on ML strategies for retrofit planning. Despite this wealth of research, no study has comprehensively linked life cycle stages, objective functions, ML algorithms, and control variables.

This study addresses this gap by analyzing the following research questions:

(RQ1): Which life cycle stages do the analyzed papers address within the scope of ML?

(RQ2): What objective functions and control variables are predominantly used in these life cycle stages?

(RQ3): What is the relationship between objective functions, simulation, ML algorithms, and optimization algorithms in each life cycle process within the context of energy efficiency?

The methodology section outlines the systematic analysis process, while the results and discussion sections present insights into life cycle stages, objective functions, and ML applications. The conclusion synthesizes findings and identifies future research directions for ML in building energy efficiency.

2. Research method

The synthesis analysis method was employed to examine publications that utilized ML and optimization tools across life cycle stages from design to retrofitting in the context of energy efficiency in building envelopes. The literature review was conducted using the WOS search engine, a widely recognized platform for academic publications. The final search was performed on April 14, 2024.

Literature Screening Process:

1. In the initial stage, 868 articles and conference papers were identified using relevant keywords entered into the WOS database.
2. Publications spanning the period from 2010 to 2023 were selected.

3. Results were filtered according to WOS categories, including "Energy Fuels," "Construction Building Technology," "Computer Science Artificial Intelligence," "Green Sustainable Technology," "Automation Control System," and "Architecture." This refinement reduced the total to 323 papers (Table 2).

Keyword Relationship Analysis:

VOSviewer 1.6.19 software was used to analyze keyword relationships within the 323 papers. Co-occurrence networks were created to visualize the frequency and connection of keywords. Larger circles in the visualization represent more frequently used keywords, and thicker lines denote stronger co-occurrence relationships (Fig. 1).

Screening Criteria:

In the fourth stage, the titles, abstracts, and results of the 323 papers were reviewed in detail, and the following exclusion criteria were applied:

1. Papers that did not utilize ML or optimization algorithms.
2. Papers unrelated to the building envelope.
3. Papers lacking sufficient information or findings relevant to the study's objectives.

As a result, 84 papers meeting the criteria were identified. Of these, 82 papers (including 80 articles and two conference proceedings) were comprehensively reviewed, and two review articles were analyzed separately.

Analysis and classification:

The objective functions of the selected papers were categorized into four groups:

1. Energy
2. Environmental
3. Comfort
4. Cost

Control variables were classified based on the following:

1. Building design
2. Climatic conditions
3. User factors (Occupancy)
4. Technical systems

The relationships between these factors were analyzed. Each paper's software, simulations, ML algorithms, and optimization algorithms were systematically evaluated. In the conclusion section, a Sankey diagram visually represents the interconnections among these elements, linking objective functions, methodologies, and outcomes.

A comprehensive literature search was conducted using relevant keywords to identify publications. Initial results were collected based on predefined criteria and subjected to preliminary filtering. The publications were screened for their temporal relevance and alignment with the research subject. The dataset was refined to a manageable subset for a more detailed analysis. The articles were thematically categorized into subject categories and focus areas. Relationships between the main themes were identified, and detailed screening was conducted. Inclusion and exclusion criteria were applied to ensure the dataset's quality and relevance. Data analysis involved examining the selected publications for patterns, trends, and interconnections. The objectives, variables, and methodologies were characterized, visualized, and integrated. Models and diagrams were developed to represent the findings, emphasizing the relationships between methods, objectives, and results (Fig. 2).

3. Results

This study analyzed the literature by categorizing the studies based on life cycle processes in the context of building energy efficiency. According to ISO 14040, life cycle processes are classified into four categories: design, construction, operation, and retrofit. While ML algorithms were employed for design and energy-oriented optimizations in the design phase, the operation phase primarily focused on energy-related studies. The selected literature was analyzed based on six categories: objective function and control variable, program, simulation, ML algorithm, and optimization algorithm. These five criteria have been utilized in various combinations in the literature to address different scenarios. Each criterion is examined in detail in this section.

The 82 selected articles examined various building typologies, including educational, commercial, hospital, tourism, sports centers, and 26 residential and 24 office buildings. Two studies were conducted at the urban scale within the ML and building energy analysis scope. Additionally, three studies utilized different building typologies to compare simulation and algorithmic data (Table 3). Residential and office buildings constitute approximately 60 % of all building typologies analyzed in the reviewed publications.

According to ISO 14040, life cycle stages are classified into four categories: product (A1-A3), construction (A4-A5), use (B1-B7), and end-of-life (C1-C4). In the reviewed articles, no studies were found

Table 1
Classification of the most widely used machine learning algorithms (Khan, Kim, Shin, Kim, and Youn, 2019; Sarker, 2021).

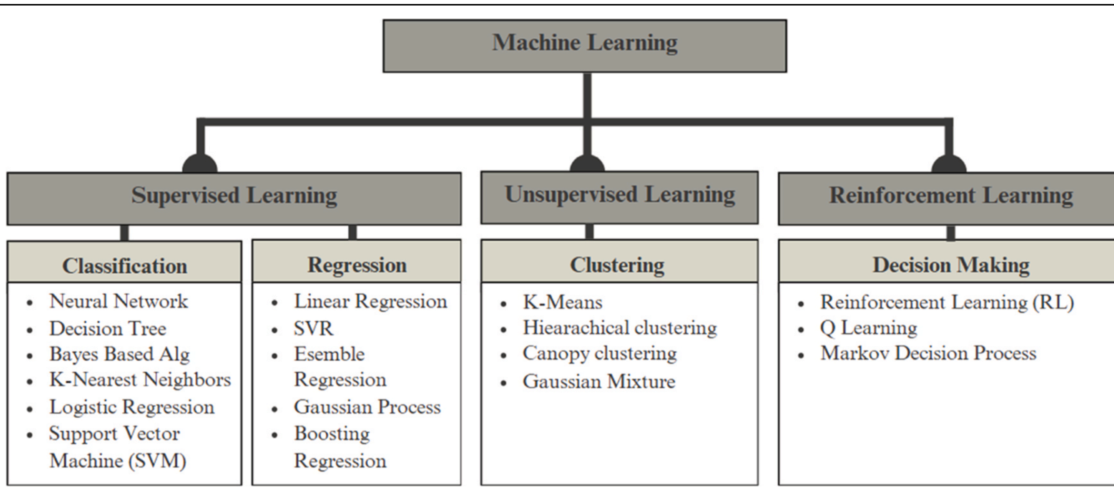

Table 2
Keywords used in the literature review.

Database	Keywords					Result
	All Fields	AND	Scope	AND	Topic	
WOS	"Machine learning" OR "Artificial intelligence" OR "ANN" OR "Artificial neural networks"		"Envelope" OR "Façade"		"Energy" OR "Consumption" OR "Generation" OR "Optimization"	868
The total year 2010–2023 Screening						715
Relevant WOS Categories Abstract Screening						323
Total Full-Text Screening						84

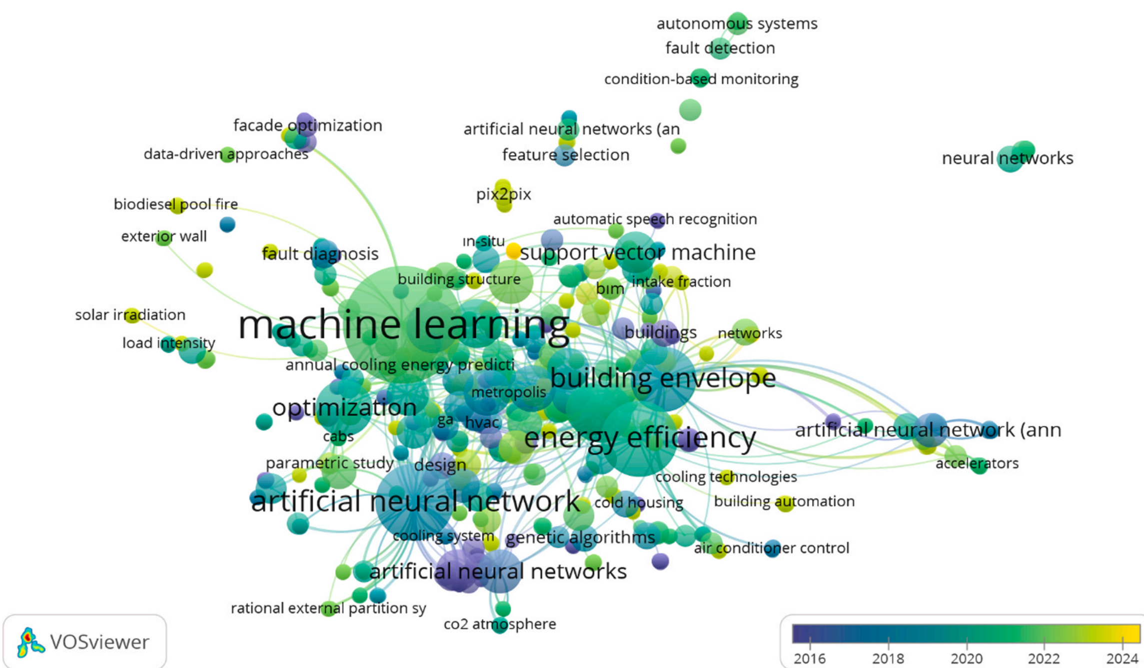

Fig. 1. Yearly density analysis of keywords in the papers whose abstracts were analyzed.

addressing the product and end-of-life stages. This study considers the life cycle stages in four main phases: the design phase (between product and construction), the construction phase, the operation phase (within the use stage), and the retrofitting phase. Since 2019, studies have been increasing, covering all stages, particularly operation and design (Fig. 3a). In this context, as stated in *Research Question 1 (RQ1)*, the distribution of studies focusing on different life cycle phases within the scope of ML is presented in the graph below.

