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Transformative role of machine learning in design optimization of reinforced concrete frames

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Abstract

Design optimization in reinforced concrete (RC) frames is crucial for achieving more efficient, cost-effective, and safe constructions. This involves determining optimal section sizes and reinforcing schemes to enhance structural performance, reduce construction expenses, and conserve natural resources. An optimized design contributes to streamlined construction procedures, shorter construction times, and improved overall sustainability. This paper critically evaluates the current literature on machine learning (ML) applications in the design optimization of RC structures, focusing on the period from 1997 to 2023. The study employs a comprehensive methodology, including bibliometric analysis, to analyze trends, research collaborations, and publication patterns. The results highlight the increasing interest in ML for RC frame optimization. Key applications of ML in design optimization include material characterization, design exploration, optimization algorithms, sensitivity analysis, predictive modeling, structural health monitoring, design code compliance, uncertainty quantification, data-driven design decisions, and design collaboration. The study identifies significant ML algorithms used in optimization, such as the trial-and-error method, linear programming (LP), and non-linear programming (NLP). Overall, the paper provides insights into the evolving landscape of ML applications in RC frame design, emphasizing the potential for interdisciplinary collaboration and future research directions.

Keywords

Machine learning, Reinforced concrete frame, Optimization, Bibliometric analysis, LinLog/Modularity.

1.Introduction

Reinforced concrete (RC) framed structures are the most commonly used structure framework worldwide. Thus, design optimization of RC frames [1] is necessary to achieve sustainability by reducing cost and carbon emissions. Optimization assists in creating the most cost-effective design [2] while maintaining structural integrity and safety. Construction expenses can be decreased and cost efficiency [3] can be improved by determining the most appropriate section sizes and reinforcing schemes. Improved structural performance is the result of optimized designs [4], which ensure that the frame can sustain the prescribed loads and retain stability throughout its service life. This can result in a more sturdy and long-lasting construction [5].

The quantity of concrete and reinforcement steel required can be lowered by using an optimized design. This conserves natural resources and contributes to a more sustainable building approach to material conservation [6]. An optimized design can frequently result in streamlined construction procedures [7] and shorter construction times. The whole construction schedule can be improved with thoughtful design decisions. An optimized structure is safer and more dependable since it takes into account different load combinations, safety considerations, and structural needs [8]. This is especially important for constructions like buildings, where occupant safety is of utmost importance. The ability of the structure to survive extreme occurrences, such as earthquakes, may be improved with an optimized design [9] or wind loads, contributing to its total resilience. During the design and construction phases, optimized designs are

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frequently more adaptive and flexible to various architectural layouts and changing needs [10]. Design optimization helps create a physical environment that is more sustainable by reducing the amount of materials and energy used during construction [11]. Regulatory compliance is ensured by an optimized design that guarantees the building complies with or exceeds applicable building rules and standards [12]. Engineers are encouraged by optimization to investigate novel and creative design techniques that might not be visible in conventional methods [13]. This may result in improvements to engineering methods and building technologies. Finally, design optimization is essential for assuring efficiency [14], safety [15], and sustainability of RC frames [16]. It integrates engineering concepts, economic concerns, and environmental considerations to produce high-performance structures that satisfy societal objectives while having the least negative environmental effect possible.

There is a huge database on design optimization of RC frames using linear and metaheuristic methods yet effective optimum results are still far from being implemented in practical designs. During the detailed design stage, individual RC frame members such as beams, columns, footings, slabs, and shear walls, as well as full RC frame structures, are optimized for various objective functions. Recently, there has been attention drawn to the cost parameter alongside efforts to optimize material usage and environmental performance in RC structures [17–19]. The primary focus of the optimization has always been the minimization of the overall cost of the RC frame structure [20, 21]. The popularity and need for design optimization of RC frame structures have led to many review articles. Discussed the evolution of design variables and objective functions in the design optimization of RC frame structure over the years [22]. Evaluated and contrasted different design formulations for structural optimization frameworks, enhancing seismic design efficiencies [23]. The comprehensive study on various metaheuristic algorithms and emerging artificial intelligence techniques in civil engineering was discussed by [24, 25] respectively. Furthermore, [26, 27] provided the details of the design optimization works in embodied carbon and overall RC structure respectively. Several techniques have been employed to achieve the optimal solutions for various objective functions. Iterative processes are usually used in traditional design optimization approaches for RC frames, where the design variables are modified to satisfy specified objectives and restrictions [28]. These techniques have been utilized often for many years and are still not commonly employed in engineering practice [29]. Each of these conventional optimization techniques has advantages and disadvantages. The problem's complexity, the kind of design variables and constraints, and the available computer resources all influence the solution that is chosen [30, 31]. The exponential increase in design parameters with an increase in the complexity of RC framed structures makes it computationally tough and impractical to use heuristic optimization techniques every time for new problems [27]. The optimization tactics have proven to be beneficial, but their limited constructability has resulted in very little implementation in practical design [32].

In recent times, there has been a tremendous explosion of design variables and objective functions which has resulted in the enormous size of solution space making metaheuristic optimization techniques cumbersome and slow. For more effective and reliable design optimization of RC frames, contemporary metaheuristic, and ML-based optimization algorithms frequently supplement these conventional methods as computing tools progress [33]. The only review paper on the application of ML in the design of building structures [34] mainly focused on the performance and behaviour aspects. The application of ML techniques in optimizing the design of RC frames has gained significant attention in the civil engineering domain. ML techniques coupled with optimization algorithms can be very effective in delivering practical and robust results for RC design optimization problems. Prediction models for the improvement of RC frames are developed using ML techniques. To provide optimized frame designs that satisfy safety and cost criteria, these models make extensive use of datasets providing details on material qualities, load circumstances, and design limitations. The use of ML expands the capabilities of conventional approaches by allowing the exploration of complicated design areas and the quick creation of solutions. *Figure 1* summarises the key elements to take into account when designing RC frames. However, integrating ML into the design optimization process presents various challenges and considerations that must be addressed to realize its full potential. These challenges include:

- *Data quality and quantity:* Obtaining a high-quality and sufficient quantity of data for training ML models can be challenging in the civil engineering domain. Incomplete or inaccurate datasets may lead to suboptimal model performance.

- *Interpretability of ML models:* ML models, especially complex ones, are often considered "black boxes," making it challenging to understand why a particular design is optimal or suboptimal.
- *Integration with engineering standards:* ML models need to align with established engineering standards and codes to ensure that the resulting designs adhere to safety and regulatory requirements.
- *Ethical considerations:* ML models may perpetuate biases present in the training data, leading to unfair or discriminatory outcomes. Lack of transparency in decision-making poses ethical challenges and raises concerns about model reliability and trustworthiness.
- *Computational complexity:* Some ML models, especially complex ones, can be computationally demanding, hindering practical implementation in real-world design scenarios.
- *Validation and verification:* Ensuring that ML-driven design optimizations are theoretically sound and practically applicable requires rigorous validation against existing designs and engineering principles.
- *Human-AI collaboration:* Achieving effective collaboration between structural engineers and ML models requires overcoming differences in language, objectives, and understanding.

