Summary of Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale

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INTRODUCTION

Summary by Ray Marange Climate change is accelerating, and buildings are a major contributor, responsible for 39% of U.S. primary energy use. With urbanization surging and building stock/demand expected to double by 2060, improving building efficiency is no longer optional but urgent. While AI has transformed industries such as healthcare and finance, its potential in building energy efficiency remains underexplored. AI demonstrates significant potential to reduce costs, enhance benefits, and improve safety across the building lifecycle. This study [1] investigates how AI can reduce energy consumption and carbon emissions in medium-sized office buildings, offering a scalable framework that could be applied globally. We will explore four key areas: **Results**, **Discussion**, **Methods**, and **Takeaways & Reflections**. The study focuses on medium-sized offices, and the results can be extrapolated to offices of any size.

AI'S IMPACT ON ENERGY AND EMISSION REDUCTIONS

Summary by Dwayne Mark Acosta

According to the 2012 U.S. Energy Information Association (EIA) survey, office buildings have the highest energy consumption among commercial types (20%), with a median energy use intensity (EUI) of 167 kWh/m^2 (EUI_{base}). In contrast, 67 verified low-energy office buildings reported a median EUI of 57 kWh/m^2 (EUI_{HEEB}). The difference between the baseline and best practice energy performance yields a technical energy efficiency saving (TEES) of 110 kWh/m^2. TEES can be improved in four categories: equipment, occupancy influence, control and operation, and design and construction.

This study focuses on medium office buildings, which comprise 70% of total office energy use. The Department of Energy's (DOE) EnergyPlus tool, defined by ASHRAE Standard 90.1, was used to simulate the annual building energy consumption of medium office buildings across four climate zones (1A, 3B, 4A, 5A) using representative U.S. cities. Both electricity and natural gas use were considered, with gas assumed to supply hot water and heating.

To estimate the TEES, a set of 24 improvement cases was developed by varying key design parameters. These include 9 cases for equipment efficiency, 9 for design and construction, and 6 for occupancy-related behavior and control. The cases, based on conservative assumptions, are summarized in Table II, and their contributions to total annual energy savings across different climate zones are illustrated in Figure 2. The results represent the maximum technical potential achievable through simulation, achieving these savings in practice may require substantial effort throughout the building lifecycle. AI technologies such as fault detection, smart sensors, robotic construction and others can help automate and streamline this process at lower cost and reduced labor.

Key Takeaway/Thoughts: Although simulation results suggest that TEES across the four categories can range from 6% to 27%, the paper assumes highly optimized performance which is often difficult to achieve in practice due to real-world constraints. While AI technologies may support these optimizations, their effectiveness is not guaranteed and remains highly dependent on a wide range of factors including data quality, user adoption, and integration with current systems.

AI'S REDUCES EMISSIONS OF BUILDINGS

Summary by David Franz

Primary focus of modeling

The paper focuses on two ways that AI can reduce the emissions of buildings.

1) By helping scale up the technologies and speed adoption by reducing the construction and labor costs;
2) By helping reduce emissions in ongoing maintenance and any new construction over the entire building's lifetime.

Scenarios simulated

The paper uses the results gained from the previous section to **simulate six scenarios**. The data is used to estimate parameters for use with complex simulation software to attempt to model the potential lifetime impact on emissions.

Scenario	Energy Use (kWh/m^2)	CO_2 Emissions (kg/m^2)
Baseline	200	50
AI Optimized	150	30

TABLE I
ENERGY USE AND CO_2 EMISSIONS FOR DIFFERENT SCENARIOS.

1) Frozen with current building efficiency;
2) BAU without AI;
3) BAU with AI;
4) Three policy-driven scenarios promoting high-efficiency energy buildings and net-zero energy buildings, and other policy implementation to achieve zero emissions by 2050.

Simulation results

The results of the simulation are shown below.

Table I shows the energy use and CO_2 emissions for different scenarios.

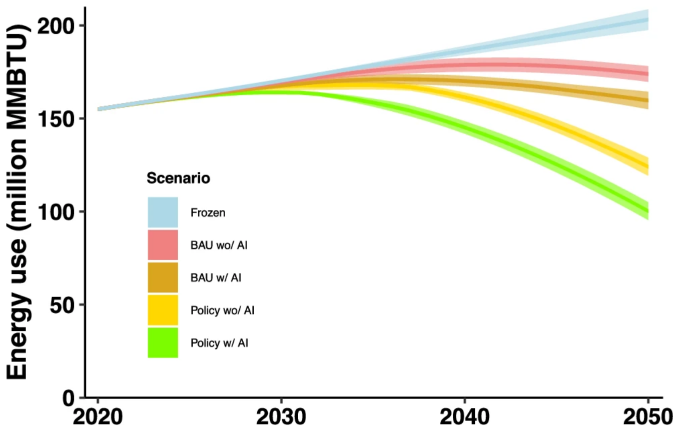

Fig. 1. Different energy use scenarios.

