

A Review of Algorithm-Based Energy-Saving Optimization in Buildings

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Abstract: The building sector is a major source of energy demand and carbon emissions, so algorithm-based energy-saving optimization has become important for low-carbon construction and operation. This review examines five recent computational intelligence approaches used in building energy efficiency and construction management: an artificial-neural-network-driven genetic algorithm (ANN-GA), a hybrid NSGA-II-MOPSO algorithm, an entropy-based grey wolf optimizer (ENTGWO), a BIM-integrated deep Q-network (BIM-DQN), and the Falco peregrinus optimization algorithm with its multi-objective extension (FPO/MOFPO). The paper compares their principles, application scenarios, and practical significance. The reviewed studies show that hybrid and adaptive algorithms improve convergence, search diversity, and engineering usability, especially when combined with surrogate models or structured digital building data. The review also identifies limitations, including weak treatment of occupant behaviour, limited real-time validation, and dependence on expert parameter tuning. Overall, intelligent optimization methods provide useful pathways for reducing building energy use, but future research should move toward transparent, transferable, and human-centred optimization platforms.

Keywords: Building Energy Efficiency; Optimization Algorithm; Genetic Algorithm; Artificial Neural Network; NSGA-II; MOPSO; Grey Wolf Optimizer; Reinforcement Learning; Building Information Modelling; Carbon Reduction

1. Introduction

Buildings consume large amounts of energy during design, construction, operation, renovation, and demolition. Their environmental

impact is distributed across envelope performance, heating and cooling demand, lighting, equipment, renewable generation, occupant behaviour, and management decisions. Building energy saving is therefore a multi-variable decision problem in which cost, comfort, carbon emissions, and reliability often compete. Traditional building design and operation still rely on experience, prescriptive codes, and isolated calculations. These methods are useful, but they become weak when many variables must be tested together. Exhaustive simulation of all combinations is usually too slow for practical design.

Computational intelligence offers a response to this complexity. Evolutionary algorithms, swarm intelligence, neural networks, and reinforcement learning can search large design spaces and identify trade-off solutions that would be difficult to find manually. Recent studies show a trend from single algorithms toward hybrid frameworks, surrogate models, and BIM-linked decision systems [1-3].

This paper reviews five representative approaches. It does not rank them as universally best or worst, because each method is designed for a different task. Instead, it asks what idea each method introduces, how it is applied, and what academic, engineering, and environmental value it offers. The review therefore provides a compact synthesis of current algorithm-based building optimization research.

Review Methodology

This paper is a narrative review rather than a systematic review. The five studies were selected because they are recent, peer-reviewed examples that represent different algorithmic families and building-sector applications, including retrofit optimization, envelope design, load prediction, construction process optimization, and integrated-energy-system scheduling. The aim is to compare representative methods and research directions rather than to provide an exhaustive database search or formal meta-analysis.

2. ANN-Driven Genetic Algorithm for Energy Retrofit Optimization

The genetic algorithm (GA) is a heuristic optimization method inspired by natural selection. Candidate solutions are represented as chromosomes; better solutions are selected, recombined, and mutated across generations. This structure makes GA suitable for discontinuous and discrete building decisions, such as retrofit packages or equipment choices. However, a conventional GA may require many building-performance simulations, which can make the method too slow for practical design work.

Ioannidis et al. [1] address this problem through an ANN-driven GA framework for a nearly zero-energy multi-family house in Greece. Their method uses artificial neural networks to support the generation and evaluation of promising candidate solutions, while the GA conducts the broader global search. The study covers energy-efficiency measures across the building envelope, active systems, renewable energy systems, and automation. It also considers different climate conditions, including Athens and Thessaloniki, and a large set of energy-price scenarios.

The value of this approach lies in the link between optimization intelligence and practical simulation. By combining TEE-KENAK building-energy software with MATLAB tools, the framework creates a closed loop between energy assessment and decision search. Its objectives include both primary energy consumption and life-cycle cost. Academically, the study shows how surrogate intelligence can accelerate evolutionary search without removing the engineering logic of simulation. Practically, the reduction in computation time from many hours to minutes is valuable because engineers need fast feedback during design and retrofit planning. Environmentally, the method identifies retrofit pathways that reduce energy demand and carbon emissions while remaining economically meaningful.