In 82 studies analyzing the use of ML for energy efficiency in buildings within the scope of life cycle processes, the operation phase was the most dominant, addressed in 42 articles, followed by the design phase in 36 articles, the retrofitting phase in 25 articles, and the construction phase in 8 articles. Notably, no study focused solely on the construction phase within the context of land consolidation. However, the construction phase was considered in a total of eight studies, in combination with the design and operation phases (Fig. 3b).

3.1. *Objective Function and Control Variable*

As a result of the literature review, objective functions in studies on energy efficiency have been classified into four main categories. This study identified energy (saving, consumption, and generation), cost, carbon, and comfort (daylight, thermal, and others) as the primary objective functions of energy efficiency. Fig. 4a presents the sub-categories of these main objective functions. For the building to be energy-efficient, it should minimize energy consumption and maximize both renewable energy generation and energy saving within the context of the energy parameter (Buratti, Lascaro, Palladino, and Vergoni, 2014). In terms of comfort, ensuring energy efficiency in the building envelope involves considering thermal comfort conditions (Hosamo, Tingstveit, Nielsen, Svennevig, and Svidt, 2022), daylight comfort (Y. Lin et al., 2021), and other comfort parameters (e.g., acoustics, air quality). These are important factors for reducing energy consumption and ensuring efficiency (Batres, Dadras, Mostafazadeh, and Kavgic, 2023; Bi, Liu, Gao, and Zhao, 2023; Chegari et al., 2021; Soheil Fathi and Srinivasan, 2019; Hussien et al., 2023; Li and Yao, 2020; Melo, Cóstola, Lamberts, and Hensen, 2014; Seo, Yoon, Mun, and Cho, 2019; Tsay, Yeh, Chen, Lu, and Lin, 2021). Many studies in the literature simultaneously target multiple objective functions. In this context, across all studies on life cycle processes, energy consumption (54 %) within the energy category (81 %), thermal comfort (41 %) within the comfort category (56 %), cost (18 %), and carbon (12 %) account for the majority.

RQ2: What objective functions and control variables are predominantly used in these life cycle stages?', when examining the study, it was found that in studies on the design phase, energy consumption (70 %) within the energy category (80 %) and daylight comfort (50 %) within the comfort category (70 %) were the primary focus. In the construction phase, studies predominantly addressed the energy category (87 %) and thermal comfort (50 %), while no studies on daylight comfort or carbon were identified. In the operation phase, the energy category (60 %) and energy savings (24 %) were examined, along with thermal comfort (56 %) within the comfort category (60 %); however, no studies on

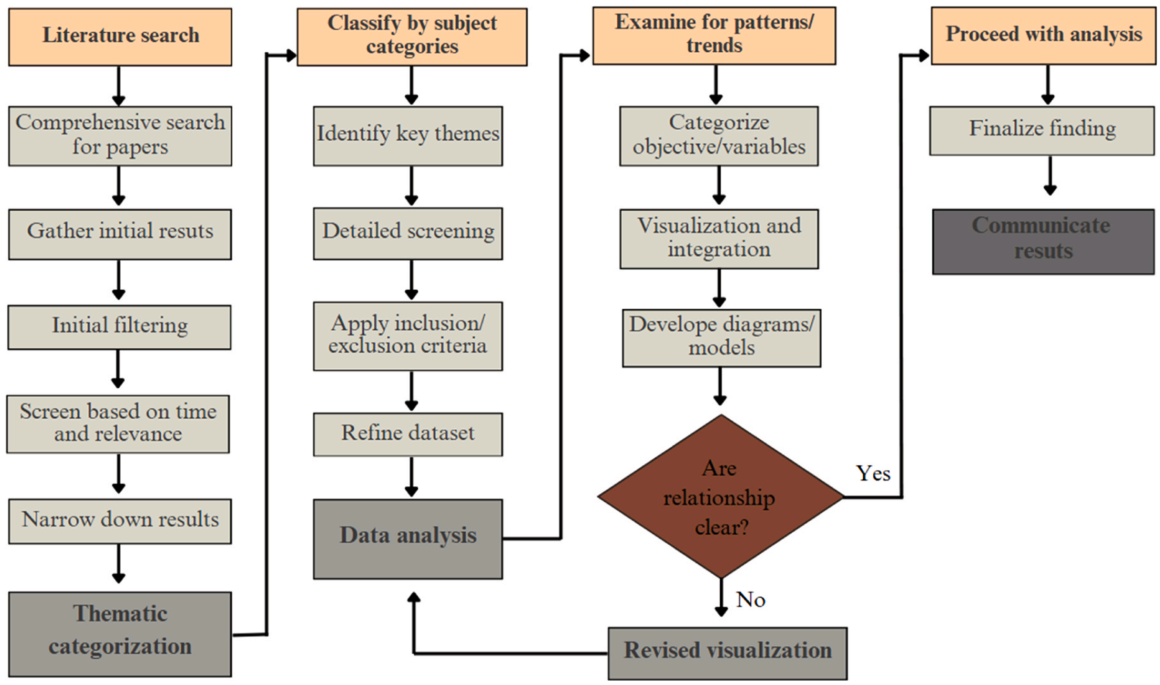

Fig. 2. Methodology flowchart.

Table 3
Distribution of building typologies in the analyzed publications.

Building Type	Number in the Literature		Building Type	Number in the Literature	
	Count	Perc.		Count	Perc.
Residential	26	31 %	Urban scale	2	2 %
Office	24	29 %	Tourism	1	1 %
Education	9	11 %	Sport center	1	1 %
Commercial	4	5 %	Different typology	3	5 %
Hospital	2	2 %	Unexplained	10	13 %

daylight comfort were found. In the renovation phase, studies on energy savings (70 %) and carbon (48 %) were conducted within the energy category (100 %), while no studies on thermal comfort were identified (Table 4).

In ML studies on building energy efficiency, the careful selection and structuring of control variables are crucial for achieving accurate objective functions. This study identified and categorized four primary control variables based on a review of the literature: building design, climate, technical systems, and user behavior (Fig. 4b). Each control variable was assessed across all studies and analyzed about its application during the design, construction, operation, and retrofit phases of the building life cycle (Table 5). The findings indicate that building design was the most frequently utilized parameter, appearing in 85 % of all studies. Additionally, climate conditions were used as a control variable in 58 % of the studies. Building design was incorporated in 100 % of the studies focusing on the design, construction, and retrofit phases, while climate conditions (80 %) emerged as the dominant parameter in studies addressing the operation phase.

