Procedia of Engineering and Life Science Vol. 8 No. 2 (2025)
Proceedings of the 8th Seminar Nasional Sains 2025
Universitas Muhammadiyah Sidoarjo

Artificial Intelligence for a Circular Economy of Renewable Energy Infrastructure: A Comprehensive Review of AI-driven Solutions for Recycling, Repurposing, and Environmental Lifecycle Management of Solar Panels and Wind Turbines

Kecerdasan Buatan untuk Ekonomi Sirkular Infrastruktur Energi Terbarukan: Tinjauan Komprehensif tentang Solusi Berbasis Kecerdasan Buatan untuk Daur Ulang, Penggunaan Kembali, dan Pengelolaan Siklus Hidup Lingkungan Panel Surya dan Turbin Angin

Mahmood Jamal Abdulhasana, Safwan Nadwehb, Aya Haider Khader c, Yaqoub Shamal Shayyish Al Rumaidh d
{M.aljaberi@utq.edu.iq; safwan.mehriz@ijsu.edu.iq; Aya.Haider.ph@utq.edu.iq ;}
a Department of Pharmaceutical Sciences, College of Pharmacy, University of Thi Qar, Nasiriyah, Thi Qar, Iraq
b Department of Computer Engineering, Technical Engineering Collage, Imam Ja'afar Al-Sadiq University, Bagdad, Iraq
c Department of Pharmacognosy and Medicinal Plants, College of Pharmacy, University of Thi-Qar Thi-Qar, Iraq
d Department of Pharmaceutical Sciences, College of Pharmacy, University of Thi Qar, Iraq

Abstract. *General Background: The rapid global deployment of solar photovoltaic and wind energy systems is central to climate change mitigation but generates a growing end-of-life waste challenge. Specific Background: By 2050, cumulative waste from solar panels and wind turbine blades is projected to reach tens of millions of tons, while current linear recycling systems face technical inefficiencies and economic constraints. Knowledge Gap: There is a lack of scalable and economically viable circular management solutions capable of addressing complex composite materials and lifecycle optimization in renewable energy infrastructure. Aims: This study systematically evaluates Artificial Intelligence applications across the lifecycle of solar panels and wind turbines to assess their role in enabling circular economy strategies. Results: Based on a systematic review of 496 publications and quantitative synthesis, AI-driven solutions demonstrate 35.8% carbon emission reduction per recycled solar panel, 33% improvement in material recovery rates, 43.8% gains in disassembly efficiency, and 62.5 kg CO2 savings per logistics operation. Novelty: The study develops an integrated analytical framework linking Machine Learning, Computer Vision, Robotics, Digital Twins, and lifecycle assessment within renewable energy circularity. Implications: The findings support AI-enabled reverse logistics, Digital Product Passports, and policy-informed lifecycle management as foundational mechanisms for sustainable renewable energy systems.*
Keywords: *Artificial Intelligence, Circular Economy, Renewable Energy Systems, Lifecycle Assessment, Waste Management*

Abstrak. *Latar Belakang Umum: Penyebaran global yang cepat dari sistem tenaga surya fotovoltaik dan tenaga angin merupakan kunci dalam mitigasi perubahan iklim, namun menimbulkan tantangan limbah akhir masa pakai yang semakin besar. Latar Belakang Khusus: Pada tahun 2050, limbah kumulatif dari panel surya dan bilah turbin angin diperkirakan mencapai puluhan juta ton, sementara sistem daur ulang linear saat ini menghadapi ketidakefisienan teknis dan kendala ekonomi. Kesenjangan Pengetahuan: Terdapat kekurangan solusi manajemen sirkular yang skalabel dan ekonomis yang mampu menangani bahan komposit kompleks dan optimasi siklus hidup dalam infrastruktur energi terbarukan. Tujuan: Studi ini secara sistematis mengevaluasi penerapan Kecerdasan Buatan (AI) sepanjang siklus hidup panel surya dan turbin angin untuk menilai perannya dalam memfasilitasi strategi ekonomi sirkular. Hasil: Berdasarkan tinjauan sistematis 496 publikasi dan sintesis kuantitatif, solusi berbasis AI menunjukkan pengurangan emisi karbon sebesar 35,8% per panel surya yang didaur ulang, peningkatan 33% dalam tingkat pemulihan material, peningkatan 43,8% dalam efisiensi pembongkaran, dan penghematan 62,5 kg CO2 per operasi logistik. Keunikan: Studi ini mengembangkan kerangka analitis terintegrasi yang menghubungkan Machine Learning, Computer Vision, Robotics, Digital Twins, dan penilaian siklus hidup dalam konteks sirkularitas energi terbarukan. Implikasi: Temuan ini mendukung logistik terbalik yang didukung AI, Paspor Produk Digital, dan pengelolaan siklus hidup yang didasarkan pada kebijakan sebagai mekanisme dasar untuk keberlanjutan.*
Kata Kunci – *Kecerdasan Buatan, Ekonomi Sirkular, Sistem Energi Terbarukan, Analisis Siklus Hidup, Pengelolaan Sampah*