3. Hybrid NSGA-II-MOPSO for Ultra-Low Energy Residential Buildings

Multi-objective building design often requires a set of acceptable trade-off solutions rather than one single answer. NSGA-II is widely used for this purpose because it can maintain a diverse Pareto front through non-dominated sorting and crowding-distance mechanisms [4]. MOPSO, by

contrast, is based on particle-swarm movement and is often strong in rapid convergence [5]. Each algorithm has weaknesses: NSGA-II can be slow on complex problems, while MOPSO can converge prematurely.

Yu et al. [2] combine the two methods in a hybrid machine-learning strategy for ultra-low energy residential buildings in Nanchang and Guangzhou. An orthogonal experimental design is used to generate representative samples, and an ANN model is trained as a fitness-function surrogate. The hybrid NSGA-II-MOPSO algorithm then searches the design space, comparing its performance with the two standalone algorithms.

This framework is significant because it recognises that building optimization has both local and global search requirements. The NSGA-II component helps preserve population diversity, while the MOPSO component improves search speed. The shared information pool allows the two methods to exchange useful candidate solutions. As a result, the hybrid approach can obtain a better-distributed Pareto solution set with fewer iterations.

For engineering practice, the study turns algorithmic outputs into climate-specific design guidance. Envelope decisions vary with solar radiation, cooling load, humidity, and heating demand. The same surrogate-assisted framework could also be adapted to public buildings, district systems, or carbon-oriented objectives.

4. Entropy-Based Grey Wolf Optimization for Load Prediction

Grey wolf optimization (GWO) is a metaheuristic inspired by the hunting hierarchy of grey wolves [6]. It models leading and follower wolves to guide a population toward promising search regions. However, it can suffer from premature convergence if population diversity is lost too quickly, especially during machine-learning hyperparameter tuning.

Tugal [7] proposes an entropy-based grey wolf optimizer (ENTGWO) to improve multilayer perceptron prediction of building heating and cooling loads. Shannon entropy measures population diversity: high entropy supports wider exploration, while low entropy shifts the algorithm toward local exploitation.

In building-energy management, accurate heating-load and cooling-load prediction is essential. Poor prediction can lead to over-conditioning, discomfort, and unnecessary carbon

emissions. ENTGWO improves MLP tuning and is compared with several algorithms, including PSO, GA, basic GWO, whale optimization, Harris hawks optimization, harmony search, and cuckoo search [7].

The contribution of ENTGWO is both methodological and applied. It shows how information-theoretic feedback can be added to a bio-inspired optimizer, and it improves prediction accuracy and convergence stability for building loads. The method also has potential in renewable-energy prediction and smart-building analytics, where model quality depends strongly on hyperparameter selection.

5. BIM and Deep Q-Networks for Construction Process Optimization

Building energy saving is often discussed at the design and operation stages, but construction management also affects resource consumption, waste, cost, and project duration. Building information modelling (BIM) provides structured digital information about geometry, materials, schedules, and resources. Reinforcement learning, especially deep Q-networks (DQN), can then be used to learn sequential decisions from interaction with a simulated or data-driven environment [8].

Li and Zhang [3] examine computer algorithm optimization of BIM and reinforcement learning for complex building-structure construction under a big-data environment. In a DQN framework, an agent observes a state, chooses an action, receives a reward, and updates a neural-network approximation of the Q-value function. Experience replay and target networks improve training stability. In construction, actions may include resource allocation, sequence adjustment, or process-priority decisions.

The main advantage of BIM-DQN is that it connects a rich project-information platform with adaptive decision-making. Instead of relying only on fixed scheduling rules, the algorithm can learn which actions improve efficiency, cost control, resource utilisation, and duration under changing project conditions.

The environmental relevance is indirect but important. Efficient scheduling can reduce idle equipment time, material waste, rework, and unnecessary transport. However, BIM-DQN systems require reliable data and careful reward design. If the reward function overemphasises speed or cost, the model may ignore safety or environmental quality, so future studies should

integrate carbon, waste, safety, and human factors.