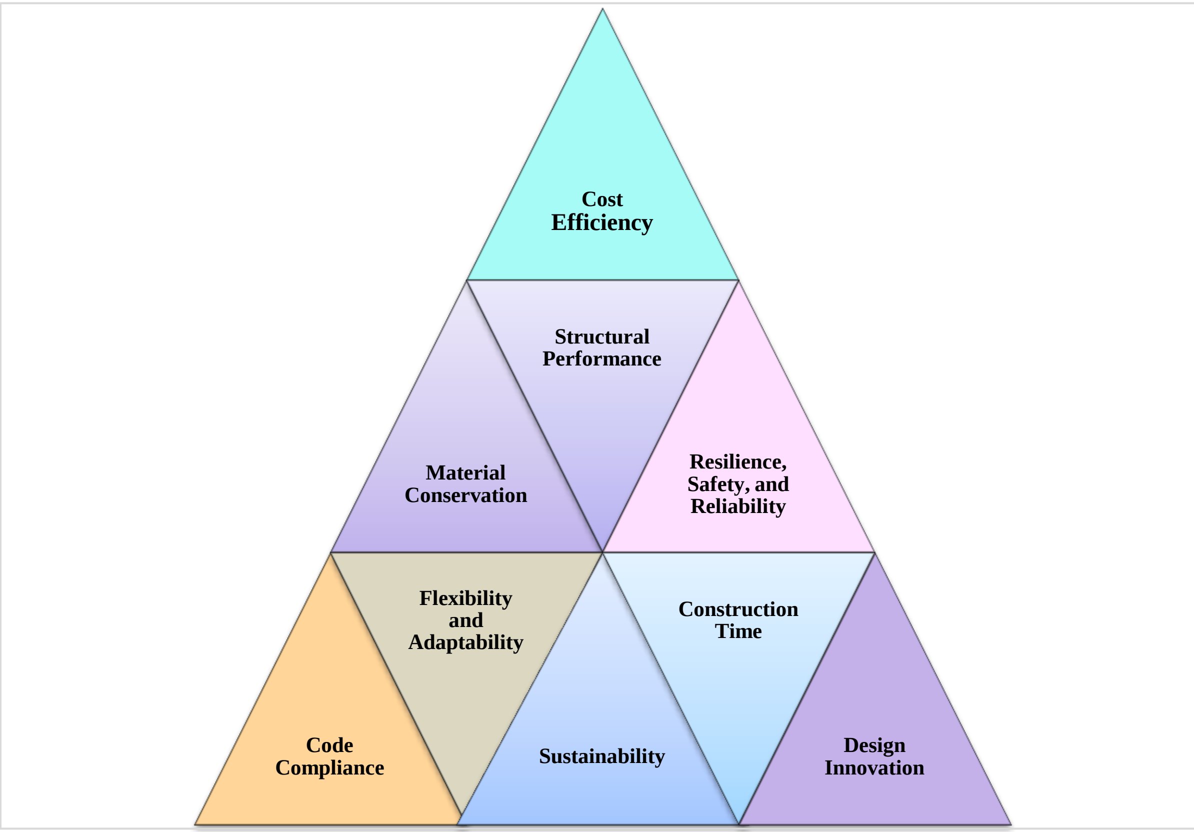

Figure 1 Essential element of RC frame design optimization

With the current popularity and advantages of ML algorithms in the design optimization of RC frame structure, there is a need to understand the current trends and developments in ML-based design optimization of RC frames. Questions regarding the main challenges and considerations associated with integrating ML techniques with metaheuristic algorithms remain unanswered. The presented work aims to bridge the gap by providing a comprehensive study on ML application in the design optimization of RC frame structure. In order to achieve the same, the objective of this study is to outline the current trends and developments in ML-based design optimization of RC frame structure along with the main challenges and considerations associated with integrating ML into metaheuristic algorithms. To achieve the intended goal, the presented work critically evaluates the current literature on the use of

ML in the design optimization of RC structures while other applications such as structural health monitoring and collapse progression have not been considered. To obtain available literature from databases using keywords, a step-by-step holistic technique was used, and then selected articles were sorted into research themes. These study themes include existing research to provide more thorough insights into the current state of research, relevant research areas for future studies, and predicted future research orientations. Theses and reports were not considered in this study as many were not peer-reviewed. This publication also presents a relatively full picture of the available related research that has been done thus far, as well as the research that is currently being conducted with all the problems being encountered during work. The work is such organized that it describes the complete methodology for the literature review along with the trends of timeline, type of paper, and geographical locations. The systematic review process involved several steps, including:

- Identification of relevant databases and search terms related to ML-based optimization of RC frame designs.
- Screening of articles based on inclusion and exclusion criteria.
- Thorough reading and analysis of selected articles to extract key insights and findings.
- Synthesis of results to identify trends, challenges, and future research directions.

Figure 2 demonstrates the methodical step-by-step strategy for retrieving literature from digital databases, categorization, and statistical analysis. The approach for retrieving literature is built on the application of ML in the design optimization of RC frames. The major literature databases like Google Scholar and Scopus were searched. More than 500 articles were acquired after the search and the keywords combinations used for the search for the published articles included “ML”, “machine learning”, “deep learning”, “neural network”, “AI”, “RC”, “design”, “optimization”, “optimal”, “minimization”, “optimal”, and “RC frame”, which are found to be adequate to cover the majority of articles within this field."

The research articles were thoroughly read and analyzed, and content analysis was performed on the retrieved works as per the inclusion and exclusion criteria shown in *Table 1*. A total of 87 articles were found to be with the theme of the current work and were divided into distinct categories based on study objectives for further analysis. Additionally, the ML models are informed by the results of the bibliometric study, guaranteeing that the optimization procedure is influenced by the most recent and pertinent research trends.

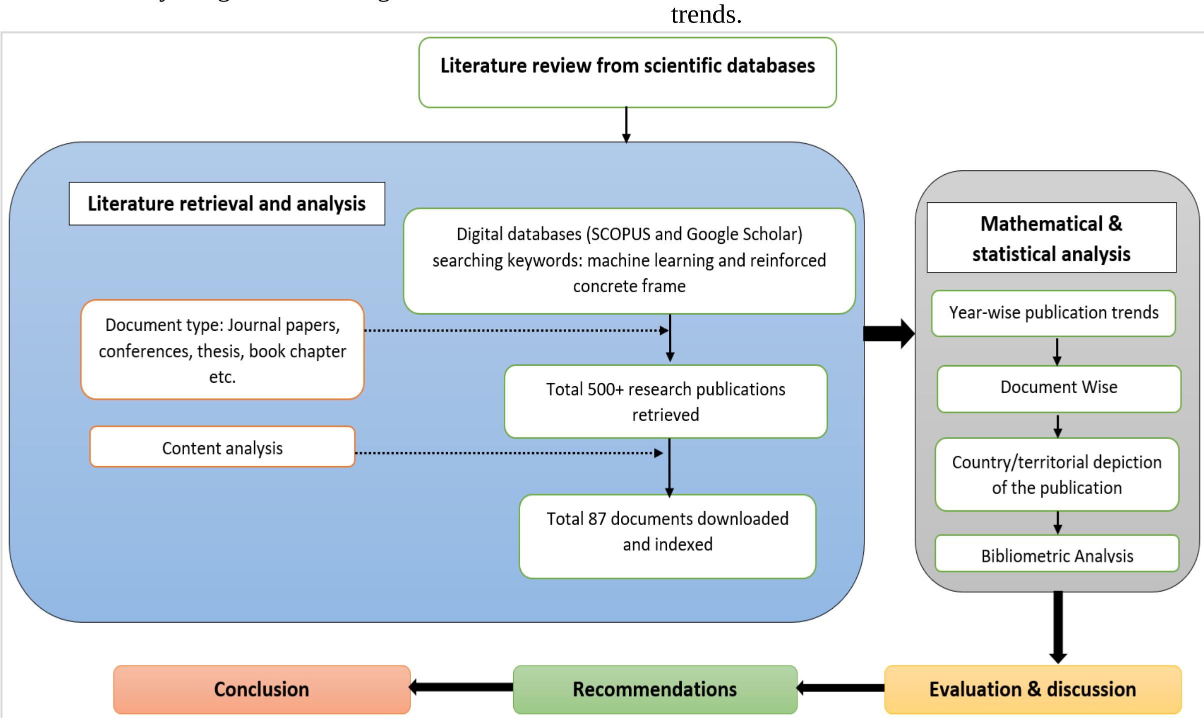

Figure 2 Literature retrieval framework

Table 1 Inclusion and exclusion criteria

Criteria	Inclusion	Exclusion
Publication period	Studies published since 1997	Studies published before 1997
Application focus	Studies with a primary focus on RC frames	Studies on other structural materials or elements
Language	English-language publications	Publications in languages other than English
Relevance to ML applications	Studies demonstrating practical applications of ML in structural design optimization	Studies only discuss theoretical concepts without practical implementation
Data quality	Studies with a clear description of data sources and considerations for data quality	Studies lacking transparency in data sources or data quality considerations