I. INTRODUCTION

The current process of global movement towards sustainable energy system is typified by unprecedented implementation of renewable energy infrastructure. The solar photovoltaic (PV) and wind power capacity is currently being deployed at a faster rate, and it is estimated that the two will be the backbone of the future power grid [1]. Nevertheless, this achievement presents another major issue; management of end-of-life (EOL) of these assets. By 2050, it is estimated that the total waste of solar panels will amount to 78 million tons of waste in the world, and 43 million tons of waste due to decommissioned wind turbine blades [2], [3]. The environmental risks posed by this impending wave of waste are very severe such as the possibility of leaching of heavy metals such as lead and cadmium through the solar panels and landfilling of complex and non-biodegradable composite material through wind turbines thus defeating the essence of renewable energy which is environmentally-friendly [4]. Figure 1 shows the projected global waste from renewable energy infrastructure (2020-2050).

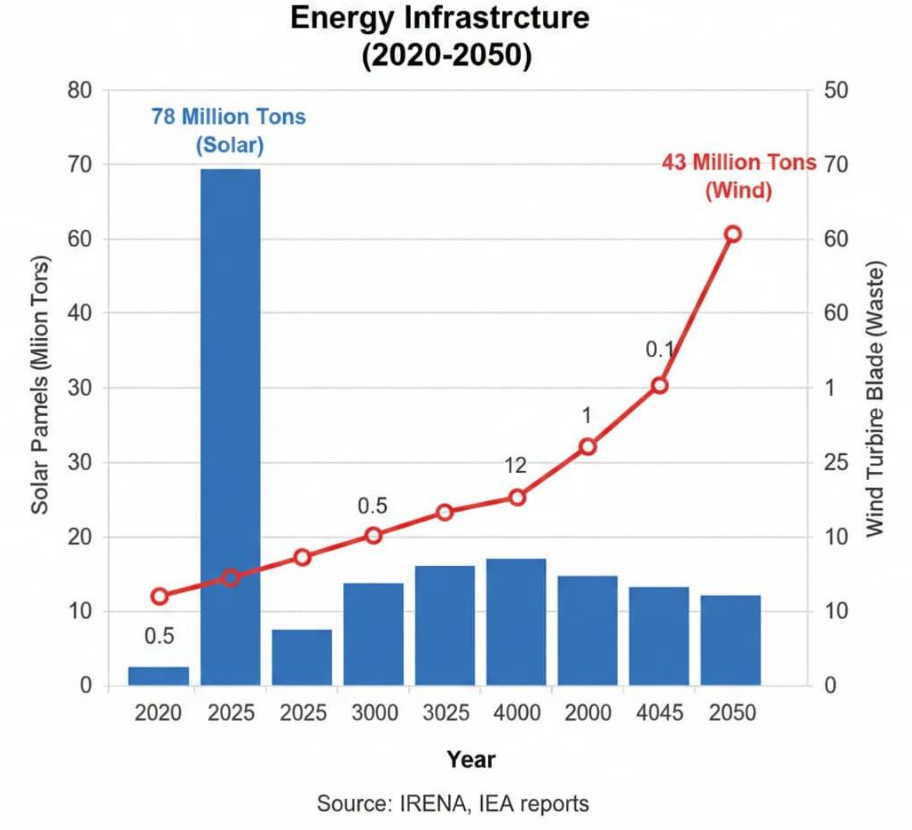

Figure 1: Projected Global Waste from Renewable Energy Infrastructure (2020-2050)

To solve this predicament, there is an urgent need to radically change the paradigm of a linear take-make-dispose mode of operation to a Circular Economy (CE) [5]. Within the framework of energy infrastructure, a CE is designed as an industrial system that is restorative and regenerative in nature, whereby there is always an aim to maintain the value of products, components and materials at the highest usefulness [6]. It is done through the main aspects of narrowing resource loops (less material), slacking resource loops (longer product life), and closing resource loops (recycle the material into the economy) [7]. In the case of solar panels and wind turbines, it corresponds to the CE strategies directed at manufacturing, direct reuse, the remanufacturing of the components, and the high-value material recycling [8].