3.2. ML Algorithm

ML encompasses a range of techniques capable of identifying patterns in data to predict future outcomes and execute various decision-making mechanisms under uncertainty. In the literature, 48 distinct ML algorithms have been applied within the life cycle processes context of building energy efficiency. These algorithms are classified into 13 subgroups based on their application areas within the broader ML categories of Supervised Learning, Unsupervised Learning, and Reinforcement Learning. The subgroups include Neural Networks (NN), SVM, DT, Bayes-based methods, KNN, Logistic Regression, Linear Regression, SVR, Ensemble Regression, Gaussian Processes, Boosting Regression, Unsupervised Learning, and Reinforcement Learning (Fig. 5a). Among all studies, supervised learning techniques trained with labeled data were the most frequently used, with NN (67 %) being the dominant approach, followed by DT (19 %), Linear Regression (16 %), and SVM (14 %). In contrast, Unsupervised Learning and Reinforcement

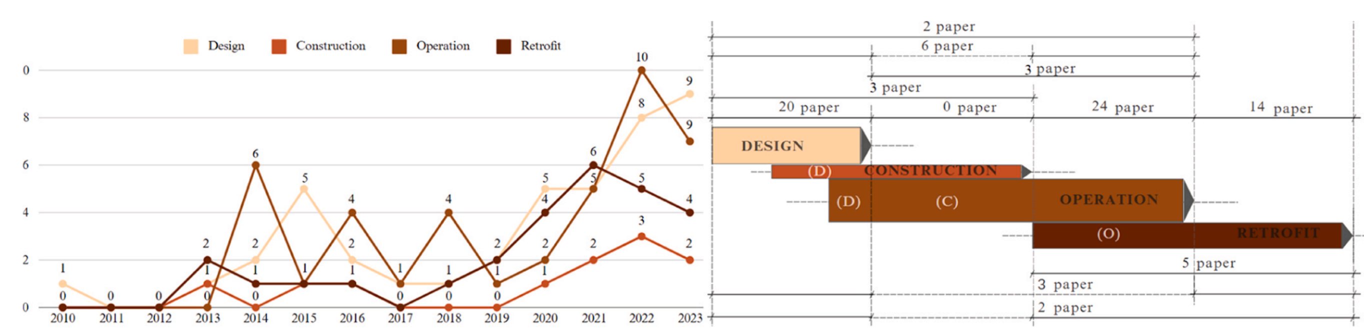

Fig. 3. Distribution of the analyzed publications on the LC stages by years, relationships of the analyzed publications in the context of LC stages.

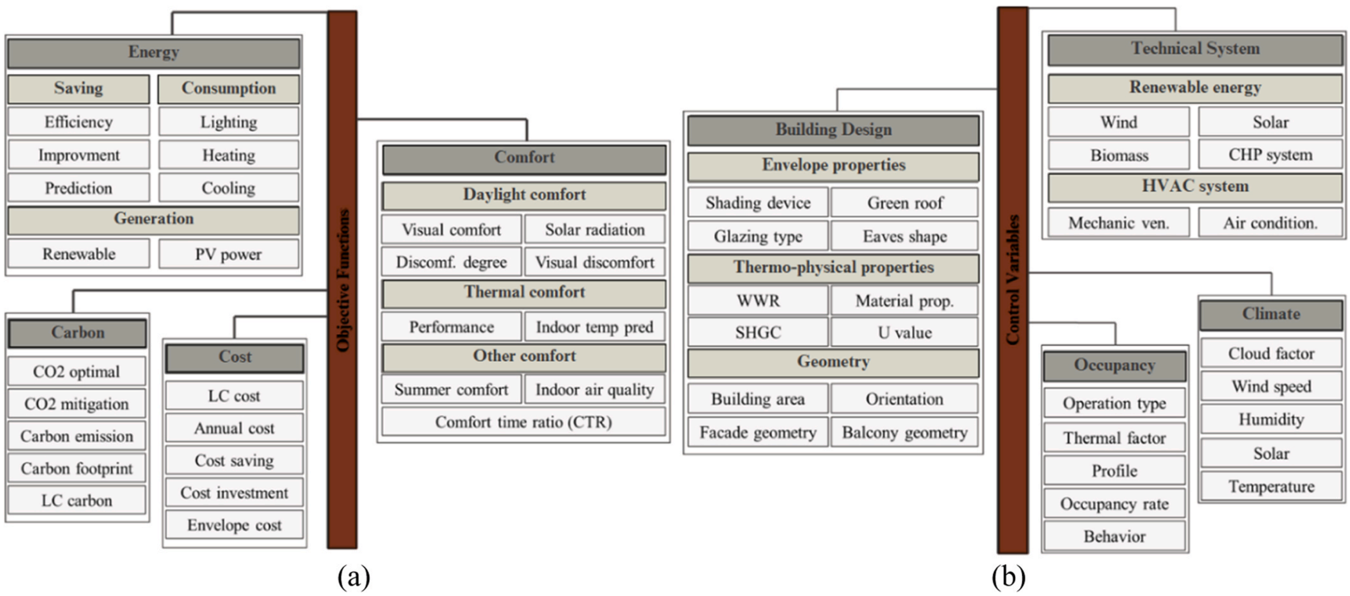

Fig. 4. Classification of (a) objective functions and (b) control variables analyzed in publications in the context of energy efficiency.

Table 4
Distribution of the analyzed studies according to their objective functions.

Objective Function	All study		Design		Construction		Operation		Retrofit	
	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.
Energy	67	81 %	16	80 %	7	87 %	15	60 %	14	100 %
Saving	20	24 %	5	25 %	2	25 %	6	24 %	10	70 %
Consumption	45	54 %	14	70 %	5	62 %	5	20 %	2	14 %
Generation	12	14 %	2	10 %	2	25 %	4	15 %	3	21 %
Carbon	10	12 %	2	10 %	0	0 %	2	8 %	6	42 %
Cost	15	18 %	3	15 %	1	12 %	2	8 %	4	28 %
Comfort	46	56 %	14	70 %	4	50 %	15	60 %	3	21 %
Daylight	13	15 %	10	50 %	0	0 %	0	0 %	3	21 %
Thermal	34	41 %	5	25 %	4	50 %	14	56 %	0	0 %
Other	2	2 %	1	5 %	0	0 %	1	4 %	0	0 %

Table 5
Distribution of the analyzed studies according to control variables.

Control Variable	All study		Design		Construction		Operation		Retrofit	
	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.
Building design	71	85 %	20	100 %	8	100 %	16	64 %	14	100 %
Climate condition	49	58 %	12	60 %	4	50 %	20	80 %	6	42 %
Technical system	9	10 %	0	0 %	0	0 %	4	16 %	3	21 %
Occupancy	10	12 %	2	10 %	0	0 %	4	16 %	1	7 %

Learning, which are typically applied in dynamic optimization problems, were used in only 2 % of the studies (Fig. 5b).

In the design process of ML algorithm applications for building energy efficiency, NN ranked first with 65 %, followed by Linear Regression, SVM, and DT. Unsupervised Learning algorithms were employed exclusively in the design phase across all processes. In the construction phase, NN (75 %) was the most frequently used algorithm, followed by SVM (25 %), DT (25 %), and Linear Regression (25 %). During the operation process, NN remained dominant (68 %), followed by DT (16 %) and Linear Regression (12 %). In the retrofit process, NN was again the most utilized algorithm (70 %), followed by DT (21 %), SVM (14 %), and Boosting methods (14 %). No Reinforcement Learning (RL) algorithms were identified in the design, construction, or retrofit phases. Furthermore, Gaussian Processes and K-Means algorithms were applied solely in the design phase and were absent from other phases (Table 6).

3.3. *Program*

The use of programming languages plays a crucial role in ML studies. A literature review revealed five distinct programming languages employed across the studies. MATLAB emerged as the most frequently used, accounting for 34 % of the studies, followed by Python at 24 %. However, 37 % of the publications did not provide details regarding the programming language utilized. MATLAB, Python, and Delphi were used in studies focused on the design phase, while only MATLAB was used in studies addressing the construction phase. No other programming languages were found in this context. In studies related to the operation phase, both MATLAB (44 %) and Python (28 %) were utilized. Finally, in the retrofit phase, MATLAB (35 %) and Python (28 %) were the predominant programming languages, with one study employing the R language (Table 7).

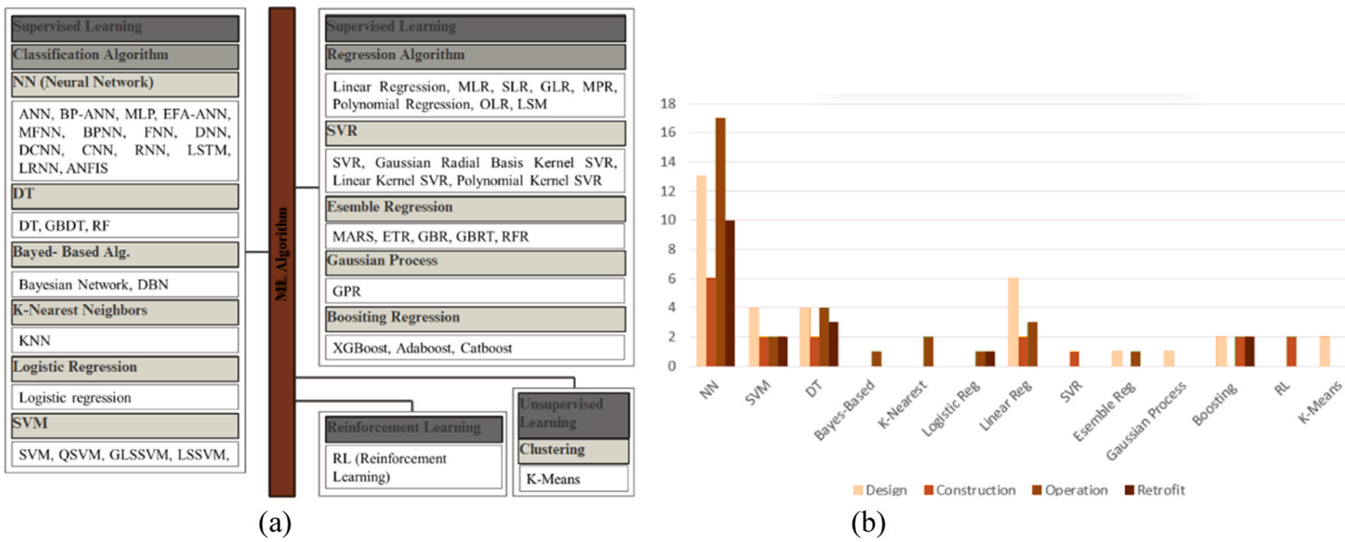

Fig. 5. (a) Classification of ML algorithms used in energy studies in buildings, (b) Number of ML algorithm classes used in LC processes.

