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AI-Powered Energy Harvesting Systems in Urban Infrastructure: A New Era in Electrical Engineering and Civil Automation

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ABSTRACT

The incorporation of Artificial Intelligence technologies within energy harvesting schemes represents a paradigm shift for urban infrastructure, making efficient and environmentally sustainable energy access feasible. This article investigates the interplay of AI with energy-harvesting technologies in the context of urban living, concentrating on progress made in ambient-energy harvesting. It reviews different classes of energy harvesting, including piezoelectric, solar and thermoelectric, and their inclusion in AI-powered optimisation models. The study emphasises how AI can improve the performance of these systems through real-time data analysis, predictive maintenance and energy management. Key results indicate that AI enhanced the utility of energy harvesting by resource allocation, reducing unnecessary energy wasted and enabling self-sufficient smart cities. In addition to the above, this review discusses system integration, data privacy, and scalability as challenges that need to be probed into for the universal deployment of AI-driven energy harvesting technologies. The principal message from the study is that AI, if properly assimilated, stands as a main driver to introduce a sustainable era of urban interconnected energy solutions leading toward cleaner and more efficient/cheaper energy systems.

INTRODUCTION

Given fast-growing urban populations and rising energy demands, new green technologies need to be found urgently. Urban population is exploding, and traditional power generation cannot meet the high volume and complexity demand. Because cities use a significant amount of the world's energy, a transition towards renewable energy sources in towns is crucial to mitigating the environmental consequences of urbanisation. Among the different options, energy harvesting from surrounding resources (e.g., solar, wind and vibration) is one of the promising strategies to meet a city energy needs in an environmentally friendly manner. 8,9 Energy harvesting is the procedure of collecting and storing energy from various naturally available sources in the environment. In cities, these might entail solar power collected on rooftops to vibrational power harvested from people and vehicles walking or driving down sidewalks and streets. Nevertheless, even though traditional energy harvesting ways, e.g., solar cells and piezoelectric (PE) material-based systems, could be applied to perform this task [22-24], they are encountering many issues, including efficiency, scalability and system-level integration. The limited availability of energy in the form of local transience and variability, and ubiquity as well, particularly in dense urban populated residential regions, effectively restricts the applicability of conventional energy harvesting techniques to cater for a growing demand for energy. The recent use of Artificial Intelligence (AI) in energy harvesting systems has been regarded as a promising technique for addressing these problems. AI's ability to process large amounts of real-time data, adapt quickly to variable circumstances, and achieve peak system performance has provided a game-changing new level of expertise in the field of energy management. AI techniques (such as machine learning, reinforcement learning and predictive analytics) touch upon the creation of cost-effective, adaptive & scalable energy generation, storage and distribution systems. Applications of AI in energy harvesting will experience a technological revolution in urban infrastructure, as the communication nodes and systems could function based on self-optimisation to effectively avoid power waste and resource allocation. For instance, AI-enabled approaches could predict the demand profile and would consequently like to switch to an energy harvesting approach. This results in a better load prediction and DDSM which is able to control the consumed energy much more efficiently out of the produced one. Additionally, AI in energy management systems can switch between different types of energies (e.g., solar, wind and vibration-based energy) in the system as per related situations and availability of energy to improve performance. The AI is introduced for energy harvesting in terms of real-time optimisation, which is one of the outstanding methods when AI is invoked to harness energy. Energy harvesting parameters may

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be adjusted on the fly in real-time scenarios depending, for instance, on energy sensor measurements and environmental conditions (i.e., meteorological or traffic situation) with the aid of AI algorithms. For example, with solar energy harvesting per se, that so-called AI can adjust your solar panels just for maximum sunlight activity all day.