2.Literature review and analysis

With a total of 87 published articles on the application of ML in the design optimization of RC frames, there has been a significant increase in the number of articles over the last few decades, from 1 publication in 1997 to 19 publications in 2023. Based on this trend, it can be inferred that the number of publications is likely to continue increasing in the future due to the growing interest in thorough design optimization and ML, incorporating various multidisciplinary elements, among both academics and industry professionals. The data regarding year-wise publications from 1997 to 2023 related to ML and the RC frame are depicted in *Figure 3.*

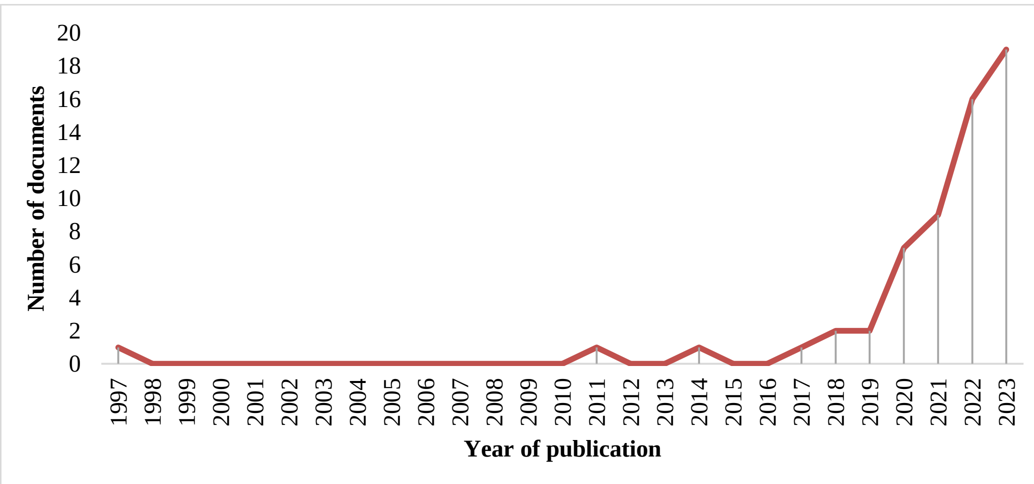

Figure 3 Year-wise publication trends related to ML and RC frames

Out of the total 87 documents, 78 were identified as journal papers, 5 as conference papers, 3 as conference review papers, and 1 as a data paper. The complete picture of the type of paper is depicted in *Figure 4*. The amount of paper related to ML in the design optimization of the RC frame was maximum from China followed by the United States of America. The design guidelines coupled with ML are largely available for only these two countries while others are lagging in generating data for ML optimization. Though, 7 papers are available for Indian guidelines, yet full-fledged work on the design optimization of RC frames is missing. The complete detail of country-wise publication is presented in *Figure 5*. The lack of publications on the subject of ML and RC frames may be related to various multidisciplinary difficulties, resource limitations, data accessibility concerns, and the intrinsic complexity of structural engineering problems. Even though these challenges could have slowed down research and publishing in this area, it's crucial to remember that the subject is continuously developing.

Data visualization was conducted by utilizing VoSviewer bibliometric analysis software version 1.6.16. It is a well-acclaimed bibliometric analysis and visualization tool [35]. It builds overlay, density, and density visualization, co-occurrence maps, citation maps, and cluster analyses. Furthermore, the bibliometric study used in the current study utilizes overlay visualization methods from the LinLog/modularity framework to map the dynamic research environment for ML in RC frame design. It demonstrates a rise in research production, highlighting the growing importance of ML in this area. The study also finds significant research collaborations and clusters, illuminating new trends and significant players. Numerous advantages come from using the LinLog/modularity function of VOSviewer for bibliometric analysis, including the ability to identify research communities, enhance literature reviews, better visualize complex networks, gain interdisciplinary insights, use quantitative metrics, and track changes over time. Researchers from a range of fields may utilize this feature to get valuable insights into the dynamics and structure of the scientific literature, which will enable them to conduct studies that are successful and more effective.

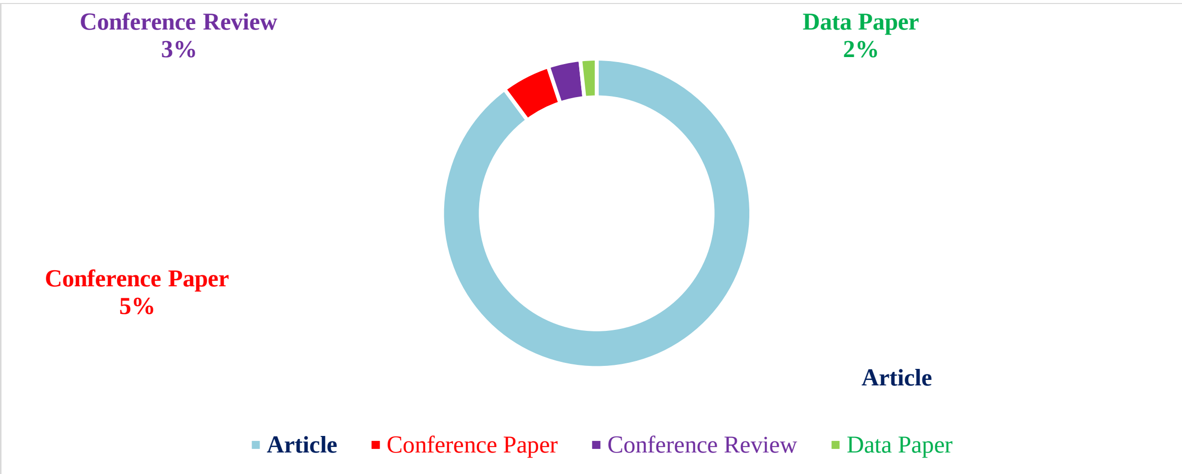

Figure 4 Doughnut representation of published documents on the topic of ML and RC frames