Key insight

"The scenario with AI leads to a higher market share of HEEBs and NZEBs over time compared with the scenario without AI. This trend continues until the market share of net NZEBs reaches its maximum share."

The paper asserts that using AI in the ways that they propose always leads to a higher market share of efficient buildings.

Thoughts on result

The paper examines various scenarios with some amount of estimation for unknowns, so each individual simulation is unlikely to be exactly right. However, the fact that all scenarios trend in a downward direction for energy use and CO_2 emissions suggest it is highly likely that AI would have some impact on building emissions, but the current lack of data leading to necessary estimation means that the current degree of this impact is still unclear.

DISCUSSION

Summary by Mohamed Amine Benaziza

Method and Scope

The study uses a combination of engineering and energy-simulation approaches, rather than focusing on a single AI technology, to estimate how AI can boost building energy efficiency and reduce carbon emissions. While the analysis centers on a medium-sized office building, the methodology is adaptable to other commercial building types with appropriate adjustments.

Why AI Helps

AI enables data-driven modeling, which can tailor solutions to specific buildings and lower costs. This accelerates the adoption of high-efficiency and net-zero-energy buildings (HEEBs and NZEBs). The paper also notes that advanced control models, such as deep learning and reinforcement learning, could further improve accuracy in future work.

Key Analytical Structure

The paper evaluates the theoretical maximum savings achievable over a building's lifetime. It highlights that different climate zones offer varying saving potentials, but in all cases, AI can help buildings achieve these potentials at lower costs.

Quantified Impacts (US Medium Offices)

- By 2050, AI adoption alone is projected to reduce energy use and CO_2 emissions by approximately 8% compared to the "business as usual" (BAU) scenario.
- When compared to a policy-only scenario, AI provides an additional 19% in savings.
- The combination of AI, strong efficiency policies, and low-emission power generation (LEPG) could result in up to 40% less energy use and 90% less CO_2 emissions than BAU.

Limitations and Future Work

The results depend on assumptions about cost declines and adoption rates. Additionally, the methodology has not yet been tested on other building types, which may limit the generalizability of the findings.

Take-aways and Thoughts

1) **Paper's Goal:** The main contribution is not a new algorithm, but rather the demonstration that AI can make existing high-efficiency designs more affordable, thereby unlocking a larger market share for these technologies.
2) **Role of Policy:** On its own, AI delivers modest (single-digit) gains. The substantial reductions of 40% in energy use and 90% in CO_2 emissions are only achieved when AI is combined with LEPG and clear regulatory policies.
3) **Scalability:** Expanding these results to other sectors will require further investigation and the development of skilled facility management teams.

METHODS

Summary by James Thompson

This paper makes a few claims around the potential energy use reduction that can happen now and as different future scenarios play out. For them to calculate the potential savings you need models and numbers to put in the models. I feel that in this study they have used simple models and come up with some numbers without adequately backing them up. Therefore I feel that their conclusions are not as strong as they could be, and future forecasted graphs feel like they could of just been drawn by hand [1].

Energy saving potentials

The first model they use is particularly simple which is the just the summation of the potential saving across the four areas of the building mutiplied by the base energy use. The values of potential savings are calculated using the building simulations and other literature. This is the strongest and most reliable model they use.

Market share of HEEB and NZEB in the future

The next models they use are for studying how different scenarios will play out. The first model is a discrete choice model that calculates what share of a population will take a particular choice . The share is calculated as simply a ratio of its availabiltiy and utilty and the sum of other choices availability and utilty E 1. The utility of each type of building is calculated by using a future discounted sum of the net benefit at each time Eq 2.

The last model is used to calculate the cost of the differnet buildings. Specifcally high energy efficient buildings (HEEB) and net zero energy buildings (NZEB). Having a look at Eq 3 there are three things parameters they have set. Firstly is how much more epxensive NZEB are then HEEB buildings. Secondly is how quickly this premium will decrease autonomosly and due to policy. Lastly is how much AI will decrease the premium.