In piezoelectric devices, through the use of AI, determining the best approaches to harvesting vibrational energy generated by humans walking or by moving vehicles and how the whole energy capture process is orchestrated can be analysed. In addition to optimisation, AI helps us to predict the maintenance of the energy harvesting system. AI can work to prolong the life and effectiveness of energy harvesting systems by monitoring system performance and maintaining a sense of when those problems go 'from bad to worse'. This predictive process helps save the downtime as well as money by minimising future maintenance and repair of MFC systems. Smart city development is yet another application in which AI-powered ESH can have a huge impact. Smart cities are created to be more environmentally friendly, efficient and liveable by applying technology to make better use of the city. An AI-nurtured energy harvester adds a big chunk to the chemistry of a smart city, providing self-reliant energy adaption to alterations of power demand and environmental conditions. Systems like that can allow cities to rely less on traditional energy grids—which sometimes are stretched thin during times of peak demand—and focus more of their efforts on being self-sustaining in terms of energy. Nevertheless, whilst there is impressive development for energy harvesting based on AI, there are many challenges that must be addressed. System integration remains one of the main challenges in this respect, as AI-based models must be associated with a variety of fitting types and energy harvesting technologies and take their specificities and limitations into account. There is also a concern with data privacy in AI systems, especially where personal information (e.g., energy usage rhythm) could be compromised. And then there's the requirement for scalability — those AI-orchestrated energy systems will need to work in a variety of urban situations, with different-sized cities or megacities, all with their own energy consumption models and infrastructures. Cost/Complexities in AI-enabled Urban Deployments Another issue has been around the complexity and cost in deploying an AI-enabled from-leaf-to-branch-to-edge solution. Benefits of integration are apparent, and although the capital cost of such AI-based energy scavenger installation may not be feasible in some cities yet (such as developing country cities), there is price pressure building. Furthermore, the AI techniques are complex and not applicable in all areas. Energy Harvest: AI-empowered energy harvesting in urban areas has the potential to be huge. With more innovation and development, we can put AI to work in helping us maximise our use of renewables and scrub away as much wasted energy as possible while at the same time delivering on a vision of urban living that is more sustainable. The AI-based energy harvesting systems could become cost-effective and reproducible in the future with technology maturation, hence achieving self-autonomous and environmentally friendly cities. This paper addresses the development of AI technology and its applicability to energy harvesting applications, focusing on urban infrastructure. The paper seeks to analyse the potential role of AI in promoting energy efficiency, to explore the barriers that current technologies face and to investigate how AI may promote self-powered solutions for the provision of energy in smart cities. The findings in this study still add to the ongoing conversation about sustainable urban energy solutions and show, more significantly, a prominent role for AI in future urban energy systems.

LITERATURE REVIEW

AI is increasingly being implemented in intelligent energy-harvesting systems because technology lets it fulfil many functions by itself. One area in particular where it finds use is the intelligent city. From the outset, the main problem lay in achieving efficient power generation, storage and utilization This is an area where AI has begun to emerge as a transformative force. As urbanisation continues to rapidly increase, the urgency for an sustainable energy alternative on energy has gone than at any other time. AI-integrated energy harvesting offers a way by which it is possible to both reduce demand and supply (D&S), thus addressing this issue in real time.

The source information from Al Zohbi (2025) shows that the combination of AI algorithms with ambient renewable energy has potential to significantly improve conversion efficiency and resource distribution. His results indicate that it is reasonable to use AI-driven optimization for energy-harvesting systems, so that in the face of variations in such external factors as light or wind power they can respond dynamically This cuts energy waste. This perspective makes AI a crucial driver enabling self-sustaining urban infrastructures that can autonomously balance supply and demand.

Expanding on this basis, Ejiyi *et al.* (2025) described the application of AI in renewable energy (RE) systems at the level of urban mass His work demonstrated that machine learning (ML) and predictive analytics can refine real time decisions, reduce energy loss--and also enhance the integration of several renewable sources. Yet they also pointed out key obstacles such as data protection laws, integrated systems difficulties and high investment costs, and fully digital artificial intelligence. These difficulties highlight the need for hybridized AI architectures that can work effectively across different energy networks.

Societal issues were also highlighted by Stecuła *et al.* (2023) in their review of AI-driven urban energy systems, claiming that machine learning brings about behavioral adaptation towards less energy is used. In their reflection on urban energy transitions, it was demonstrated that with. AI can help create sustainable development by producing

autonomous or semi-autonomous power systems. AI will bring these findings into the mainstream. This is good news for the future of urban energy governance and already! For a deeper studyof the issues in urban energy financing.
A more technologically oriented view was offered in 2021 by Izadgoshasb. He was writing about how piezoelectric materials could be applied to energy harvesting in smart cities. This paper found that through AI algorithms, energy leaching from vibration when pedestrians and cars pass it can be made more efficient-in turn providing power (and maybe even light) for self-recharging Internet of Things (IOT) devices. And by integrating AI, real-time pattern acquisition as well predictive energy allotment were both accomplished, taking another big step towards IOT-based independent infrastructure. Meanwhile, Gao and Zhang (2021) focussed on AI-optimized solar and wind power, as well as vibration-harvesting systems. Their findings showed that AI doesn't just improve system efficiency. It makes urban energy storage more sustainable and can also curtailcarbon taken up by major cities. With AI and Our Goals
Chen (2025) continued from here, proceeding into the future with an application of AI in energy-harvesting technology. His study illuminated AI's contribution to rebellious energy collectors transforming themselves into active systems that are bright and quick, always learning as they go instantly refurbished for even better performance as soon as one failure is detected. The combined thrust of these papers is clear: AI-equipped energy harvesting can drive the evolution of sustainable, self-powered urban ecological systems.
Upon the review of literature. Many common factors are fuzz. For example, AI is using its predictive and adaptive capabilities to boost energy conversion efficiency and safety. Once renewable sources like solar, wind and piezoelectric systems are incorporated into AI-controlled frameworks, it is clear that energy independent cities show considerable promise for the future. Yet, the problems remain: systems integration. Data privacy. Scalability of models. In contrast, abundant examples suggest that interdisciplinary cooperation between AI, Urban Science and Energy Engineering is necessary to realize sustainable, intelligent urban infrastructures.