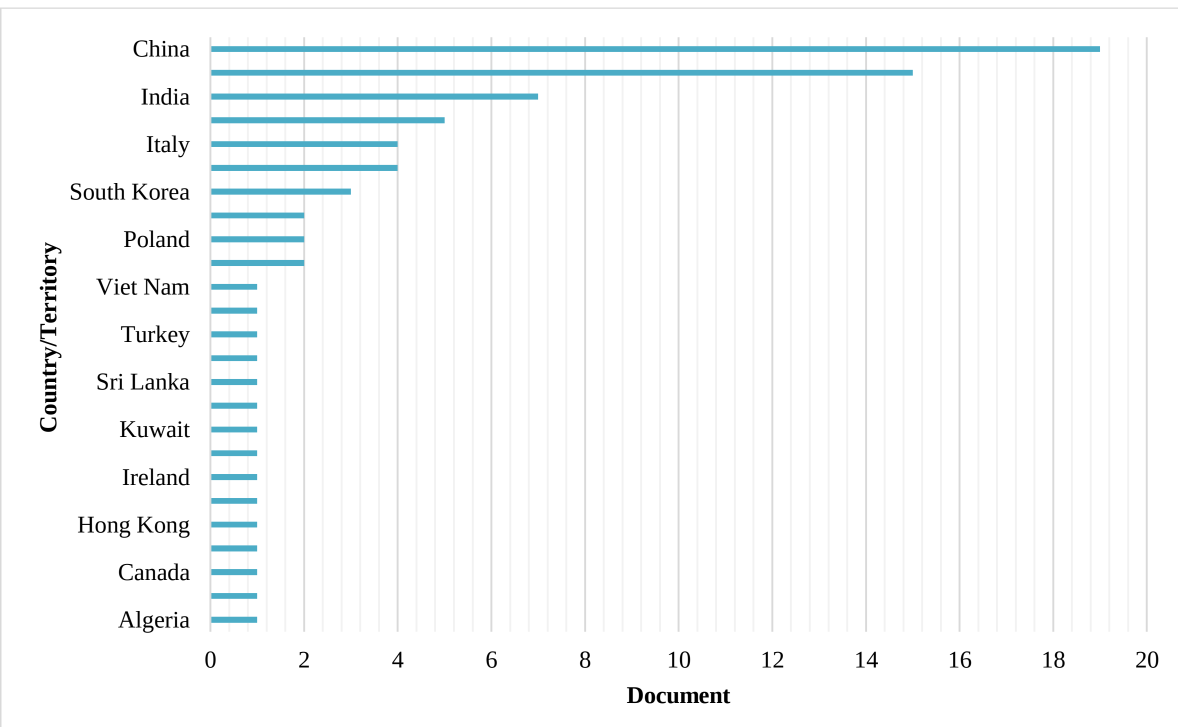

Figure 5 Country/territorial depiction of the publication on the topic of ML and RC frames

Comprehensively assessing the 87 retrieved documents, a total of 621 keywords were found. The minimum number of co-occurrences of a keyword was taken as 5. Out of the 621 keywords, only 26 met the threshold. Two keywords were excluded because of repetitions leaving 24 keywords. The clusters were formed as cluster 1 (14 items) and cluster 2 (10 items). The depiction of overlay visualization by LinLog/modularity analysis of keywords co-occurrence on the topic of ML and RC frames is shown in *Figure 6*. Thus, unlocking the full potential of this multidisciplinary topic will depend on addressing the difficulties and encouraging cooperation between specialists in ML and civil engineering. It is expected that we will witness a sharp rise in publications and research projects in the fields of ML and RC frames over time as more data become accessible, computational capabilities advance, and interdisciplinary bridges are constructed. The top ten authors' details on the topic of ML and RC frames retrieved from the bibliometric analysis are depicted in *Figure 7*.

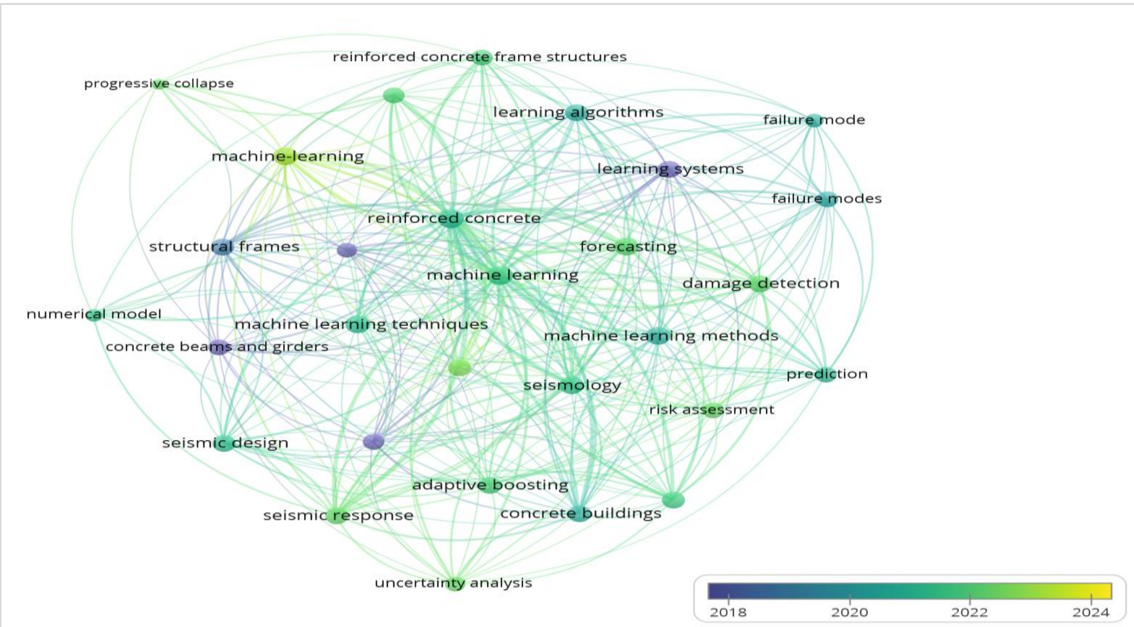

Figure 6 Overlay visualization by LinLog/modularity Analysis of keywords co-occurrence on the topic of ML and RC frames

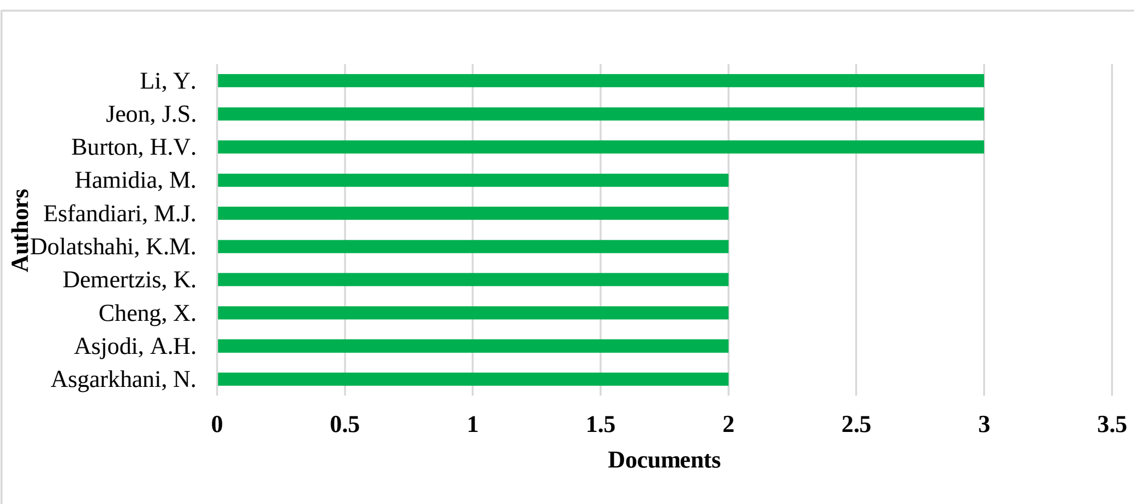

Figure 7 Top ten documents by authors published on the topic of ML and RC frames

The analysis of the retrieved papers by numerous engineering disciplines has found a use for ML, including the design optimization of RC frames. The following are some examples of how ML is used to improve the design process:

- *Material characterization:* Algorithms for ML can be used to examine the characteristics of reinforcing materials and concrete. This makes it possible for engineers to create precise material models, which are necessary for carrying out simulations and optimizations [6].
- *Design exploration:* By creating and analyzing various RC frame configurations, ML algorithms may effectively investigate a large variety of design alternatives. This can assist in locating the best designs that satisfy particular performance goals and limits [36].
- *Optimization algorithms:* The RC frame's design parameters may be automatically optimized using ML approaches such as genetic algorithms (GA), particle swarm optimization (PSO), or reinforcement learning (RL) [37]. Until an ideal solution is found, these algorithms iteratively improve the design based on performance feedback.
- *Sensitivity analysis:* Engineers can use ML to do sensitivity assessments to determine how changes to various factors influence the functioning of the structure [38]. This aids in locating crucial design elements and comprehending how they affect the final product.
- *Predictive modelling:* Under various loads and environmental circumstances, RC frame performance and behaviour may be predicted using ML algorithms. The viability and dependability of design choices are assessed with the aid of these prediction models [39].
- *Structural health monitoring:* Sensors and ML algorithms may be combined to track the performance and well-being of RC structures throughout their useful lives. For condition-based maintenance and performance optimization, this real-time monitoring delivers useful data [40].
- *Design code compliance*: Engineers may benefit from ML by ensuring that their designs adhere to all applicable construction rules and standards. It may evaluate the design and compare it to the relevant rules, lowering the possibility of mistakes and omissions [41].
- *Uncertainty quantification*: ML may be used to quantify uncertainties [42] in design parameters and material characteristics, enabling probabilistic design optimization that takes into account changes in real-world situations.
- *Data-driven design decisions*: Large datasets from previous projects may be analyzed using machine-learning techniques to uncover patterns and insights [43]. This data-driven method helps with decision-making during the design process, resulting in more dependable and efficient designs.