Although the conceptual potential of a CE is quite obvious, there exist significant technical and economic bottlenecks in the practical implementation of this concept in relation to the renewable energy infrastructure [9]. The problem facing the recycling of solar panels is the high cost of disassembling them through labor intensive processes and the contamination of the glass that lowers the value of the glass and inefficient recovery of valuable material such as silicon and silver [10]. Likewise, recycling of wind turbines encounters significant challenges, especially in the decoupling of tough composite materials of the turbines, practical logistical challenges of transporting large parts, and creation of cost-effective and high-value recycling routes of streams of resultant products [11]. These bottlenecks make most of the existing recycling activities financially unsustainable and restrict the magnitude of repurposing projects [12].

The new force that can serve as the catalytic enabler to break these barriers is Artificial Intelligence (AI). Transformative potential exists in such advanced fields of AI as predictive modeling and process optimization by use of Machine Learning (ML), automated identification and sorting by Computer Vision (CV), and precise disassembly with Robotics, and virtual simulation and lifecycle management through Digital Twins [13], [14]. The hypothesis of this review is that AI-driven solutions will alleviate the severe technical and economic constraints and the EOL of renewable resources will become one of the sources of value creation and the component of a sustainable energy system [15].

The areas of this broad review are clearly narrowed down to the uses of AI to support a circular economy of solar panels and wind turbines. It does not have sight of other renewable energy technologies. The main aims of the research are:

1. To identify and enlist the state-of-the-art AI-driven solution to the recycling, repurposing and lifecycle management of solar panels and wind turbines systematically.
2. To critically examine how these AI applications respond to certain technical and economic issues in the CE framework.
3. To generalize the results to uncover the research gaps over time, operational problems, and the future of the field.

The booming international development of solar and wind energy infrastructure is creating a waste crisis in the future, with current end-of-life management practices that are characterized by technical inefficiencies and fail to achieve economic viability, and, therefore, cast the sustainability attributes of the renewable energy transition into doubt, and do not realize the latent value of decommissioned facilities.

The paper has three significant contributions that include: (i) it includes a new synthesis of the interdisciplinary research at the intersection of AI, circular economy, and renewable energy; (ii) it consists of the systematic framework of understanding and classifying applications of AI throughout the lifecycle of solar and wind assets; and (iii) it offers a critical roadmap to the future research, development, and policymaking in this area of emerging opportunities.

After this introduction, the literature review methodology is described in Section 2. Section 3 gives an intro to the basics of AIs applicable to CE. In section 4 and 5, respectively, the applications of AI to the solar panel and wind turbine are thoroughly analyzed. Section 6 discusses cross-cutting themes and the paper concludes with a synthesis of challenges and a research roadmap in the future in Section 7. Section 8 represents the conclusion of the paper, which summarizes the major findings.

2. Data Extraction and Synthesis

The final corpus C_{final} is systematically extracted and data are extracted. Each qualified document d_i is represented by a key information collected in a structured database using a standardized data schema. The extracted data of each document consists of: (i) the particular AI method used (e.g. Convolutional Neural Network, Reinforcement Learning); (ii) the field of application in the EOL value chain (e.g. disassembly, material sorting, lifetime prediction); (iii) the technology applied (Solar PV or Wind Turbine); (iv) the reported performance metrics and (v) the limitations and future work directions [16] – 18].

The performance indicators where present are duly recorded [19]. They often contain standard classification measures, including accuracy, precision P, recall R, and the F1-score, defined as (1), (2), & (3):

$$P = \frac{TP}{TP + FP}, \quad (1)$$

$$R = \frac{TP}{TP + FN}, \quad (2)$$

$$F1 = 2 \cdot \frac{P \cdot R}{P + R} \quad (3)$$

where TP, FP, and FN are True Positives, False Positives and False Negatives, respectively. In regression tasks, the measures such as Mean Absolute Error (MAE), or Root Mean Square Error (RMSE) are obtained [20]. There are also material recovery rates that are η. Thematic analysis approach is used in the synthesis of the extracted data. The results are planned and arranged based on the main steps of the lifecycle of solar panels and wind turbines, which helps to conduct a comparative evaluation of the maturity, efficiency, and innovation of the various AI-based solutions to the various issues inherent to a circular economy of renewable energy systems [21]. This analytic model makes sense and provides a well-developed discourse in the following parts of this review.