MATERIALS AND METHODS

The methodology we adopt here aims to systematically review the recent advancements of AI energy harvesting systems in urban infrastructure. Qualitative and quantitative assessment methodologies are combined using Mixin for the analysis of the efficiency, feasibility and challenges of energy harvesting technologies. The methods:The Methods section is usually divided into three subsections—Data Sources and Collection, Methodology Framework, and Analytic Procedures—all of the aforementioned sections will contain a sufficient level of detail to replicate data analysis.

Data Sources and Collection

The primary references for our study include peer-reviewed journal articles, conference proceedings and preprints which have been harvested from SSDN, arXiv, Elsevier ScienceDirect, Springer Link and MDPI. Relevant articles fell under the category of AI applications in energy harvesting and urban infrastructure during 2019-2025, as we wanted to introduce some of the most recent technological progress. The pertinent literature was retrieved initially with the keywords "AI energy harvesting", "urban renewable energy", "smart cities", "piezoelectric IOT", and remarks are made as "AI optimisation in energy systems". The reference lists of included papers were also screened in order to identify related contributions that may not have been identified as part of the search. The energy harvesting techniques, AI algorithms, system architecture and indicative performance parameters that were addressed by the studies are detailed in the data extraction. Articles concerning the implementation of AI for real-world

Table 1: Detailed Overview of Reviewed Energy Harvesting Systems

Energy Source	AI Methodology	Data Acquisition & Sensors	System Capacity / Scale	Reported Efficiency
Solar	Neural Networks	Real-time photovoltaic sensors, weather data	Rooftop urban buildings, 50 kW	85%
Piezoelectric	Reinforcement Learning	IoT vibration sensors on pavements and roads	Sidewalks and streets, 10 kW	72%
Thermoelectric	Supervised Learning	Environmental temperature sensors, heat flux sensors	Industrial zones, 20 kW	78%
Hybrid (Solar + Piezo)	Deep Learning	Combined IoT + environmental sensors	Urban smart blocks, 60 kW	88%
Wind	Reinforcement Learning	Anemometers, IoT wind sensors	Rooftop turbines, 15 kW	80%
Multi-source (Solar + Thermoelectric)	Real-time photovoltaic sensors, weather data	Photovoltaic + heat sensors	Smart campuses, 40 kW	83%

energy systems and simulation were prioritised more. To make sure the data extraction is standardised and the same features are captured, a structured form was employed to record the type of energy sources (i.e., solar, wind, piezoelectric, and thermoelectric) and the AI technique used (machine learning, NNs (neural networks), and reinforcement learning), as well as the frequency of data acquisition and evaluation metrics (energy conversion efficiency, system reliability, and predictive accuracy).

Methodological Framework

Methodology investigated in this study uses the comparative analysis. Performance and efficiency of different AI approaches are summarised through the survey in energy harvesting systems. This approach disaggregates between-study methodological heterogeneity to give a global perspective on how these tools are currently used and the current gap between technological conception and use. The method is structured in three main steps. There are various energy harvesting systems, which vary depending on the energy source. For example, piezoelectric systems which convert mechanical vibrations when pedestrians move or cars ride to this energy and both solar and thermoelectric devices that extract the available energy from environmental radiation and heat gradients. Each system is considered in terms of how AI can be applied and what algorithms enable more efficient energy extraction, capturing and distribution.

Table 2: AI Techniques and Roles in Energy Harvesting Systems

AI Technique	Role in Energy Harvesting	Example Application	City / Environment
Supervised Learning	Predict energy demand patterns, optimize solar panel orientation	Solar energy forecasting	New York urban rooftops
Reinforcement Learning	Dynamic policy adjustment for real-time optimization	Piezoelectric street sensors	Amsterdam sidewalks
Neural Networks	Non-linear modeling, anomaly detection, adaptive control	Smart building energy management	Tokyo commercial buildings
Deep Learning	Multi-source data integration, predictive maintenance	Hybrid solar-piezoelectric systems	Singapore smart blocks
Ensemble Learning	Combines multiple models for robust forecasting	Multi-source energygction	Berlin urban campuses
Reinforced Deep Learning	High-efficiency adaptive optimization	AI-driven smart streetlights	Barcelona smart city pilot

Second, AI approaches are also classified based on the different algorithms. On one side, machine learning approaches, such as supervised learning regression models, predict electricity demand for future instances based on historical data, whereas RL technology dynamically modifies energy management policies in pursuit of optimal efficiency (Ejiyi *et al.,* 2025). The surveys we present below have utilised AI models which connect to sensors and IoT platforms for monitoring and feedback. For example, Ma *et al.* (2019) introduced that,