6. Falco Peregrinus Optimization and Multi-Objective Scheduling

Bio-inspired optimization continues to expand because natural hunting, navigation, and group behaviours can be translated into search strategies. Wei and Zhong [9] propose the Falco peregrinus optimization algorithm (FPO), inspired by the hunting behaviour of the peregrine falcon. The method includes mechanisms such as chaotic population initialization, adaptive energy control, and prey-diving search. These features are designed to improve population diversity, escape local optima, and balance global exploration with local exploitation.

The multi-objective extension, MOFPO, uses an external archive to store non-dominated solutions and applies sorting and grid-density control to maintain a diverse Pareto front. This makes it suitable for building integrated energy systems. The tri-objective model minimizes renewable-energy-related cost, the overall CCHP-system cost, and end-user energy-purchase cost. The method is compared with established algorithms including PSO, GWO, GA, MOPSO, MOGWO, and NSGA-II [9].

The academic significance of FPO lies in enriching adaptive metaheuristics. A new algorithm must demonstrate robustness beyond an attractive metaphor, and the reported tests on standard functions and energy-system scheduling indicate stable convergence and a well-distributed solution set.

For engineering practice, MOFPO is relevant because energy systems are becoming more integrated. Combined cooling, heating, and power systems, renewable generation, and user-side demand require coordinated scheduling. A smooth Pareto front gives decision-makers several feasible options and helps align economic operation with carbon-reduction goals.

7. Cross-Study Synthesis and Research Gaps

Across the five studies, three broad patterns are visible. First, hybridization is becoming a central strategy. ANN-GA and NSGA-II-MOPSO show that combining algorithms can address weaknesses that are difficult for one method to solve alone. Second, surrogate modelling is increasingly important. Detailed simulation remains necessary for accuracy, but repeated simulation can be too slow; ANN surrogates allow the optimization loop to operate at a

practical speed. Third, adaptive search mechanisms are becoming more refined. ENTGWO and FPO both adjust search behaviour according to population state or energy-inspired mechanisms.

Another shared pattern is the movement from abstract optimization toward engineering deployment. The Greek retrofit case, Chinese ultra-low energy residential cases, HVAC-load prediction task, BIM-based construction problem, and integrated-energy scheduling scenario all connect algorithms to concrete building-sector decisions.

Nevertheless, the reviewed literature still has limitations. Many studies focus on design-stage or planning-stage optimization, while fewer demonstrate real-time control in occupied buildings. Occupant behaviour is also weakly represented, even though occupants affect heating, cooling, ventilation, lighting, plug loads, and window operation. Generalization is another challenge, and some algorithms require expert knowledge to set parameters, select objective weights, or interpret Pareto fronts.

Future work should pursue five directions. Optimization platforms should become more user-oriented; building-level studies should expand toward district and urban systems; human-in-the-loop models should include comfort diversity and behaviour; the field needs standardized building-energy benchmarks; and algorithm selection should be studied through automated machine learning and meta-optimization.

8. Conclusion

This review has examined five algorithmic approaches to energy-saving optimization in buildings and related construction processes. The studies show a clear shift from isolated heuristic search toward hybrid, surrogate-assisted, adaptive, and data-integrated optimization. ANN-GA improves retrofit optimization by reducing simulation time; NSGA-II-MOPSO improves multi-objective envelope design by combining diversity with fast convergence; ENTGWO improves load-prediction accuracy through entropy-guided adaptation; BIM-DQN links digital construction information with sequential decision-making; and FPO/MOFPO extends bio-inspired search to complex multi-objective energy scheduling.

The overall lesson is that algorithmic innovation matters most when it is connected to real building

decisions. Energy saving requires not only mathematical performance but also usable outputs, understandable trade-offs, and compatibility with engineering workflows. The reviewed methods contribute to this goal by reducing computational burden, improving prediction and scheduling accuracy, and helping designers and managers explore competing objectives.

At the same time, algorithm-based optimization should not be treated as a complete solution by itself. Buildings are socio-technical systems. Their performance depends on climate, equipment, maintenance, user behaviour, finance, regulation, and construction quality. Future research should therefore integrate optimization algorithms with transparent data, practical interfaces, real-time validation, and human-centred objectives. If these challenges are addressed, intelligent optimization can become a powerful tool for reducing energy consumption and supporting the transition to low-carbon built environments.

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