The cost premium of NZEB buildings over regualr buildings is 13-19% when looking at the four climate zones with HEEB buildings being about 5% cheaper than NZEB. These figures are estimated from construction cost data. The amount the premium will decrease autonomously and due to AI seem to have no baseing. Furthermore AI is simply assumed to decrease the cost premium by an extra 10% overall without any justification.

The last part to the model of the market share is availability, while not stating explcitly how it is done the availability is a combination of retrofiting old buildings and maximum amount allowed in the market. The NZEB buildings have a market share cp of 59%-79% depending on the scneario. With an estimated annual retrofit of 0.5%-3.5% depending on scenario. These values have been estiamted by the author with some being adpated from previous studies. In this they assume AI can increase the maximum share by 2%.

[1] I think that Thane Ruthenis (prominent commentator of AI forums) comment says it best [2]

$$\text{share}_{i,t} = \frac{a_{i,t} \exp\left(u_{i,t}\right)}{\sum_{i=0}^{N-1} a_{i,t} \exp\left(u_{i,t}\right)} \tag{1}$$

$$u_{i,t} = \sum_{t}^{\max_t} d_t (B_{i,t} - C_{i,t}) \tag{2}$$

$$\begin{aligned} C_{i,t} = CC_0 + \nabla CC_k \times (1 - \alpha_{k,t} - \xi_{k,t}) + \\ DC_0 + \nabla DC_k + (1 - \beta_{k,t} - \zeta_{k,t}) \end{aligned} \tag{3}$$

REFERENCES

[1] C. Ding, J. Ke, M. Levine, and N. Zhou, "Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale," *Nature Communications*, vol. 15, no. 1, p. 5916, Jul. 2024.

[2] T. Ruthenis. A deep critique of AI 2027's bad timeline models - comment. [Online]. Available: https://www.lesswrong.com/posts/PAYfmG2aRbdb74mEp/a-deep-critique-of-ai-2027-s-bad-timeline-models#fnrefij8bs5zqpa

APPENDIX

TABLE II
SUMMARY OF ENERGY EFFICIENCY IMPROVEMENT CASES ACROSS ALL CATEGORIES

Case	Improvements	Adjustments
Equipment Efficiency Improvements		
E1	HVAC – Cooling	+20%
E2	HVAC – Heating	+12%
E3	HVAC – Cases E1 and E2	+20%, +12%
E4	Lighting – Power density (LPD)	-15%
E5	Lighting – Power density (LPD)	-21%
E6	Equipment – Power density (EPD)	-10%
E7	Equipment – Power density (EPD)	-20%
E8	Combined – Cases E1–E7	
E9	Case E8 + Heat Pump for space heating	
Design and Construction Improvements		
D1	Orientation	East (90° rotation)
D2	Orientation	South (180° rotation)
D3	Orientation	West (270° rotation)
D4	Envelope (walls, slabs, roofs, windows)	High insulation
D5	Envelope (walls, slabs, roofs, windows)	Increased infiltration (60%)
D6	Window-to-wall ratio (WWR)	Variation 1
D7	Window-to-wall ratio (WWR)	Variation 2
D8	Window-to-wall ratio (WWR)	Variation 3
D9	Combined – Orientation, insulation, WWR	
Occupant Behavior and Control Improvements		
B1	Ventilation control	Open/close windows
B2	Lighting use	Switch on/off lights
B3	Electricity consumption	Turn off plug loads
B4	Lighting use	Dim lights
B5	HVAC	Turn on/off HVAC systems
B6	Thermostat	Adjust thermostat settings
Energy savings: Equipment = 11.5–17.3% Design and Construction = 5.9–9.1% Occupant Behavior and Control and Operation = 15–20%		

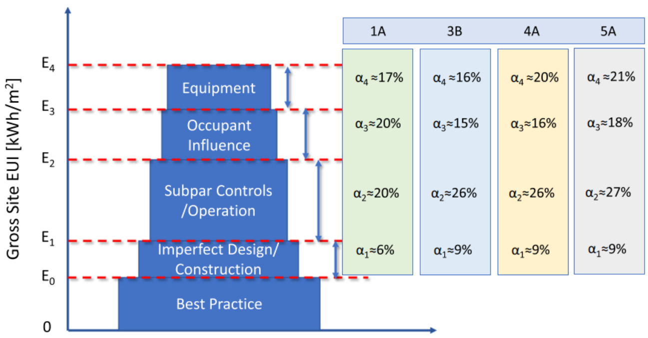

Fig. 2. Integrated building energy-saving breakdown by category and climate zone.