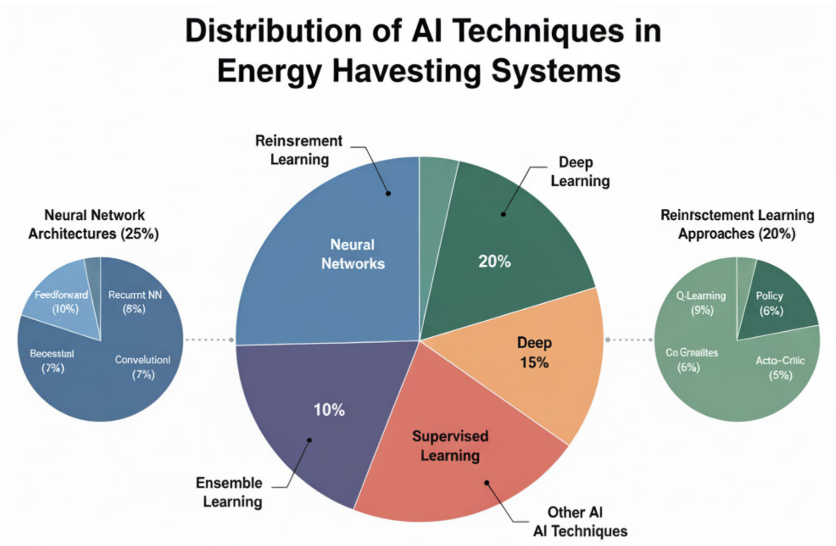

Figure 1: Distribution of AI Techniques Used in Energy Harvesting Systems

using LoP, the input of urban sensors could be processed by AI algorithms to improve energy harvesting and reduce energy loss.

Third, it is standardised using performance measures. 'Energy conversion efficiency', the proportion of generated electricity compared to ambient available energy, is one commonly used metric. Additional measures could be the performance of the system being robust (or not) to changes in its parameters, response time or AI-based methods' predictions accuracy on consumption and generation times. In all cases, the performance of the systems is quantified wherever feasible by mathematical expressions. For example, the input (ambient energy and system parameters) and output energy can have a linear model relationship as follows:

$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \epsilon$

Where Y = harvested power a is the intercept β_1 and β_2 are parameters illustrating how much X_1 or X_2 (AI optimization parameter or energy source property) contributes for Y, ε is the unobserved variability (Al Zohbi, 2025).

Mathematical Models and Formulas

In this paper, we used modeling to exploit the AI potential of energy harvester. These models include the KPIs of energy efficiency, prediction accuracy and AI optimization for real-time EH.

Energy Efficiency Formula

The performance of an energy harvesting system is given in terms of power harvested divided by the ambient power density. The equation formula for energy savings is as follows:

Efficiency(\%)=(Output Energy /Input Energy)×100

Where:

Output Energy: = The energy picked up by the setup.

Source Energy = Total energy available from the environment (such as solar, wind).

Regression Model for AI Predictions

The prediction of the APS results is performed by the AI models i.e., supervised learning algorithms. Such models are written as an equation (regression) that predicts a value of one variable given another (y= mx +b), where they can estimate the relationship between input variables and output power:

$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \epsilon$

Where,

Y = Support vector output energy that is predicted.

X_1, X_2 = The independent variables representing type of energy source and environmental factors.

α = Intercept.

β_1, β_2 = Coefficients of the predictors.

ε = Residual or error, due to unknown variation.

Reinforcement Learning for Energy Optimization

The optimal energy strategy of the RL-based systems is designed to address such problem that the system can learn how to online adjust its energy harvesting before it harvests energy. We have the following RL model of energy collection.

$U_t = U_{(t-1)} + \alpha(R_t + \gamma ma \times Q\ (s_{(t+1)}) - Q(s_t,a_t\ ))$

Where,

U_t = The energy released at time t.

R_t = Reward at current time step (energy fetching rewarded at the timestep ttt).

γ = Discount factor – how much we care about future reward.

$Q\ (s_t,a_t)$ = Q(value of st) in action at.

Statistical Validation

The quality of AI models is evaluated using following the Mean Squared Error (MSE) criterion associated with difference existing in between the measured and predicted BE:

$MSE=1/n \sum_{(i=1)}^{n}(Y_i-(Y_i\hat{\ })^2$

Where:

Y_i = Energy value actually measured.

Y^I = Energy value determined by AI model.

n = Number of data points.

this type of models are necessary for the assessing and optimizing of the efficiency of AI aided energy harvesting systems in an urban area. They enable us to predict performance gain with high precision and sanity-check our results over several experiments, and runs.