Table 6
Distribution of ML algorithms used in the analyzed studies.

ML Algorithm	All study		Design		Construction		Operation		Retrofit	
	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.
NN	56	67 %	13	65 %	6	75 %	17	68 %	10	70 %
SVM	12	14 %	4	20 %	2	25 %	2	8 %	2	14 %
DT	16	19 %	4	20 %	2	25 %	4	16 %	3	21 %
Bayes-Based	2	2 %	0	0 %	0	0 %	1	4 %	0	0 %
K-Nearest	3	3 %	0	0 %	0	0 %	2	8 %	0	0 %
Logistic Reg	2	2 %	0	0 %	0	0 %	1	4 %	1	7 %
Linear Reg	14	16 %	6	30 %	2	25 %	3	12 %	0	0 %
SVR	3	3 %	0	0 %	1	12 %	0	0 %	0	0 %
Ensemble Reg	2	2 %	1	5 %	0	0 %	1	4 %	0	0 %
Gaussian Pro	2	2 %	1	5 %	0	0 %	0	0 %	0	0 %
Boosting	7	8 %	2	10 %	0	0 %	2	8 %	2	14 %
RL	2	2 %	0	0 %	0	0 %	2	8 %	0	0 %
K-Means	2	2 %	2	10 %	0	0 %	0	0 %	0	0 %

Table 7
Distribution according to the programs used in the studies examined.

Program	All study		Design		Construction		Operation		Retrofit	
	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.
Matlab	29	34 %	4	20 %	5	62 %	11	44 %	5	35 %
Python	20	24 %	5	25 %	0	0 %	7	28 %	4	28 %
Delphi	2	2 %	2	10 %	0	0 %	0	0 %	0	0 %
R	2	2 %	1	5 %	0	0 %	0	0 %	1	7 %
Fortran	1	1 %	1	5 %	0	0 %	0	0 %	0	0 %

3.4. Simulation Tools

A total of 33 different simulation tools were utilized in the literature reviewed to apply ML in the context of energy efficiency in buildings. These simulation tools are categorized into nine groups based on their functionalities within the scope of this study. The categories include GIS and spatial analysis, solar energy and lighting, optimization, city-level tools, ML tools, building modeling, building energy simulation, visualization and modeling, and LCA tools (Fig. 6). Among all the publications, building energy simulation tools were the most frequently used for analyzing building energy consumption and thermal performance. Building energy simulation and modeling tools were most commonly employed in the design and construction phases, depending on the process and objectives. In the operation phase, 'building energy simulation' was predominantly used. Building energy simulation, GIS and spatial analysis (for spatial data analysis), and optimization tools (for optimizing design processes) were most frequently utilized in the retrofit phase.

3.5. Optimization Algorithm

In ML studies, optimization algorithms are essential for achieving optimal results. In this context, 42 different optimization algorithms were utilized in the studies reviewed. These algorithms are categorized into seven distinct groups based on their fundamental working principles, application areas, and usage contexts: Evolutionary Optimization, Swarm Intelligence Optimization, Deterministic Optimization, Multi-Objective Optimization, Rule-Based and Agent-Based Models, Simulation-Based Optimization, and Other Optimization Algorithms (Fig. 7). Evolutionary Optimization, capable of solving complex and

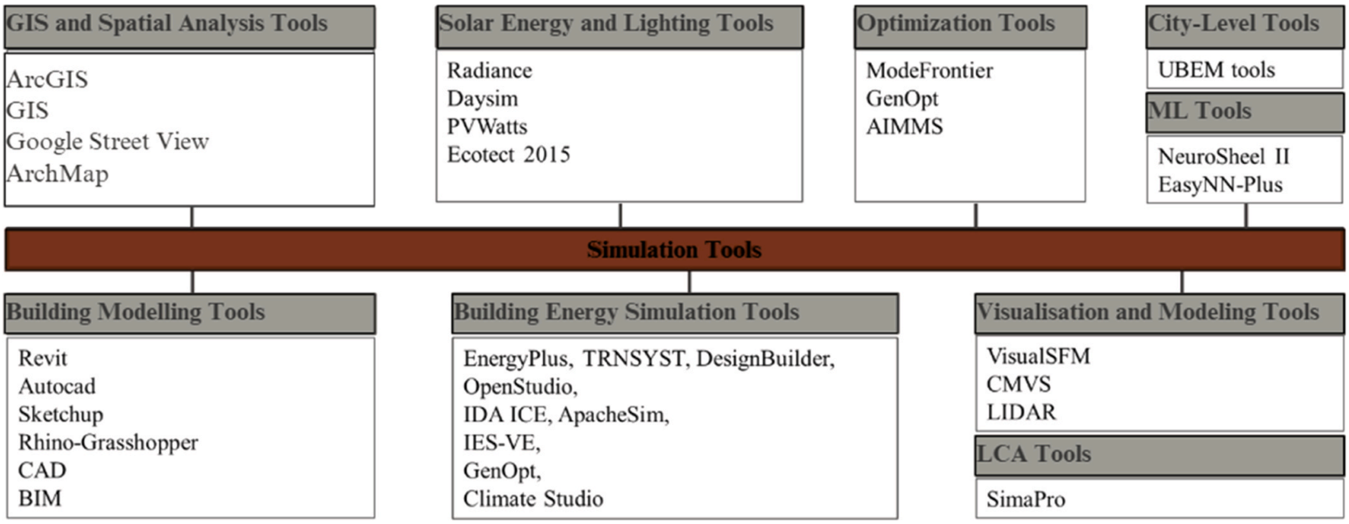

Fig. 6. Categorization of simulation tools used in the studies.

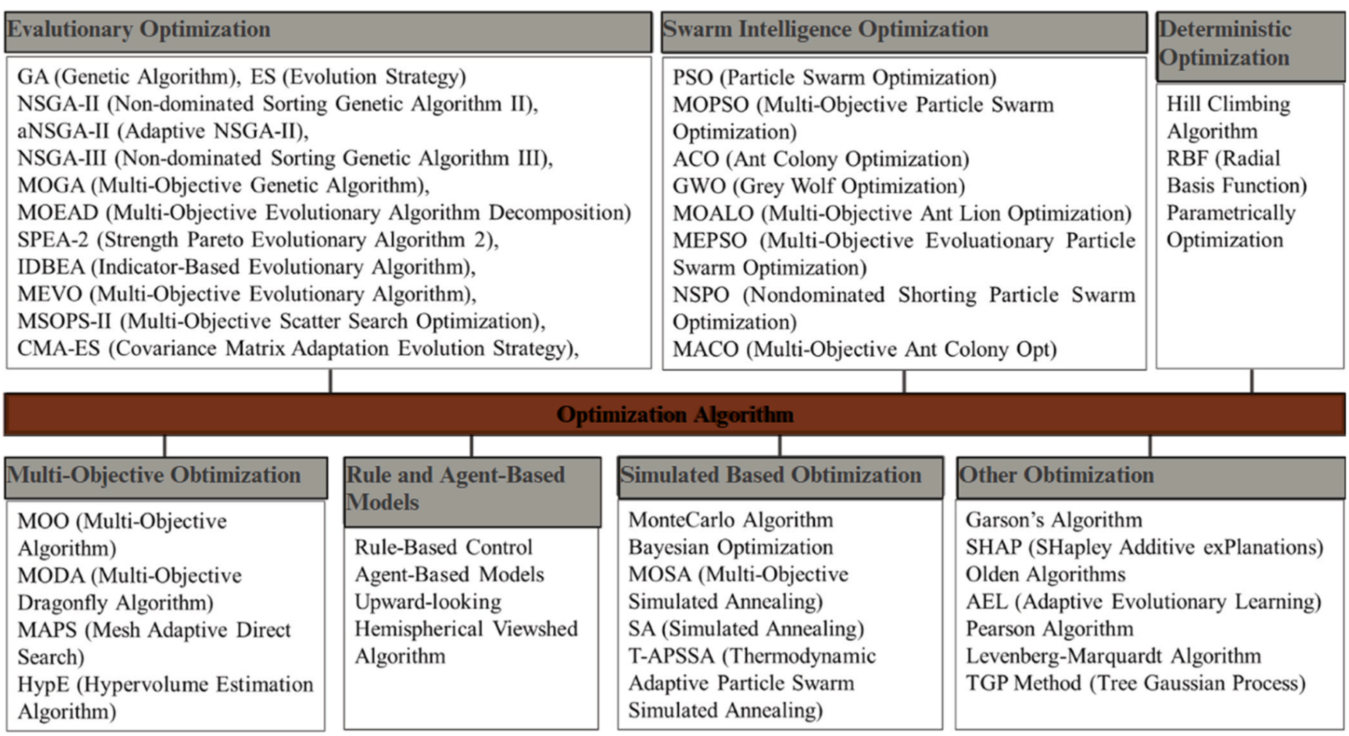

Fig. 7. Categorization of optimization algorithms in studies.

multi-objective optimization problems, and Multi-Objective Optimization, which can generate optimal solutions for multiple objectives in energy system optimization, were frequently employed in the studies.