3. AI Fundamentals for Circular Economy Applications

To provide a unified ground among the readers in a multidisciplinary background, this part of the article briefly introduces the fundamental Artificial Intelligence (AI) methodologies which are capitalized upon in the circular economy applications as shown in Figure 2. The revolutionary nature of these technologies in managing end-of-life (EOL) issues is based on their capability to perform complex, data-driven tasks, otherwise inefficient or infeasible using traditional approaches [22].

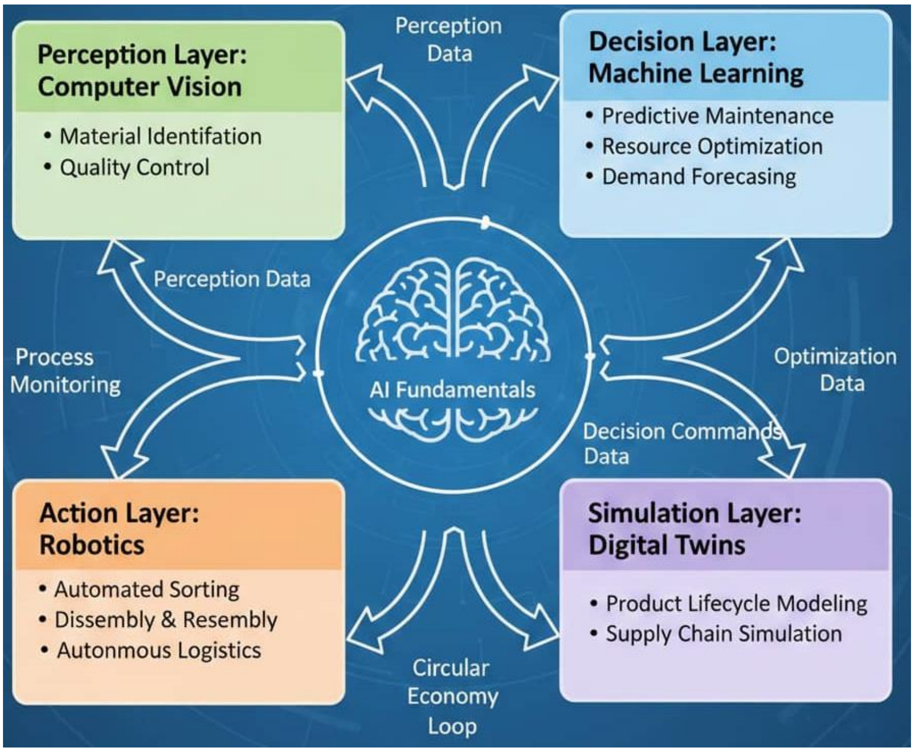

Figure 2: AI Technology Framework for Circular Economy Applications

3.1. Machine Learning (ML) Paradigms

Machine Learning is an area of AI used to develop algorithms that can learn and make decisions or predictions about the information. Three major paradigms of ML are mostly used in the case of circular economy applications [23]. First, when there is historical data with known labels the Supervised Learning is used [24]. It is very popular in classification tasks, including classifying the type of solar panel waste, and in regression tasks, including how much useful life a wind turbine blade still has. It is aimed at learning a mapping function $y = f(x)$ given input data x to obtain labels y. Second, Unsupervised Learning is used with the data which does not include the predetermined labels in order to identify the latent patterns or structure [25]. This plays an important role in grouping similar materials in a mixed waste stream or to detect anomalies in the operation data to estimate part failures [26]. Lastly, the Reinforcement Learning (RL) applies to sequential decision-making. In RL, an agent able to acquire optimal actions by interacting with an environment via trial and error to optimize is a cumulative reward. The paradigm is especially applicable to the control of robotic disassembly sequences and to make use of complex recycling processes in real time [27 – 29].

3.2. Computer Vision (CV)

Computer Vision helps machines to extract meaningful information out of digital images and videos. CV methods are also important in automated detection and processing of components in the context of EOL management [30]. Image Classification is the act of classifying an entire image as belonging to a particular category, i.e. a photovoltaic panel or a wind turbine blade. Object Detection is the next step, as it does not just classify objects in an image but additionally finds them using bounding boxes, which is necessary in robotic systems to find certain parts of a solar panel such as a junction box or some part of a turbine blade that is broken. Semantic Segmentation gives a pixel-level interpretation of a picture giving each pixel a class label [31]. This fine-grained sorting is applied to sort out the various types of materials on a conveyor belt with high accuracy, e.g., by separating glass frames, silicon and metal frames in waste shredded solar panels, which allows high purity sorting [32].