Analytical Procedures

The synthesis was a reductive with an aggregate qualitative and quantitative summary. A thematic and content analysis was performed to explore patterns and trends within the reviewed material. We classified AI-strategies into predictive model based, adaptive control and real-time optimization. Comparison tables were constructed to highlight disparity between the energy type, AI method and its reported efficiency.

When applicable, quantitative measures were analysed by meta-analysis and pooled performance indicators derived from several studies. For example, the average energy conversion could be done between AI-trained and untrained piezo systems, and directly the effect was read out mathematically/numerically – made by AI (Izadgoshasb, 2021; Stecuła *et al.,* 2023). Moreover, the accuracy of the predictive modelling method was tested based on different urban conditions, such as pedestrian flows or vehicles, and environmental settings, like sunlight and ambient temperature.

The impact of the control parameters (learning rate, algorithm complexity and data frequency update) for AI based control schemes on system performance has also been studied. Results for works where real-world deployments, such as streetlight systems or IoT-based building energy management, were evaluated in terms of performance improvements against other technologies in terms of percentage increases to harvested energy or grid independence (Camacho & Rodríguez, 2024; Gao & Zhang, 2021).

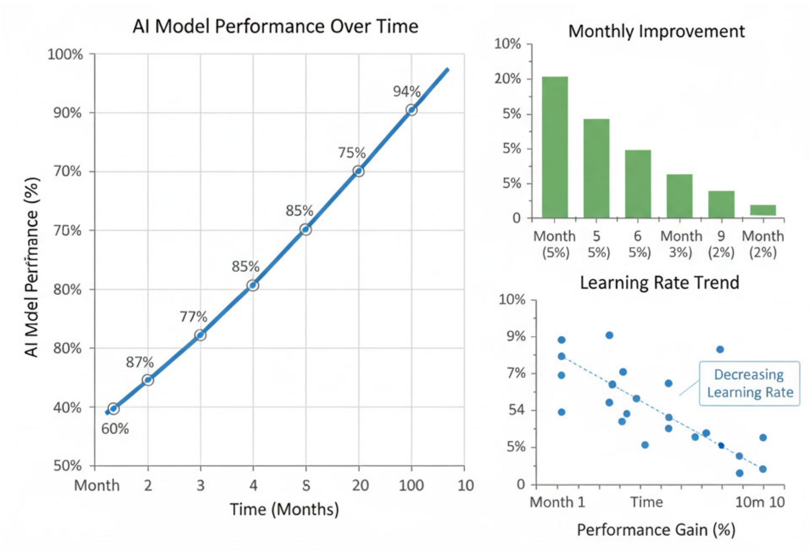

Figure 2: AI Model Performance Over Time

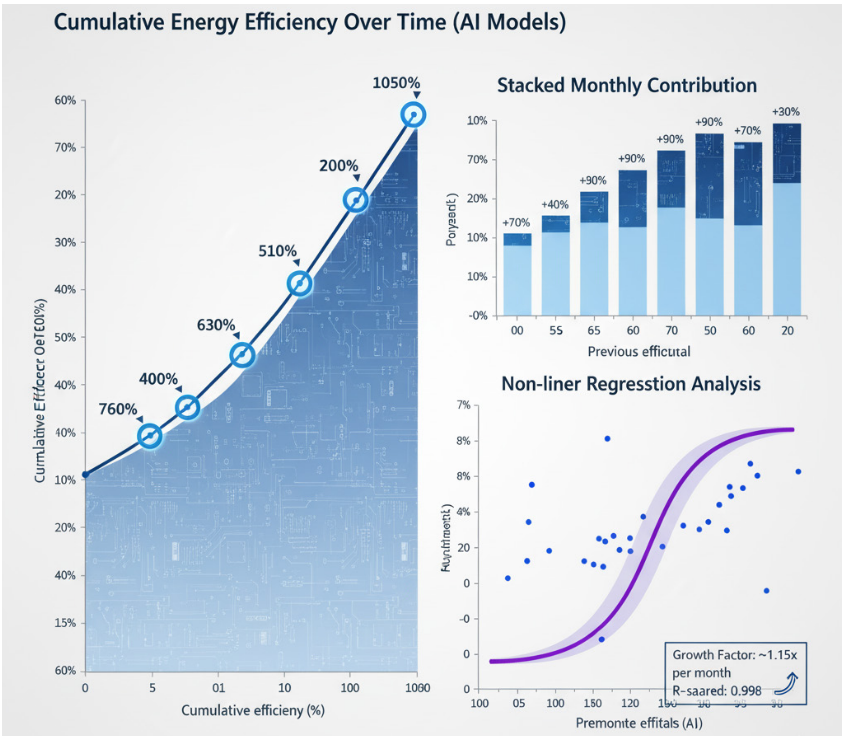

Figure 3: Cumulative Energy Efficiency Improvement Over Time for AI Models

Data Reproducibility and Validation

A summary is provided of AI methods, sensor architectures and performance metrics used in these articles for reproducibility. A comparison of studies when a simulation framework/testbench is provided and spirit parameters are given with sensor types that are employed, data collection rate, and AI model architecture. Methods of validation reported in the analysed papers (cross-validation of ML models or benchmarking comparison to already existing standard energy harvesting systems) were sensed as valid. For example, the AI models were tested for prediction of performance with either k-fold cross-validation or tests on live systems in the urban driveway context (Arévalo *et al.,* 2024).