Evolutionary optimization algorithms were predominantly used in the studies focusing on the design process, followed by multi-objective optimization algorithms. In the construction process, deterministic and other optimization categories, which can perform mathematical modeling, were most commonly explored. In the operation process, the Levenberg-Marquardt algorithm, categorized under ’other’ optimization, was the most extensively applied to enhance ML processes. Evolutionary optimization and multi-objective optimization algorithms were utilized in the retrofit process.

4. Discussion

This review study aims to analyze the methodology of machine learning-supported studies in the literature for building energy efficiency within the scope of building LSC. In this context, 84 publications were analyzed according to the screening criteria out of 323. The machine learning method was used for energy efficiency in the last fourteen years through the specified database. These analyses are addressed through three-stage research questions, and RQ1 and RQ2, the life cycle processes of the publications and the usage cases of the five categories determined (objective function, software, simulation, ML algorithm, optimization algorithm) are examined in the findings section. RQ3 "What is the relationship between objective functions, simulation, machine learning algorithms, and optimization algorithms in each life cycle process in the context of energy efficiency?" is discussed in this section based on the findings.

As a result of the findings, it was determined that a total of 48 ML algorithms were used in the studies involving LCS, with eight different objective functions, four of which were four, and ML algorithms were handled in 13 basic groups according to their functions. In addition, four different programs, 33 different simulation tools divided into nine basic groups according to their functions, and 42 different optimization algorithms divided into seven basic groups were found to be used. When all the processes are examined, studies have been carried out for maximum energy consumption in the literature in general, and prediction has been carried out with the ANN algorithm in the Python program-supported NN. EnergyPlus simulation was used to build energy simulations for energy calculations. Evolutionary and multi-objective optimization algorithms were used together for optimization.

In this context, RQ3, 'What is the relationship between objective functions, simulation, machine learning algorithms, and optimization algorithms in each life cycle process in energy efficiency?' was addressed. Most studies were conducted on energy consumption and daylighting comfort in the 20 publications that focused solely on the design process. Python and MATLAB were commonly used for these topics. Regarding the targeted areas, building energy simulation tools such as EnergyPlus and DesignBuilder, and building modeling tools like Rhino-Grasshopper were widely utilized. In this context, commonly used ML algorithms, including ANN, Linear Regression, SVM, and DT, along with optimization techniques such as genetic algorithm, NSGA-II, and other multi-objective optimization algorithms in evolutionary optimization, achieved high accuracy results (Fig. 8). In the design process, a study was conducted to achieve thermal comfort by optimizing the building envelope and geometry. The building's comfort and thermal load were estimated using the ANN algorithm. Subsequently, the data generated by ANN was utilized to determine the optimal design solutions through optimization algorithms such as NSGA-II and MOALO, ensuring the building's energy efficiency (Y. Lin et al., 2021). The K-Means algorithm, used in Unsupervised Learning, was applied only to the design process. In this context, another study, including the design process, aimed to provide energy efficiency in the campus by using K-Means clustering and LTSM time data algorithms together on the effect of future climate changes on building energy consumption through improvements in the building envelope (Soheil Fathi and Srinivasan, 2019).

Eight publications covering the construction process extensively studied energy consumption and thermal comfort. Only MATLAB was used for these purposes, and energy and thermal comfort calculations were performed through EnergyPlus simulations. The simulation data were predicted using NN and ML algorithms. High accuracy results were achieved using Pearson, Levenberg-Marquardt, and Radial Basis optimization algorithms, which fall under the other and deterministic categories and work well with ML algorithms (Fig. 9). In a study covering the design, construction, and operation phases, SVR, ANFIS, and ANN algorithms were compared for energy consumption calculation, with ANFIS achieving the highest accuracy. It was determined that parameters related to insulation materials play a crucial role in estimating energy consumption (Naji et al., 2016).

In 24 publications focusing solely on the operation process, topics related to consumption, saving, and generation under the broader thermal comfort and energy category were frequently covered. EnergyPlus, which is used for building energy simulation, and TRNSYS, which can yield reliable results in energy generation and consumption calculations, were the primary simulation tools. The simulation results were predicted using the ANN, ML algorithm in NN. To achieve optimal results, the Levenberg-Marquardt algorithm from the other category was predominantly used alongside the genetic algorithm optimization algorithm from the evolutionary category (Fig. 10). The ANN algorithm was used in the operation phase to estimate the performance of building-integrated photovoltaic (BIPV) systems. The algorithm was trained and tested on accurate building data, achieving high accuracy in energy production estimation (Polo, Martín-Chivelet, and Sanz-Saiz, 2022).

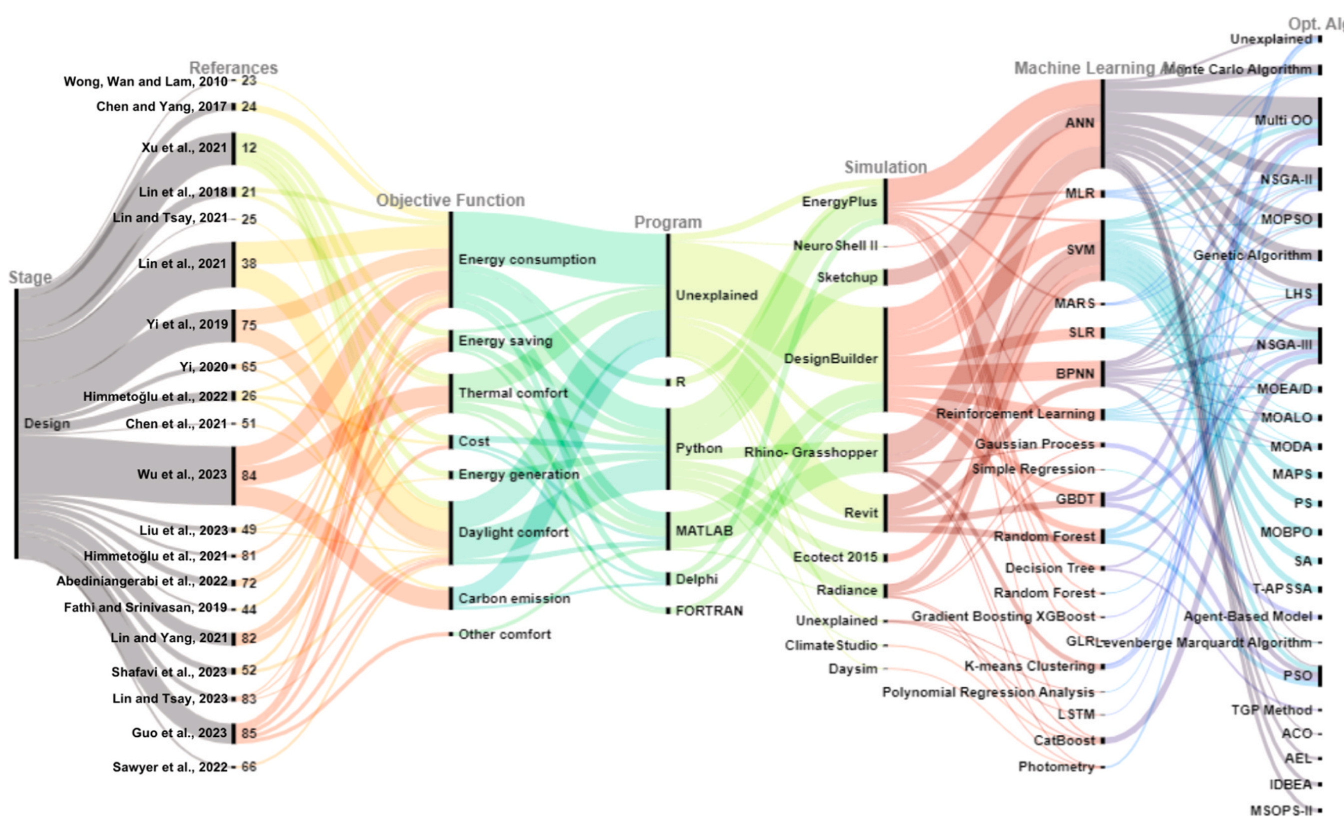

Fig. 8. Design stage Sankey diagram.