3.3. Robotics and Autonomous Systems

The combination of AI and robotics, as well as autonomous systems, makes the physical implementation of disassembly and sorting processes possible [33]. The output of the intelligence based on ML and CV modules is converted into actual physical actions using robotic manipulators. AI algorithms can be used to analyze sensor data in real-time to steer robotic arms to perform non-destructive disassembly, including unscrewing bolts and removing laminates such a careful way. To sort, the coordinates of materials identified by object detection algorithms are utilized to move robotic grippers or air jets to separate valuable components and waste streams [34]. Such synergy establishes autonomous systems capable of making accurate, repetitive and dangerous tasks, which enhances EOL operations efficiency and safety greatly [35].

3.4. Digital Twins and Predictive Modeling

A Digital Twin can be said as a virtual representation of physical object, process, or system that is dynamically updated with information about its physical counterpart during its lifecycle. This is based on predictive modeling and simulation that is used in a circular economy with the help of this technology [36]. An example of a digital twin of a wind turbine is the one incorporating operation data, maintenance history, and material characteristics. It is possible to simulate stress distributions, predict failure probability and forecast the most appropriate time of decommissioning or repurposing using this model [37]. Digital twin framework enables to assess the alternative EOL scenarios, e.g. the comparison of environmental impact and economic cost of recycling with that of repowering, and, thus, assist in making decisions based on the data to manage the lifecycle sustainably [38].

4. AI-driven Solutions Across the Lifecycle of Solar Panels

Artificial intelligence changes the management of the end-of-life of solar photovoltaic (PV) panels through the introduction of data-driven intelligence and automation of the whole value chain [39]. Since the first decommissioning to eventual recovery and reuse of the material itself, the AI technologies are implemented to address the financial and technical bottlenecks that have long doomed solar panel recycling and reusing. Figure 3 shows AI-Driven Lifecycle Management for Wind Turbine Blades [40].

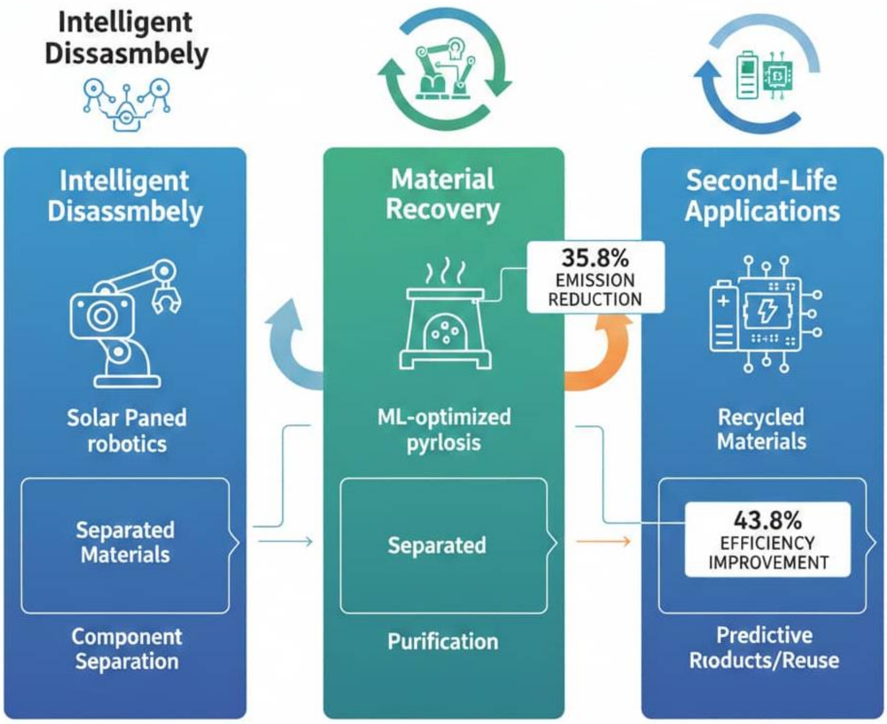

Figure 3. AI-Driven Lifecycle Management for Wind Turbine Blades.