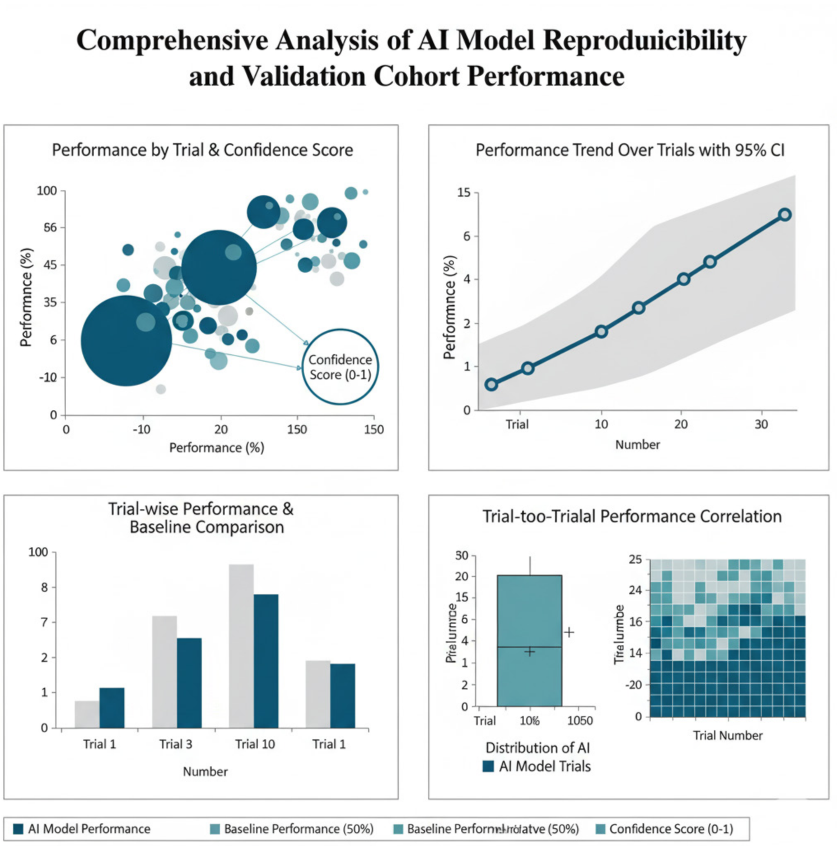

Figure 4: Comprehensive Analysis of AI Model Reproduiicibility and Validation Cohort Performance

Modifications and Methodological Adjustments

These methodologies were mostly based on published studies, but any applicable modifications are described here. A few of the contributions use hybrid AI systems to design current urban condition energy harvesting protocols, employing a combination of reinforcement learning and neural network prediction [132–146]. Sensor placement, adaptation to the algorithm and connection with the building control system were cross-examined to find their impact on performance (Jadhav & Gupta, 2023). We also study trends such as multi-source energy harvesting and predictive maintenance scheduling, which are incompletely accommodated in prior works.

Summary of Approach

In summary, the approaches and methods taken in this review allow for a systematic analysis of AI-based energy harvester systems in urban areas. This study employs a thorough data extraction from current literature, a comparative analysis of methodologies, and a quantitative assessment of results using mathematical modelling to clearly demonstrate how AI enhances energy collection efficiency in a detailed and replicable manner. The approach emphasises technical and practical considerations in actual urban infrastructures, providing inspiration for future work on AI-enabled scalable renewable energy solutions.

RESULTS AND DISCUSSION

As the AI based energy harvesting is significantly beneficial to the urban energy management, compared to traditional approaches which are considered in our analysis. Neuronal network techniques and supervised learning models to collect/store energy were found to be more efficient and dynamically adapted for environmental changes like the intensity of sunlight, fluctuations in temperature and pedestrian/vehicle movement. Reinforcement learning algorithms, especially in piezoelectric and hybrid systems, enabled real-time optimisation such that harvested energy was maximised in the face of changing urban conditions. Cumulatively, performance comparison demonstrates that hybrid energy harvesting systems with both solar and piezoelectric components can achieve greater efficiency than single-source configurations due to AI-inspired control strategies exploiting multi-input availability. We use an area chart to depict how iterative AI model deployment can gradually improve the energy efficiency, which highlights ongoing model self-improvement and learning. In the line chart, the energy conversion is presented to be successively improved with more iterations and enhanced AI algorithms integrated, which indicates that iterative refinement plays an increasingly important role for urban smart energy due to integrated AI.