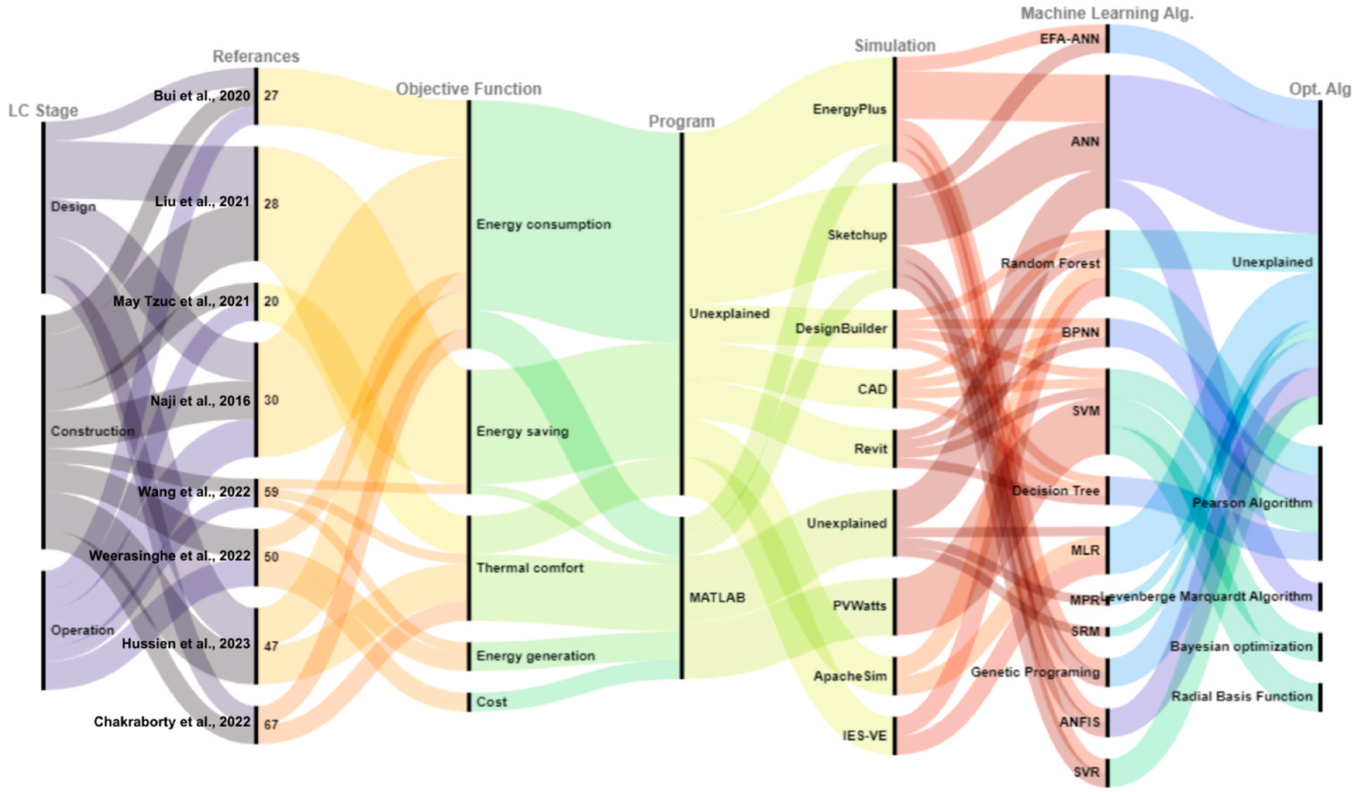

Fig. 9. Sankey diagram of the whole construction stage in the analyzed publications.

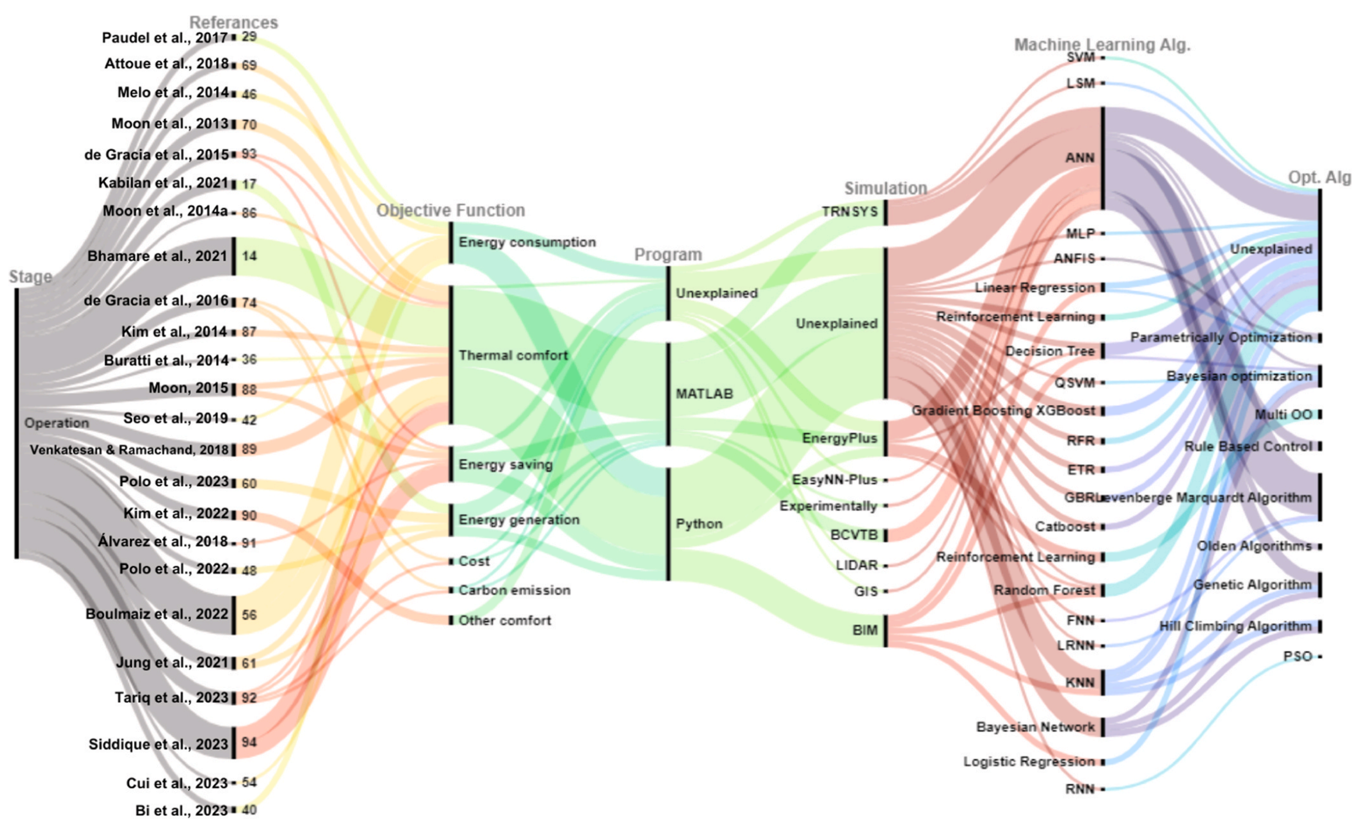

Fig. 10. Operation stage Sankey diagram.

In publications focusing solely on the retrofit process, the most frequently used simulation programs for energy saving, carbon, and cost analysis were EnergyPlus, DesignBuilder, and TRNSYS in the building energy simulation category, as well as GIS and Google Street View (GSV) in the GIS and spatial analysis category. The SimaPro program, which conducts LCA analysis, was also utilized in the retrofit process. The data from these simulation tools were predicted using ANN, DT, and Boosting ML algorithms. To achieve the best predictions, genetic algorithm, multi-objective, and swarm intelligence optimization tools within evolutionary optimization, which are compatible with ML algorithms, were frequently employed (Fig. 11). To improve building energy saving and cost during retrofit, SVM and Logistic Regression algorithms were used on GSV data to estimate and optimize building energy performance (von Platten et al., 2020).