Design collaboration and knowledge sharing: ML technologies can make it easier for design teams to collaborate by offering a common forum for exchanging information, design thoughts, and lessons from previous projects [44]. Depending on the optimization case, a variety of ML techniques is used in the optimization of RC frames, each with unique benefits. The various significant metaheuristic techniques that are being used in collaboration with ML approaches in the available literature are described in *Table 2* where the characteristics describe the advantages of the associated technique.

Table 2 Algorithms for optimizing the design of RC frames

S. No.	ML algorithms	Characteristics	References
1.	Trial-and-Error Method	• Engineers manually modify design parameters, such as section dimensions, reinforcement ratios, and member sizes, and then assess the performance of the frame using structural analysis software. This approach is an easy optimization technique. • The procedure is repeated until a workable resolution is found.	[45]
2.	LP	• LP is a mathematical optimization approach to determine the best solution for linear objective functions subject to linear inequality constraints. • It may be used to optimize design variables under linear constraints, such as stress limitations, deflection restrictions, and material availability, in the context of RC frames.	[46] [47] [48]
3.	Non-linear programming	• NLP encompasses LP to handle non-linear objective	[49]

S. No.	ML algorithms	Characteristics	References
	(NLP)	functions and constraints. • It is appropriate for more difficult design issues involving nonlinear structural behaviour or material characteristics, which are frequently present in RC frames.	
4.	GA	• GA is a population-based optimization method that uses heuristic search techniques and is motivated by genetics and natural selection. • Through selection, crossover, and mutation procedures, they produce a population of candidate solutions and iteratively develop them. • GA has been successfully used to optimize design variables in RC frames. • GA is particularly effective for exploring a large design space to find global optima. • It is suitable for optimization scenarios where the design space is discrete or continuous and contains multiple local optima.	[50] [51] [52] [53] [54] [55]
5.	Gradient-based optimization	• Gradient-based optimization techniques employ the gradient of the objective function to iteratively locate the local optimum. Examples include the steepest descent method and the quasi-Newton method. • These techniques call for the computation of gradients, which for intricate structural models can be computationally demanding.	[1] [56] [57]
6.	Response surface methodology (RSM)	• RSM entails creating a mathematical model (called a response surface) that roughly represents the association between the design factors and the goal function. • Once the reaction surface has been created, the best design may be quickly found using it.	[37]
7.	Sequential linear programming (SLP)	• SLP is an iterative optimization technique that approximates the objective function while linearizing the nonlinear constraints. • The best answer is then obtained by solving a series of LP issues.	[58]
8.	Active set method	• The active set technique is a specialized optimization algorithm used for problems with inequality constraints. • It finds active constraints (those that are fulfilled with equality) and iteratively updates the design variables to meet the active requirements until convergence.	[59]
9.	PSO	• A swarm of particles, each of which represents a potential solution, is maintained using PSO, an optimization approach that draws inspiration from the social behaviour of fish schooling and birds flocking. • When the design variables are continuous and the objective function is reasonably smooth, PSO is ideally suited for continuous optimization problems with smooth and convex objective functions. • It can effectively discover the best solutions in the design of RC frames.	[60] [61] [62] [63]
10.	Modified genetic programming (GP)	• GP represents solutions as tree structures rather than as fixed-length vectors. • In optimization situations where the design variables are hierarchical or have complicated interactions, GP might be useful. It can manage issues with layered or hierarchical design and record interactions between variables.	[64] [65] [66]
11.	Surrogate Models	• Surrogate models are ML models that approximate the	[67]

S. No.	ML algorithms	Characteristics	References
	(Gaussian Processes, neural networks, etc.)	behaviour of complex and computationally expensive simulations. • Surrogate models greatly minimize the number of structural studies necessary throughout the optimization process, making it more computationally efficient and suited when the structural analysis is computationally demanding and time-consuming.	[68] [69]
12.	RL	• It is a type of ML where an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards. • It can be applied to optimize RC frames in scenarios where the optimal solution is not well-defined or when the environment is uncertain.	[70] [71] [10]
13.	Evolutionary strategies (ES):	• Based on the fitness of the solutions, ES updates the model parameters and generates new solutions using a probabilistic model. • ES works well for optimization issues involving stochastic objective functions and continuous design variables. • It is useful for the optimization of RC frames with unclear material qualities or loads because it can handle noisy or uncertain objective functions with efficiency.	[72] [73] [71]
14.	Simulated annealing (SA)	• SA is a probabilistic optimization method that draws inspiration from the metallurgical annealing procedure. • By accepting less-than-optimal answers with a gradually diminishing probability, it enables the algorithm to escape local maxima. • When the design space is extremely non-convex and the objective function landscape is rough and has a large number of local optima, SA is appropriate for optimization scenarios.	[74] [75]

The nature of the design variables, the complexity of the objective function and constraints, the available computer resources, and the degree of problem uncertainty; all play an important role in determining which metaheuristic technique should be used in collaboration with ML. The GA and PSO are the most used metaheuristic techniques followed by LP and NLP. GA and PSO are the earliest space search methods to solve space search problems. Even though they are frequently used techniques, GA suffers from premature convergence, parameter sensitivity, and limited constraint handling; and PSO suffers from limited global exploration, poor convergence speed, and lack of adaptability. SA algorithm is found to be very slow but guarantees the best solution for the objective function. The capability of SA techniques to overcome local minima-maxima while accepting the poor solution makes it an exceptional algorithm for optimization. There has been a constant flow of newly developed metaheuristic methods, which are still to be tested for the design optimization of RC frame structures. Furthermore, hybrid strategies that integrate several ML algorithms or combine ML with conventional optimization techniques can be successful in solving challenging optimization issues involving RC frames. The latest trend in the field of ML and RC frame optimization is shown in *Figure 8*. Integrating physics-based constraints into ML models seeks to combine the strengths of physics-based models with the data-driven capabilities of ML, enhancing the accuracy and reliability of design optimizations [76]. Placing a greater emphasis on incorporating user preferences, stakeholder input, and human-centric factors in the design optimization process. This is being achieved by using an artificial neural network (ANN) [77, 78]. ML models are being designed to consider not only engineering constraints but also human-centric aspects. Addressing multiple conflicting objectives simultaneously in the design optimization process. ML models are being employed to navigate complex, multi-dimensional design spaces and identify trade-offs between different performance criteria. Continued emphasis on making ML models more explainable and interpretable. This trend ensures that engineers and stakeholders can understand the reasoning behind design recommendations, promoting trust and adoption.

Meta-heuristic algorithms are the past of artificial intelligence, but when coupled with ML can lead to simple but effective results [10].