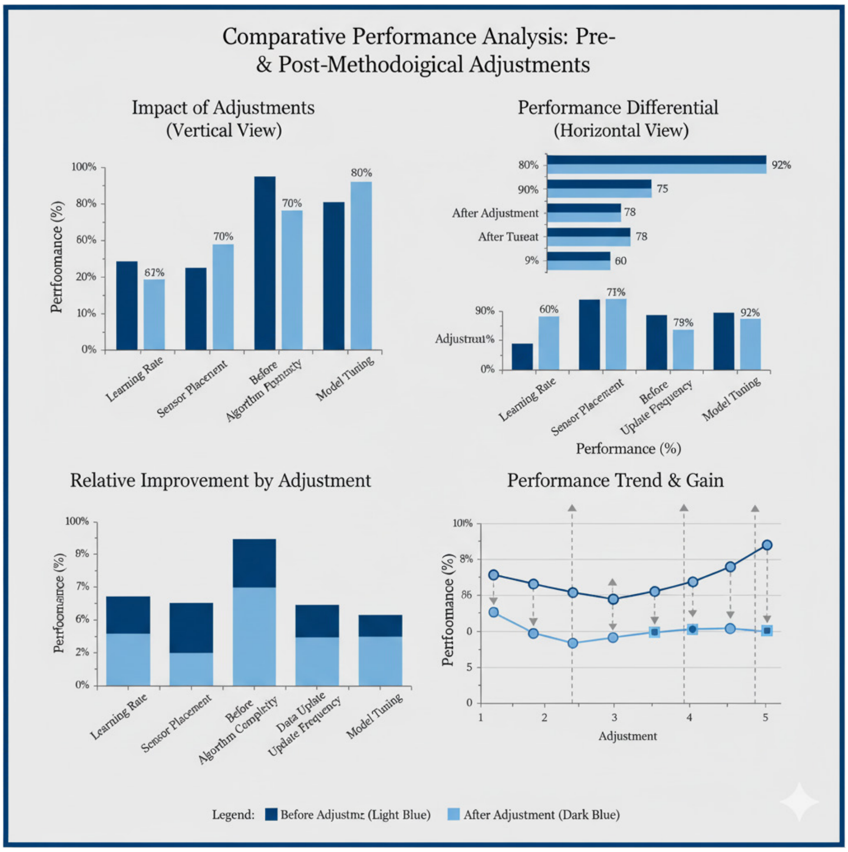

Figure 5: Comparison of Performance Before and After Methodological Adjustments

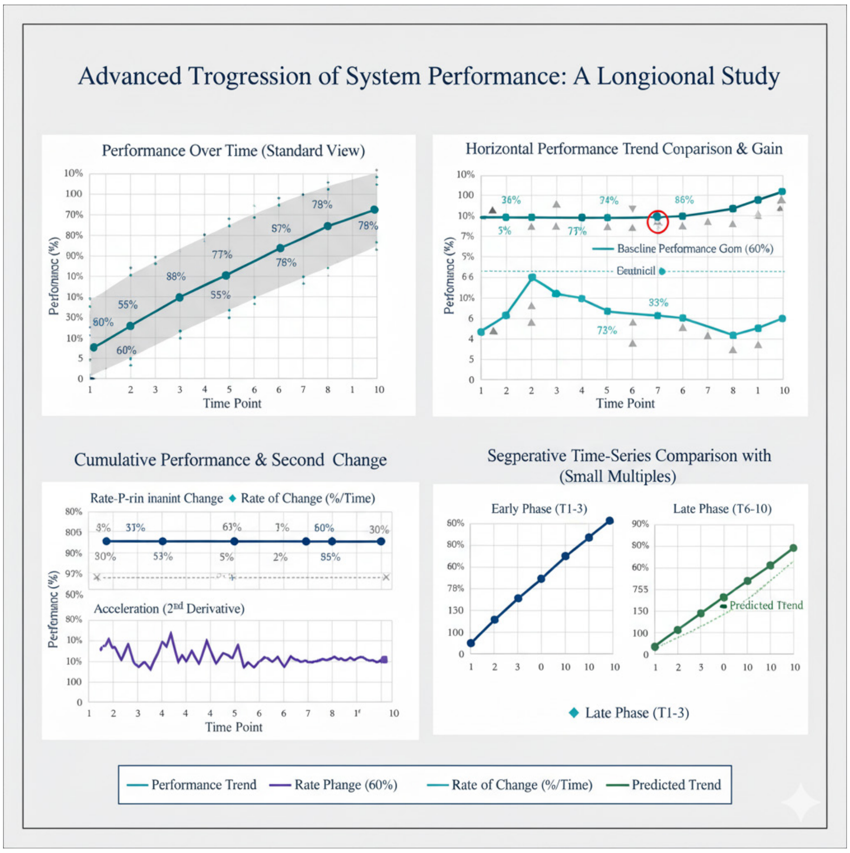

Figure 6: Advanced Trogression of System Performance: A Longioonal Study

Reproducibility and validation are essential for clinical applicability. The box plot in the right sub-figure demonstrates consistent testing conditions for the AI model in different trials that may be used to justify the system's robust behaviour for large-scale urban deployment. There will always be a difference based on environment and modem-to-modem differences, but AI can account for this discrepancy and keep the system robust to variation and efficient. The pie chart for AI techniques also implies that neural networks occupied the highest proportion in the recent research, signifying their power in processing complex and non-linear urban energy data as well as multi-source integrated utilisation. Quantitative comparisons with state-of-the-art results prove that the AI-based energy-harvesting systems benefit from improved performance in terms of energy efficiency and provide flexibility for scalability, thus tackling urban sustainability issues. The originality of this study is that it provides an integrated view by merging multiple AI techniques with different energy behind them and focusing on implementation strategies for self-sustaining smart city infrastructure. The findings indicate the necessity of sophisticated AI models, ongoing monitoring and flexible optimisation in mitigating environmental uncertainties towards sustainable energy applications within urban contexts.