5. Conclusion

This study observed that research on ML in the context of ensuring energy efficiency in buildings has been rapidly increasing, particularly in recent years. The primary reasons for this growth include using ML as a powerful tool for optimizing energy efficiency stages and utilizing resources more effectively. This study analyzed the use of software and simulation tools, as well as ML and optimization algorithms, which influence the objective functions in stages from design to retrofitting, within the papers examined in the context of the building life cycle, mainly focusing on the building envelope, which has a significant impact on energy consumption. The analysis results indicate that:

- In the publications examined, research was conducted intensively on residential (31 %) and office (29 %) buildings, with additional studies also carried out at the urban scale.
- Studies on the design (36 papers) and operation (42 papers) stages constitute the majority of the publications analyzed, followed by retrofitting (24 papers) and construction (8 papers) stages. This indicates the significance of the design and operation stages for future research on the subject, while also highlighting the need for increased focus on the construction stage.
- In accordance with the literature's energy-efficient and sustainable building criteria, the publications primarily addressed four main objective functions: energy, comfort, cost, and carbon emissions.
- When examining the objective functions, energy consumption dominates all stages except the operation stage, where thermal comfort is prioritized. In the design stage, daylight comfort emerges as an additional key objective function alongside energy consumption and thermal comfort, distinguishing it from other stages. At this stage, energy simulation and modeling tools were used within these objective functions. Predictions were made mainly through ANN and Linear Regression ML algorithms, and the predictions were supported by 'evolutionary optimization' algorithms.
- Studies on energy consumption, saving, and generation are prominent in the operation stage. Research on solar energy technologies (PV, BIPV), which are renewable energy systems, has increased recently, particularly within the scope of the energy generation objective function in the operation stage. This trend is expected to continue growing rapidly in the future. In this context, it was determined that energy simulations were mainly used during the operation process, and it was concluded that Levenberg-Marquardt's optimization algorithm was used in the foreground along with ANN, DT, and ML algorithms.
- In the retrofitting stage, cost, energy consumption, and thermal comfort have been considered significant objective functions in many studies. For this reason, energy simulation and GIS tools were used more frequently during the retrofit phase. As in all processes, it was determined that the ANN algorithm was predominantly used in this phase.

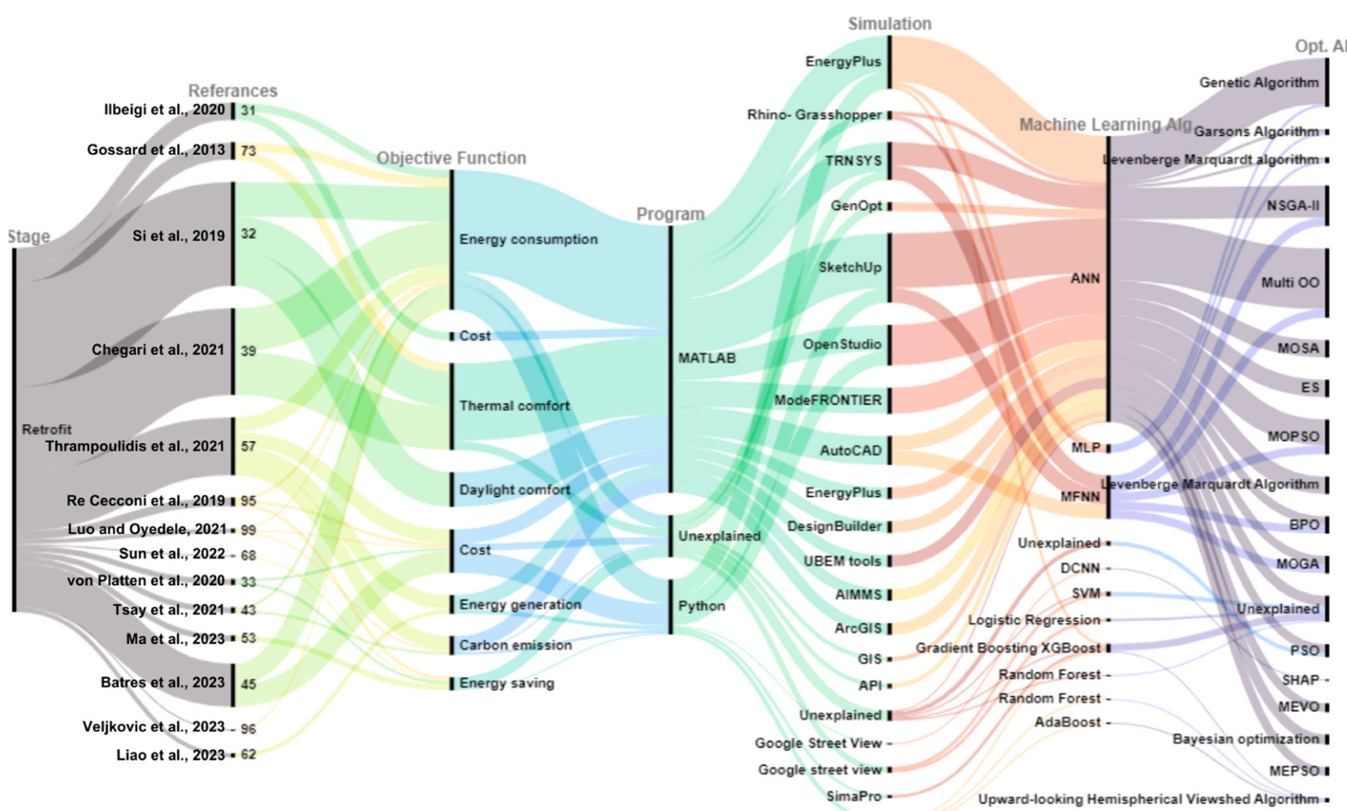

Fig. 11. Retrofit stage Sankey diagram.

- It has been determined that the simulations, ML algorithms, and optimization algorithms used vary depending on the objective functions within the identified life cycle stages. The accuracy rates of ML algorithms also vary by objective function, with the ANN, RF, and SVM algorithms generally demonstrating high accuracy across all objective functions.

Based on these findings, it has been determined that ML, a state-of-the-art technology product, is intensively used in the retrofitting stage, especially in the operation and design stage, in the studies examined within the scope of LC stages and energy in buildings. The high number of studies focused on the operation stage is attributed to the significant energy consumption of buildings during this stage. However, it has been observed that research on the construction stage is insufficient compared to other stages. For this reason, in studies where ML is used within the scope of energy efficiency in buildings, research on the construction stage should be increased in the future.

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CRediT authorship contribution statement

KAYA GEVHER NESIBE: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **CUDZIK Jan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Data curation. **BEYHAN Figen:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **İLERİSOY Zeynep Yeşim:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