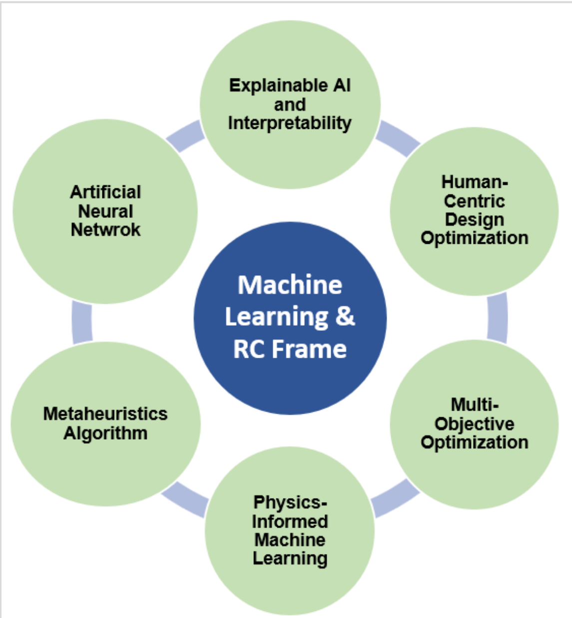

Figure 8 Latest ML Techniques being used in the optimization of RC Frame

The restrictions and elements that must be taken into account while developing and optimizing a concrete building frame are referred to as constraints in RC frame optimization [79]. These limitations cover a wide range of topics, such as structural specifications [80], material qualities [81], adherence to building standards [82], economic variables [83], aesthetics [84], safety [85], environmental considerations [86], and geotechnical elements [65]. A cost-effective and structurally sound design that satisfies project objectives and regulatory requirements must strike a balance between these restrictions. To work around these limitations and create the best concrete frame design that meets performance, safety, and efficiency standards, engineers employ specialized software and optimization techniques. Therefore, the optimization of RC frames in civil engineering depends critically on constraints [87]. These limitations aid in ensuring that the proposed structures adhere to particular standards for performance, safety, and use. RC frame optimization aims to provide safe, effective, and sustainable designs that fulfill particular project needs and abide by industry norms and regulations by properly identifying goal functions and limitations [69]. Finding the most effective and compatible design solution for RC frames in civil engineering projects involves balancing these limitations, which is a challenging process that frequently calls for the application of optimization techniques, including ML [88]. To produce a successful and useful design, engineers must carefully take these restrictions into account and manage them throughout the design process. The main restrictions are getting every constraint into the objective function that affects the optimization of RC frames are shown in *Figure 9*.

3.Discussion

The design of RC frames may be optimized by taking into account objective functions and limitations. For effectively managing complicated design constraints including structural stability, financial effectiveness, and environmental sustainability [35], ML offers a flexible framework. This study examines multiple ML-based optimization strategies and how well they may change with the goals of a design, giving engineers effective tools for producing the best possible frame designs. The target functions and constraints in RC frame optimization are essential for establishing the design goals [10] and assuring the frame's structural integrity, safety [89], and sustainability [90]. Following are a few typical goal functions and restrictions applied in this circumstance:

- *Minimization of material usage:* Minimising overall material consumption while meeting structural performance standards is one of the key goals of optimizing RC frames [91]. Lowering the quantity of concrete and reinforcing steel needed, can result in more affordable designs.
- *Maximization of structural performance:* The goal is to maximize the frame's structural performance while taking factors like load-carrying capacity, stiffness, and serviceability constraints into account. This guarantees that the frame can support the imposed loads and function at its peak during its service life [92].
- *Optimization of durability and service life:* The goal is to increase the RC frame's toughness and service life by taking things like corrosion prevention into account [93], crack control [94], and suitable cover thickness [59].
- *Sustainability and environmental impact:* The goal is to include sustainability factors in the optimization process to minimize the structure's overall environmental effect [95]. This may entail reducing waste production [35], energy use, and carbon emissions [96].
- *Cost-effectiveness:* To create an economically feasible design, it is necessary to strike a balance between material utilization [97], building costs, and ongoing maintenance costs [98].

- *Multi-objective optimization:* Sometimes, competing goals are taken into account at the same time. For example, minimal material use while maximizing structural performance [99]. Engineers can select the best design solution by using multi-objective optimization to determine the Pareto front [55], which represents trade-offs between several objectives.

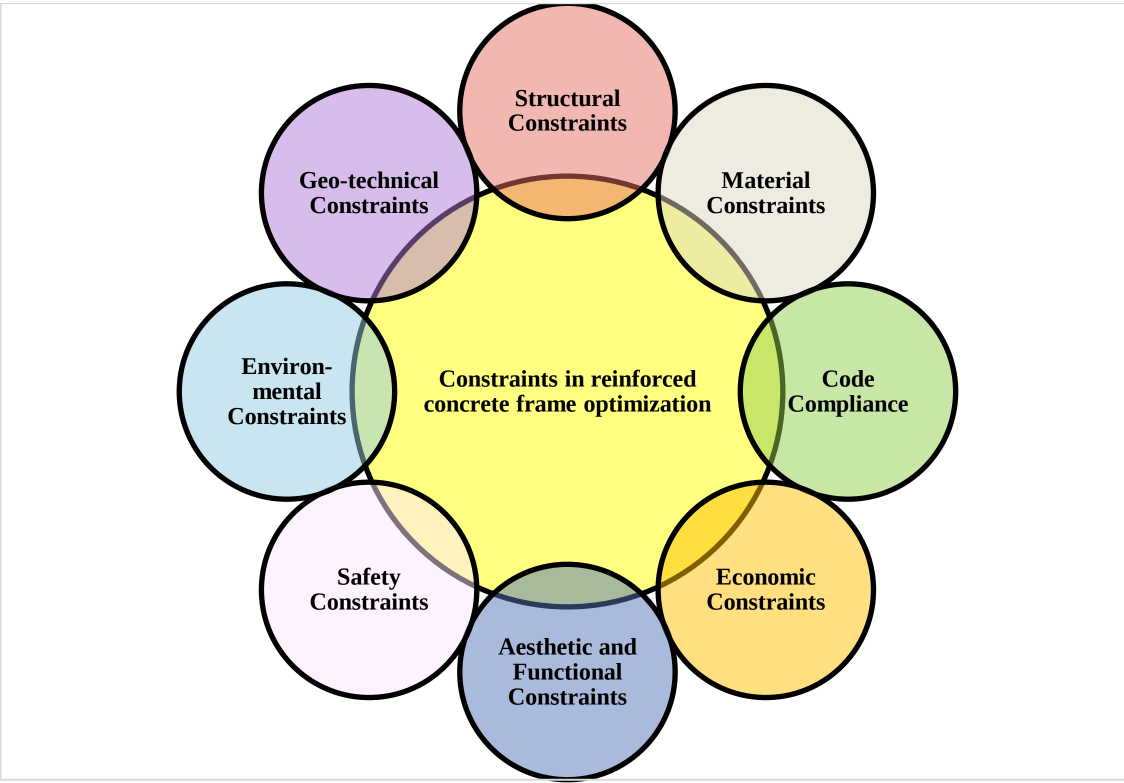

Figure 9 Constraints in RC frame optimization

The use of ML to optimize the design of RC frames is a viable path for increasing efficiency and performance. The ML model's accuracy is an important parameter that is calculated by averaging the accuracy values across the test datasets. The common metrics used to evaluate models are coefficient of determination (R), root mean squared error (RMSE), mean absolute error (MAE), standard deviation (SD), and mean squared error (MSE). Some of the ML techniques used in collaboration with other optimization techniques are presented in *Table 3.*

Table 3 Summary of ML techniques in collaboration with other algorithms

Work	ML Technique	Optimization algorithm	Structure type	Objective	ML performance metric
[100]	ANN	PSO	RC Frame	Material minimization	R
[101]	Linear regression, Decision tree regression, Elastic net regression, K-neighbor regression, Support vector regression, Random Forest regression, Gradient boosting regression, and Stacking models	Harmony Search	RC Column	Carbon dioxide emission minimization	R, RMSE, MAE, and MSE
[102]	ANN	Generalized Reduced Gradient (GRG)	RC Beam	Cost minimization	---