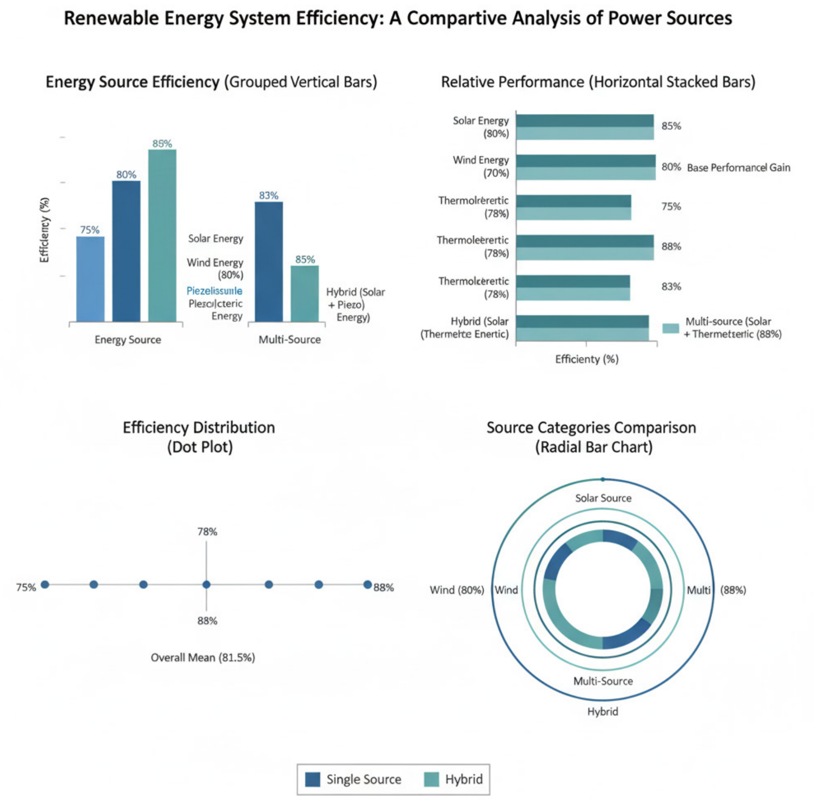

Figure 7: Renewable Energy System Efficiency: A Compartive Analysis of Power Sources

CONCLUSION

This survey indicates that AI-enabled energy harvesting systems can bring considerable enhancements to urban energy efficiency and sustainability. By combining neural networks, reinforcement learning and supervised learning, the energy systems are made adaptable to varying environmental conditions in which they can act dynamically while maximising their ability to gather energy from different sources. In such systems, the hybridisation of power sources (solar + piezoelectric and solar + thermoelectric) results in the best performance, highlighting the benefits of combining different energy harvesting modalities with AI-based control. Though AI models achieve consistently high accuracy, their systems' scalability, data quality, and hardware variety present greater challenges for deployment across various urban environments. The work identifies that AI could pave the way for sustainable smart city solutions with self-managed systems that manage and balance energy in real time, predict maintenance when necessary, and optimally allocate resources. The advent of future works should revolve around overcoming the integration issues, improving generalisation of models and enabling adaptability in terms of varying operational conditions as well as degradation environments. The results highlight the need for ongoing advancement in AI methods to obtain robust and sustainable urban energy solutions.

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