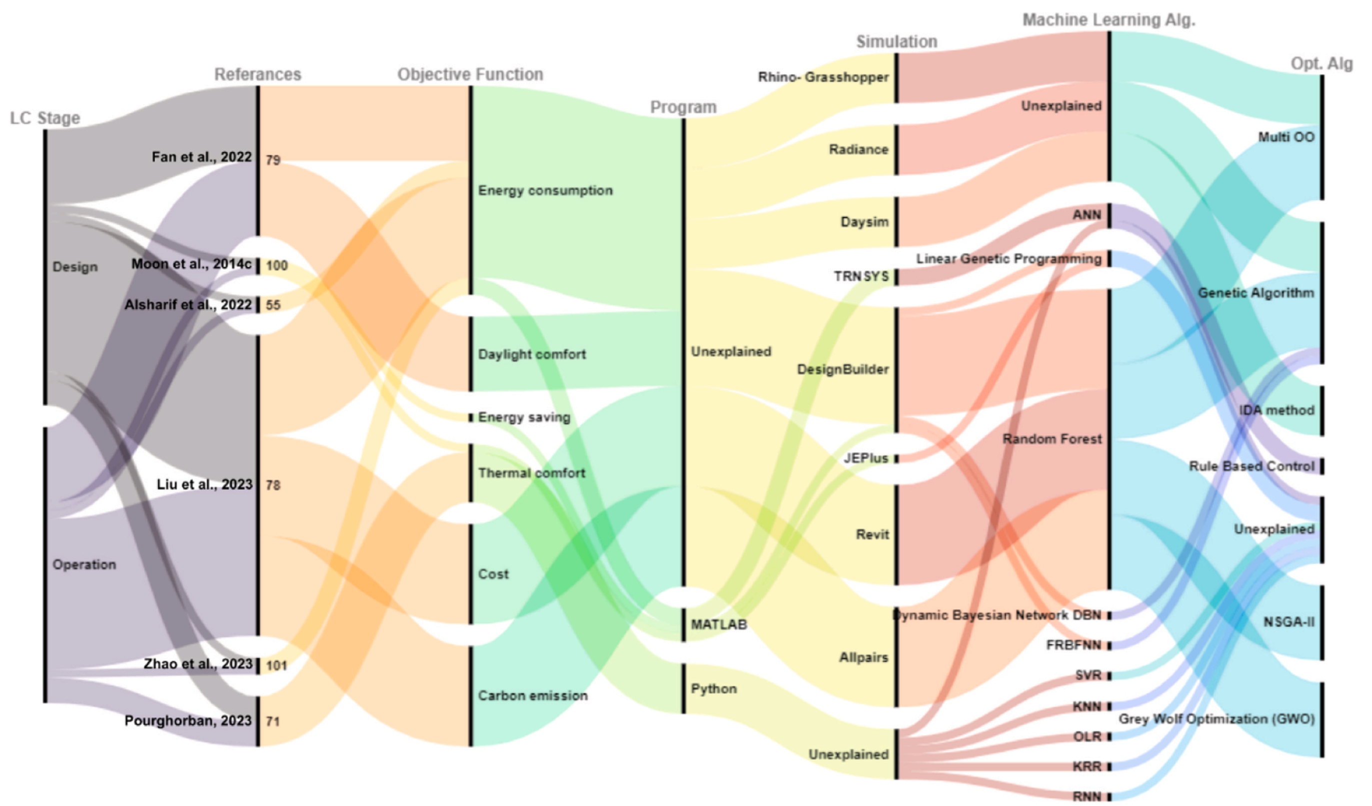

Fig. A.1. Design and operation stage Sankey diagram

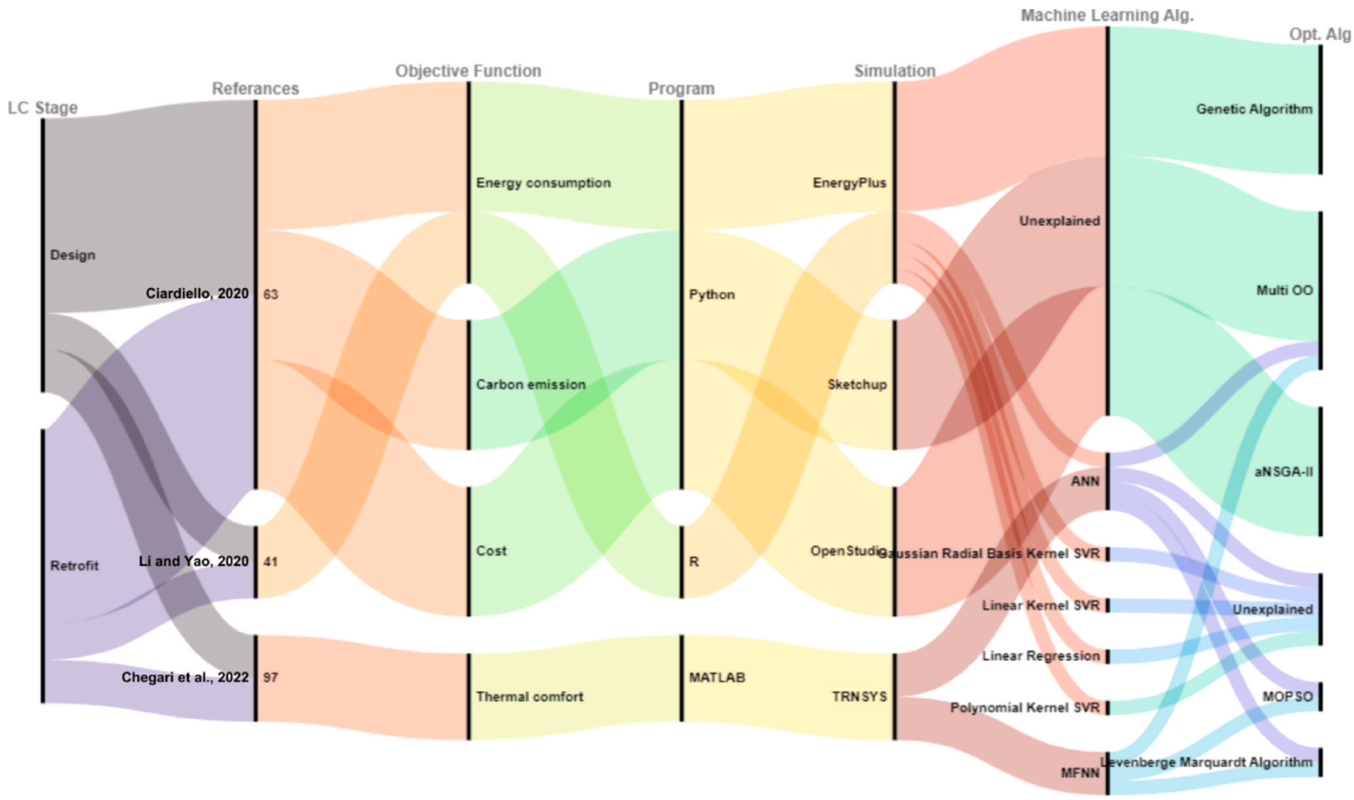

Fig. A.2. Design and retrofit stage Sankey diagram

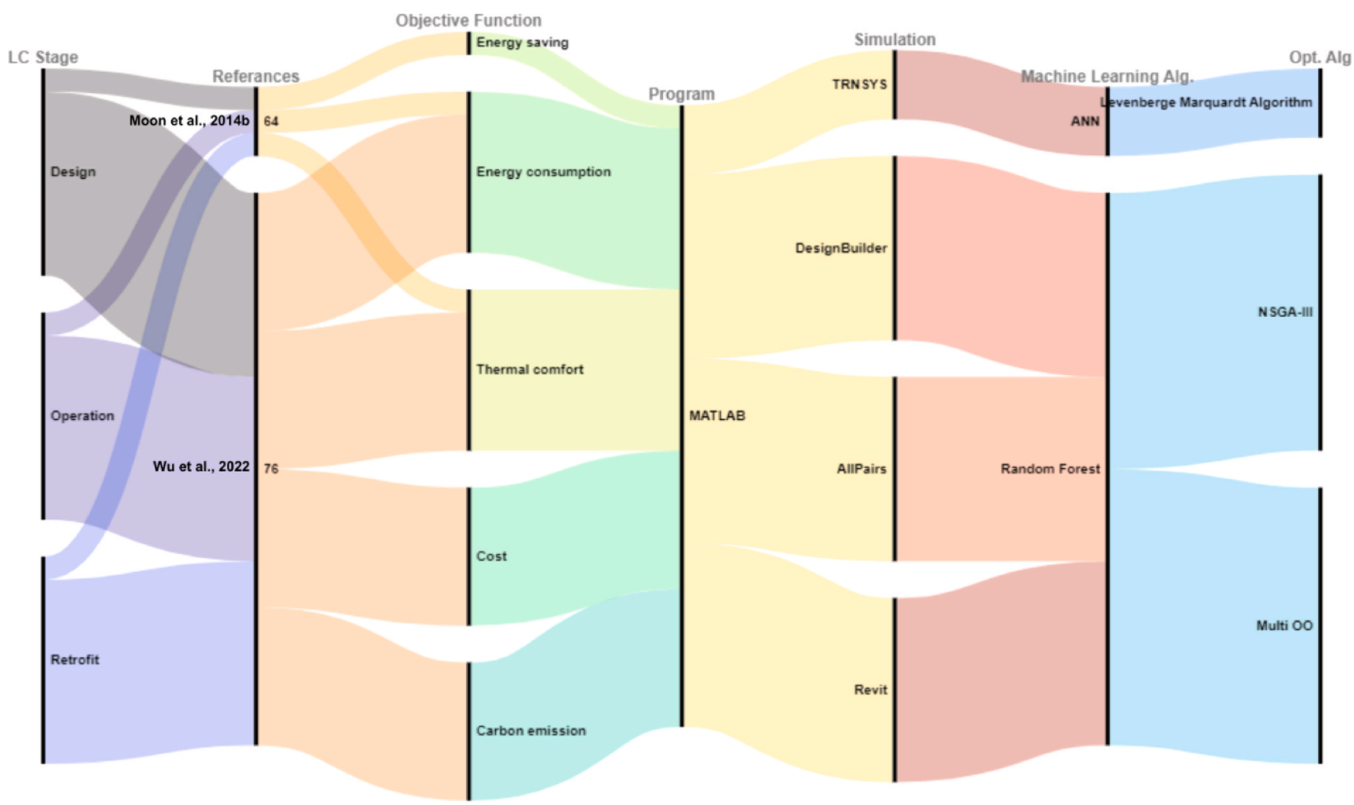

Fig. A.3. Design, operation, and retrofit stage Sankey diagram

Data availability

Data will be made available on request.

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