Work	ML Technique	Optimization algorithm	Structure type	Objective	ML performance metric
[37]	ANN	Evolutionary algorithms	RC Frame	Cost minimization	R
[103]	Shapley Additive exPlanations (SHAP)	Harmony Search	RC Column	Cost minimization	R, MAE, and RMSE
[104]	Deep Learning	Heuristic algorithm	RC slab	Cost and Carbon dioxide emission minimization	RMSE
[71]	RL	Bat algorithm	RC Beam	Weight minimization	SD
[69]	ANN	GA	RC Frame	Cost minimization	---
[105]	ANN	GA	RC Footing	Cost minimization	RMSE
[106]	ANN	GA	RC Beam	Cost minimization	RMSE
[107]	ANN	GA	RC Beam	Cost minimization	---
[108]	ANN	Harmony search	RC Column	Cost minimization	RMSE, and MAE
[109]	ANN	Heuristic algorithm	RC Frame	Cost minimization	RMSE
[110]	Deep learning	Heuristic algorithm	RC Column	Carbon dioxide emission minimization	SD

Among the various ML techniques suitable for integration with meta-heuristic algorithms, ANN stand out as one of the most accurate and widely used approaches. ANNs offer the capability to model complex nonlinear relationships and capture intricate patterns within the optimization problem space. When combined with meta-heuristic algorithms such as GA, PSO, or SA, ANNs can effectively guide the search process toward optimal or near-optimal solutions for RC frame structures. The only problem associated with ANN is that the process of optimization remains a "black box" for the users. Among the meta-heuristic techniques, the GA has been used most in combination with any ML techniques and new meta-heuristic technique collaboration is still missing. A diverse set of techniques exist for optimizing the design of RC frames using ML algorithms. Depending on the specific requirements of the optimization problem, engineers can choose the most appropriate approach or combine multiple approaches to achieve the desired design objectives efficiently and effectively. The values of R, RMSE, and SD are important matrices to measure the performance of the ML technique and together present a complete picture of the effectiveness of the applied algorithm. The significant performances of the various ML approaches for RC frame design can be evaluated based on several criteria such as efficiency, accuracy, robustness, scalability, and ease of implementation. A Likert chart representation of the performance and applicability of ML techniques in the design optimization of RC frame structure is presented in *Table 4*.

Table 4 Likert Chart for ML approaches for RC frame design optimization

ML Technique	Efficiency	Accuracy	Robustness	Scalability	Ease of implementation	Remarks
Deep learning with ANN	High	High	Medium to High	High	Medium to Low	Requires large datasets, computational resources, and expertise
Surrogate models	Medium to High	Medium to High	Medium to High	Medium to High	Medium to High	Useful for approximating complex models, interpretable results
RL	Medium to High	Medium to High	Low to Medium	Medium to High	Medium to Low	Suitable for sequential decision-making tasks
Q-learning	Medium to High	Medium to High	Low to Medium	Medium to High	Medium to Low	Basis of many RL algorithms
Linear regression	Low to Medium	Low to Medium	Low to Medium	High	High	Simple, interpretable, suitable for linear relationships
Support vector	Medium to	Medium to	Medium to	Medium to	Medium to High	Effective in high-

ML Technique	Efficiency	Accuracy	Robustness	Scalability	Ease of implementation	Remarks
machines	High	High	High	High		dimensional spaces, can handle complex data
K-nearest neighbor regression	Low to Medium	Medium to High	Low to Medium	Low to Medium	High	Simple, instance-based, sensitive to noise
Decision tree regression	Medium to High	Medium to High	Medium to High	Medium to High	Medium to High	Easily interpretable, prone to overfitting
Random forest regression	High	High	High	High	Medium to High	Reduces overfitting, handles high-dimensional data well

However, ML techniques are not without difficulties. The complicated nature of structural engineering, along with the necessity for accurate and dependable forecasts, makes integrating ML models problematic. Addressing these issues necessitates a multifaceted strategy that includes enhanced data quality, rigorous model validation approaches, and a thorough understanding of structural behaviour. To tackle these challenges, structural engineers, data scientists, and ML experts must work together. The mitigation of obstacles will pave the way for more resilient, cost-effective, and sustainable design solutions in the arena of RC frames by encouraging synergy between domain expertise and innovative technologies. The description of the challenges and their mitigation is presented in *Table 5*.

Table 5 Challenges and mitigation in the application of ML in the design optimization of RC frames

Challenges	Description	Mitigation Strategies
Data quality and quantity	• Obtaining high-quality and sufficient quantity of data for ML models. • Incomplete or inaccurate datasets may lead to suboptimal model performance.	• Collaborate with industry partners for comprehensive datasets. • Implement data pre-processing techniques and quality assurance protocols.
Interpretability of ML models	• ML models, especially complex ones, are often considered as "black boxes." • Challenges in understanding why a particular design is optimal or suboptimal.	• Explore explainable AI (XAI) techniques for insights into model decisions. • Use feature importance analysis and model-agnostic interpretability methods.
Integration with engineering standards	• ML models need alignment with established engineering standards and codes. • Deviations from standards may hinder acceptance and adoption.	• Collaborate with structural engineers to incorporate domain knowledge. • Ensure model outputs adhere to established standards.
Ethical considerations	• ML models may perpetuate biases present in the training data. • Lack of transparency in decision-making poses ethical challenges.	• Implement fairness-aware ML practices. • Audit training datasets for biases. • Incorporate ethical considerations into the development process.
Computational complexity	• Some ML models, especially complex ones, can be computationally demanding. • Computational complexity may hinder practical implementation.	• Balance model complexity with computational efficiency. • Explore model compression techniques. • Optimize algorithms for efficiency.
Validation and verification	• Ensuring ML-driven design optimizations are theoretically sound and practically applicable. • Real-world applicability may be uncertain.	• Rigorous validation against existing designs and engineering principles. • Verification through physical testing and monitoring.
Human-AI collaboration	• Achieving effective collaboration between structural engineers and ML models. • Differences in language, objectives, and understanding may hinder collaboration.	• Foster interdisciplinary collaboration. • Provide training to engineers on ML concepts. • Develop user-friendly interfaces facilitating interaction.

By utilizing their distinct capabilities and methodologies, ML techniques have the potential to overcome some of the drawbacks of conventional design optimization techniques for RC frames. ML techniques with metaheuristic algorithms, such as GA, and PSO, are better able to thoroughly explore the design space and potentially overcome the local optima problem that is present in conventional approaches. These algorithms can efficiently look for global optima by employing population-based search techniques [57]. Gaussian processes or neural networks are ML approaches. [111], may be used to create surrogate models that simulate intricate and costly computer structural evaluations [67]. The computing complexity of the optimization process is greatly reduced by these surrogate models, which enable quick assessments of the objective function and constraints. Discrete design variables may be handled well by ML-based optimization methods by adopting the right encoding techniques or algorithms created for combinatorial optimization issues [112]. As a result, more sensible and realistic design options are possible. By adding penalty functions or employing constraint-handling strategies like constraint satisfaction or repair mechanisms [113], these algorithms may manage a variety of constraints, including non-linear and interactive constraints [114]. To handle noisy data and offer probabilistic predictions, ML models may be trained on data that has intrinsic uncertainties [115]. Accepting fluctuations in material qualities, loads, and other input factors, enables more reliable optimization under unpredictable situations [116]. By using data-driven insights from earlier designs and simulations, optimization may be directed [117]. ML can spot trends, patterns, and linkages that human skill alone would miss by examining a database of previous designs and their performance. By incorporating many performance criteria, such as structural strength, durability, and cost into a single objective function, ML approaches may solve interdisciplinary optimization challenges. This makes it possible to use an optimization strategy that is more thorough and integrated [118]. To extract key design factors and interactions, feature engineering may be automated with the use of ML, which eliminates the need for manual feature selection and domain-specific knowledge [119]. The algorithms' ability to dynamically adapt and change their search methods during the optimization process can result in greater performance and faster convergence to optimum solutions [120]. During the optimization process, the algorithms' search methods may be dynamically adjusted and adjusted, which can enhance performance and improve convergence to optimal solutions. By uniting surrogate models [11] and population-based optimization algorithms [121], ML techniques can considerably lessen the number of costly structural analyses required, resulting in more effectual optimization procedures. In conclusion, ML approaches open up fresh viewpoints and design methodologies for RC frame design optimization. They offer the potential to improve optimization by getting around some of the drawbacks of conventional techniques. [122], ultimately resulting in more reliable, effective, and data-driven design solutions [123].