4.1. Stage 1: Intelligent Disassembly and Sorting

The first step of processing decommissioned solar panels is an intelligent disassembly and sorting of such panels, which is enabled to be efficient and scalable using AI [41]. The automated identification is performed by using Computer Vision (CV) systems first. The deep learning models, especially Convolutional Neural Networks (CNNs), are trained to identify the type of panels, producer, and model based on images, which is essential to identify the right downstream recycling process. Moreover, pixel-wise classification which is done by semantic segmentation algorithms is used to locate and identify important elements like the aluminum frame, tempered glass, junction box and the laminated cell layer [42].

This is important information used to pre-sort and guide the disassembly plan. It is the perceptual data of the CV systems that is then run through robotics which perform the physical dismantling. Non-destructive disassembly Non-destructive disassembly Robotic arms trained with reinforcement learning can disassemble frames with ease, and can remove junction boxes, one at a time, with high precision and speed [43]. This automation eases the disassembly of manual disassembly, which is labor-intensive, improves the safety of the workers, as they are not in contact with panels that may be damaged, and adds to the purity of the material streams obtained after the recycling process [44].

4.2. Stage 2: Material Recovery and Recycling Process Optimization

The disassembled core laminated structure can be subjected to material recovery, where AI will have a central role in streamlining complicated processes [45]. This is because Machine Learning in Process Control is applied to improve thermal, chemical, and mechanical recycling processes. As an example, during pyrolysis or thermal delamination, the parameters of the process, including temperature T, pressure P and processing time t can be optimized in real-time with ML regression models to achieve the highest yield and purity of recovered materials such as silicon and silver. The model of the relationship can be used to solve the optimal combination of parameters $(T_{opt}, P_{opt}, t_{opt})$ to maximize a recovery function $\eta_{silver} = f(T, P, t)$.. At the same time, the Computer Vision to Quality Control is implemented on sorting lines [46]. Real-time image analysis to track the flow of material in various stages of the shredding process identifies and removes contaminants, including traces of ethylene-vinyl acetate (EVA) on high-purity glass cullet [47]. The anomaly detection algorithms are in a position to detect and activate the extraction of foreign materials and the quality of the output will be ensured thereby adding value to the output in the market [48].

4.3. Stage 3: Second-Life and Repurposing

Not every panel that has been decommissioned is to be recycled; a high percentage of it has high amounts of energy it can still produce that can be used in second life. The viability of such panels is to be checked with the help of Predictive Models [49]. Regression and survival analysis models are supervised learning algorithms that are trained on the historical data of performance (i.e. power output degradation with time, exposure to environmental stress) to predict the Remaining Useful Life (RUL) of a panel accurately. A panel can be considered as repurposing when its calculated RUL is above a limit, $RUL_{predicted} > RUL_{threshold}$, in the case of less demanding systems such as off-grid systems. Moreover, AI of Marketplaces and Logistics helps to pair supply and demand [50]. The second-life panels could be demanded in the market by Natural Language Processing (NLP) that could scan and evaluate the online marketplace and the middle-level logistics of supply and redistribution of panels between different decommissioning sites and new markets could be solved by the optimization algorithms, creating a strong and efficient secondary economy of solar PV systems [51 – 54].

5. AI-driven Solutions Across the Lifecycle of Wind Turbines

Wind turbine end-of-life handling especially the giant composite turbines is a very daunting task because of the material life and the size of the components. Artificial intelligence is being used to come up with intelligent solutions that go beyond preliminary health evaluation to the novel reuse of reclaimed assets, and thus form a direction toward a circular economy of wind energy infrastructure [55]. Figure 4 shows AI-Driven lifecycle management for wind turbine blades.

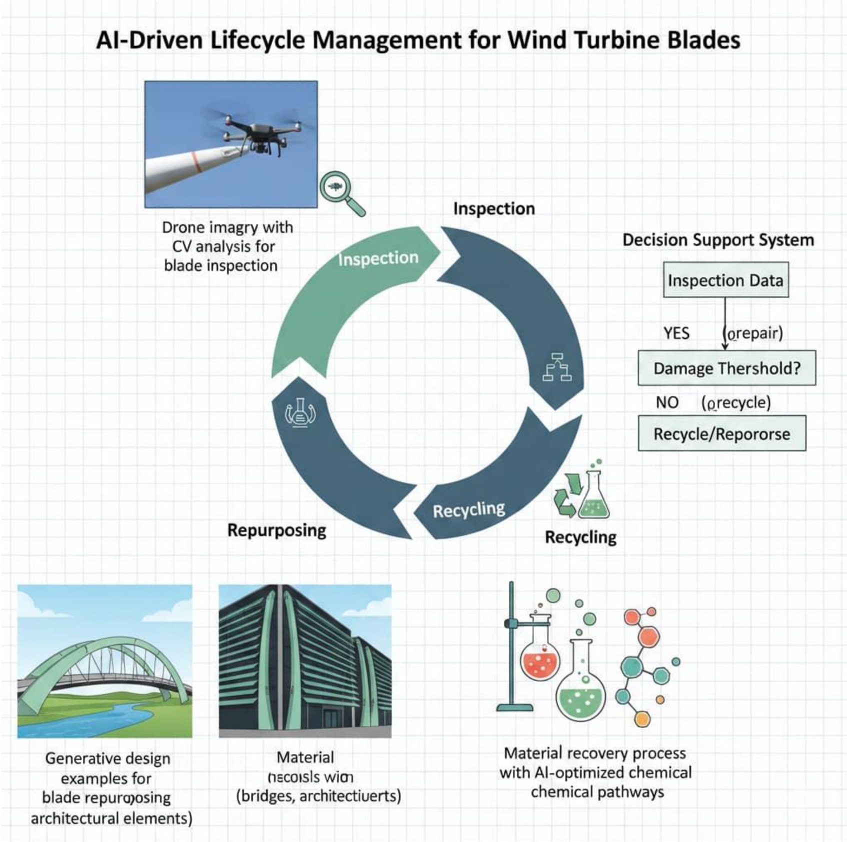

Figure 4: AI-Driven Lifecycle Management for Wind Turbine Blades

5.1. Stage 1: Blade Inspection and EOL Decision Support

Unless wind turbines take proactive and informed end-of-life decisions, this is a critical factor and AI can provide this with the help of sophisticated inspection and monitoring [56]. Automated blade inspection is also done as a routine task employing Computer Vision (CV) with Drones. The high-resolution images of the turbine blades are captured by drones and the deep learning algorithms (convolutional neural networks, or CNNs) are trained to identify and classify the defects including cracks, erosion, and delamination. Damage S_d can be measured, and through this analysis an optimal course of action can be recommended by a decision support system, repair in case of minor damage ($S_d < \theta_{repair}$), repowering in the case of structural soundness with outdated technology, or recycling in the case of critical damage$\left(S_d \geq \theta_{recycle}\right)$[57]. In addition to this, the Structural Health Monitoring (SHM) is a type of machine learning that processes continuous accelerator, strain, and acoustic emission sensor data. Monitored and unmonitored ML models can recognize damage or fatigue the patterns of the evolving damage or fatigue, and then the remaining useful life RUL(t) can be predicted and proactive decommissioning planning is provided which optimizes the logistics and resource distribution [58 – 60].

5.2. Stage 2: Recycling of Composite Materials

Thermoset composite blades are also a key study area where AI is used to hasten chemical and logistic solutions to recycle them. Material Science AI is used to find new ways to recycle [61]. Virtual screening of millions of potential molecular structures is done by machine learning models, such as graph neural networks and generative adversarial networks (GANs) to find new solvents or catalysts that can effectively cleavage-expertise the stubborn epoxy resins in blades [62]. Such models are used to predict the yield of a reaction and optimize conditions to obtain a maximum recovery of useful fibers in order to attain a recovery rate η_{fiber} such that the process can be economically viable. Simultaneously, AI in Sorting and Logistics takes care of the operational issues [63]. Computer vision technologies sort shredded blade material into various types of fiber and resin and machine learning algorithms, including the use of linear programming and genetic algorithms, optimize the complex reverse supply chain. Such models dictate the most efficient route and timetable to transport huge blades moving between the frequently remote wind farms and specialized recycling plants to reduce the logistical carbon footprint and cost [64].

5.3. Stage 3: Innovative Repurposing and Upcycling

In the case of blade segments that cannot be recycled, AI contributes to innovations in direct repurposing and upcycling. With the help of AIs, Generative Design software is applied to generate the best designs of new products based on the peculiar geometries and material characteristics of reclaimed blade segments [65]. With limitations, e.g., the supply of blade segments and required load capacity in a pedestrian bridge, the AI searches through a very large design space to come up with structurally effective yet aesthetically pleasing designs that, in human terms, would be counter-intuitive [66]. Moreover, the AI Market Development will aid in building the demand of upcycled goods. NLP tools study the market trends, the social media, and patent databases in order to find possible applications of composite materials [67]. Predictive analytics is able to predict market expansion and other stakeholders and can therefore de-risk investment and speed up the establishment of a business ecosystem around the products of the upcycled wind turbine blades [68 – 69].