Data preparation for ML algorithms requires a crucial step called feature engineering [119]. It entails converting unprocessed data and pertinent design criteria into appropriate features that can be fed into ML models. Feature engineering is the process of choosing, extracting, and converting design data into meaningful and representational features in the context of RC frame design. The steps involved in feature engineering are shown in *Figure 10.*

For instance, while creating a RC frame, relevant design criteria could include section dimensions, reinforcement ratios, loads, material characteristics, and environmental factors, the following stages would be involved in feature engineering:

- *Selection:* determining the most important design factors, such as column size, beam depth, and concrete strength, that have an impact on the frame's structural performance [124].
- *Normalization:* By scaling the chosen design parameters to a similar range (for example, between 0 and 1), biases caused by variations in units and magnitudes may be avoided [125].
- *Interaction terms:* Merging two or more design characteristics to create new features that capture how they interact. For instance, calculating the structural capacity by multiplying the column size by the concrete strength [28].
- *Categorization:* Transforming continuous design parameters into categorical features, where applicable. For instance, classifying reinforcement ratios as high, medium, or low [126].
- *Encoding:* Employing methods like one-hot encoding [127] or label encoding [128], to convert categorical information into numerical values so that ML algorithms can process them.
- *Dimensionality reduction:* Using methods like Principle Component Analysis (PCA) or feature selection approaches to reduce the number of features will help to alleviate the effects of dimensionality and boost computing performance.
- *Handling missing data:* Using imputation techniques like mean, median, or regression-based imputation to deal with missing data, making sure the dataset is full [129].

The dataset is organized and informatively generated through feature engineering, making it acceptable as an input to ML approaches. This strengthens the models' performance and interpretability and gives engineers the information required to make informed decisions during the design optimization of RC frames.

A complete list of abbreviations is summarized in *Appendix I.*

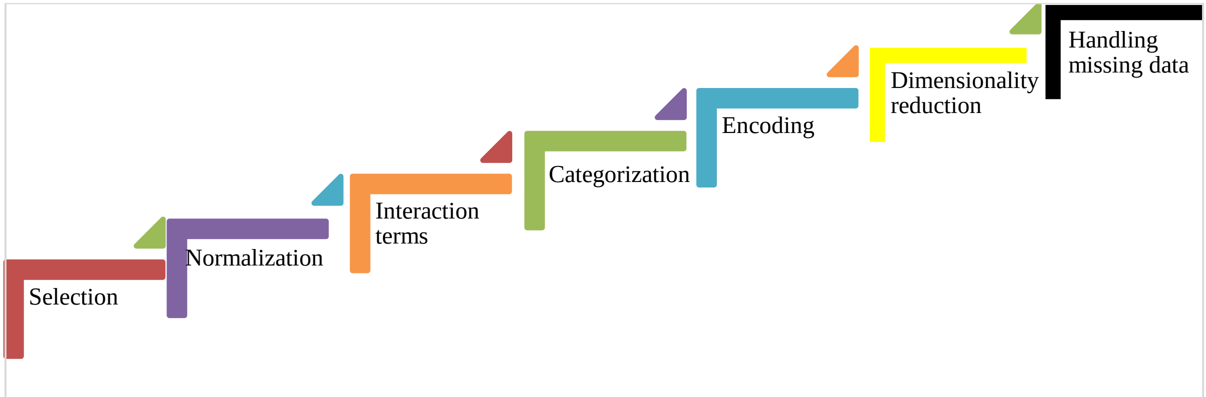

Figure 10 Steps Involved in feature engineering

4.Conclusion and future work

In order to effectively optimize the design of RC frames, this study examines the revolutionary effects of ML, highlighting the vital significance of affordability, sustainability, and safety in the building industry. This study promotes the use of modern metaheuristic and ML-based algorithms to improve efficiency and reliability in the face of obstacles faced by classic design optimization methods. A detailed examination of the body of literature indicates a notable increase in publications, with the United States of America and China spearheading worldwide research initiatives. With the use of VoSviewer, the bibliometric analysis reveals important patterns, study groups, and cooperative networks, providing insightful information on the ever-changing field of ML in RC frame design. The integration of ML techniques with meta-heuristic algorithms for the design optimization of RC frame structures offer significant advantages along with some inherent limitations. Throughout this paper, various benefits have been highlighted such as improved efficiency, enhanced accuracy, and the ability to handle complex optimization problems efficiently. ANN is one of the most used ML techniques with the best performance due to its inherent nature of handling complicated relationships between design variables. GA is the most used metaheuristic technique to be used with the ML algorithm. Though, GA is slow and time-consuming, its ability to reach global minima enhances the performance of the ML algorithm. There are many other improved faster and consistent metaheuristic algorithms to be used in collaboration with ML techniques, which remain an unexplored area. By harnessing the power of ML, engineers and researchers can explore vast design spaces, identify optimal solutions, and streamline the iterative design process. Further, the presented work also elaborates on the challenges and mitigation strategies to combine ML techniques with metaheuristic algorithms effectively and effortlessly.

In the future, the study predicts that the fields of ML and RC frames anticipate an increase in publications and research initiatives. The full potential of this multidisciplinary topic is expected to emerge when computational capabilities progress, interdisciplinary collaboration becomes stronger, and data accessibility improves. The research gaps and obstacles that have been presented highlight the necessity of continuous efforts to address transdisciplinary issues, resource constraints, and data accessibility concerns. By presenting trends, challenges, and potential future directions, it provides a valuable resource for researchers, practitioners, and policymakers. The integration of ML not only holds promise for advancing design optimization but also for fostering a new era of sustainable, safe, and innovative construction practices. As the field continues to evolve, collaboration and knowledge-sharing between ML and civil engineering experts will be instrumental in unlocking the full potential of this transformative approach to RC frame design.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

None.

Author's contribution statement

Tabish Izhar: Conceptualization, Investigation, Writing-original draft. **Syed Aqeel Ahmad:** Data collection and organization. **Tasneem Ahmed:** Analysis and interpretation of results. **Neha Mumtaz**: Proof-reading the original draft, and Supervision.

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Appendix I

S. No.	Abbreviation	Description
1	ANN	Artificial Neural Network
2	ES	Evolutionary Strategies
3	GA	Genetic Algorithm
4	GP	Genetic Programming
5	GRG	Generalized Reduced Gradient
6	LP	Linear Programming
7	MAE	Mean Absolute Error
8	ML	Machine Learning
9	MSE	Mean Squared Error
10	NLP	Non-linear Programming
11	PCA	Principle Component Analysis
12	PSO	Particle Swarm Optimization
13	R	Coefficient of Determination
14	RC	Reinforced Concrete
15	RL	Reinforcement Learning
16	RMSE	Root Mean Squared Error
17	RSM	Response Surface Methodology
18	SA	Simulated Annealing
19	SD	Standard Deviation
20	SLP	Sequential Linear Programming
21	XAI	Explainable AI