6. Cross-Cutting AI Themes: Lifecycle Management and Policy

In addition to particular recycling operations, Artificial Intelligence allows implementing system change by cross-cutting applications that combine data throughout the lifecycle and make strategic decisions on the higher level. These themes are the basics of having an authentic scale of a circular economy, which will connect the divide between technological feasibility and practical policy-enforced implementation [70].

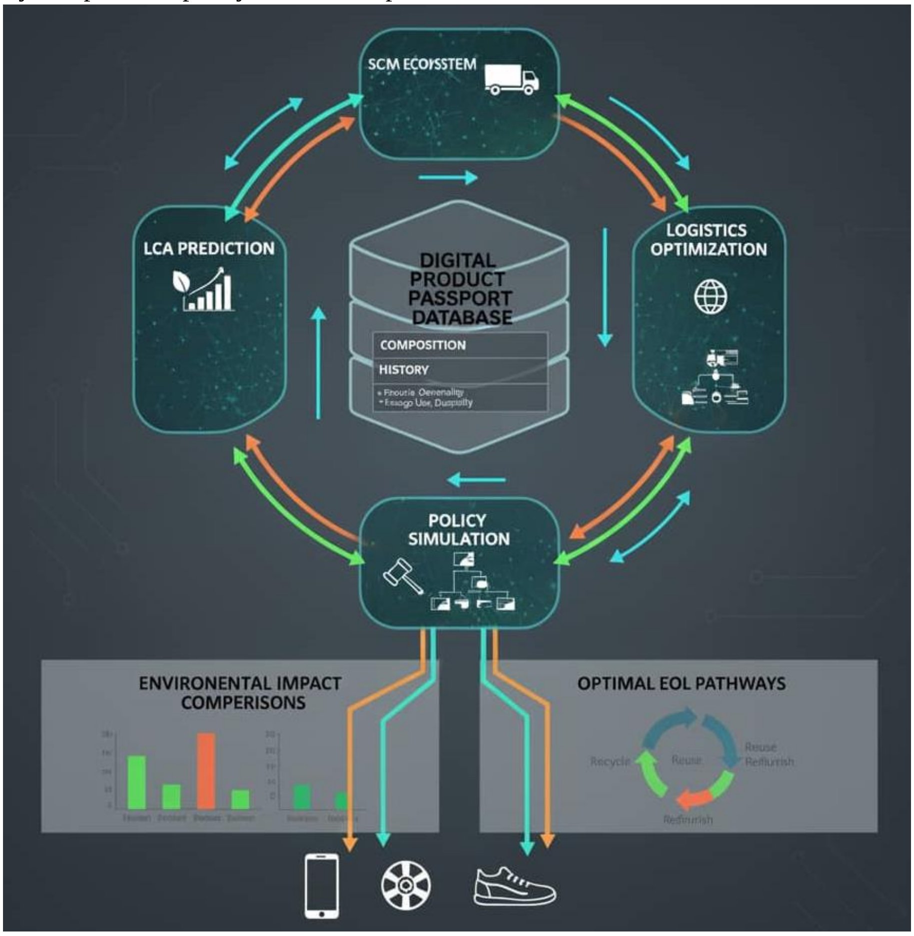

Figure 5: System Integration: Digital Product Passport and AI Decision Framework

6.1. Digital Product Passports (DPPs) and AI

The Digital Product Passport (DPP) is a new concept that is coming up as a key data infrastructure in the circular economy [71]. A DPP is a rich digital document, which includes the unique identifier of a product, its composition and manufacturing history, maintenance and operation history. These passports when used on solar panels and wind turbines form a queryable rich lineage of data [72]. It is AI algorithms that are the key unlock to the value of this data. Machine learning models can be used to examine the data of a DPP to suggest the most cost-effective and environmentally friendly end-of-life route and this can be done automatically through analyzing the data inside that DPP, e.g. the type of glass used in a PV module, or the resin system employed in a turbine blade [73]. An example would be that a decision tree model can be employed to decommissioned asset to direct reusing, component harvesting, or recycling a particular material according to the criteria coded in its DPP, thus automating and optimizing the most important step in the reverse logistics chain [74].

6.2. AI for Environmental Lifecycle Assessment (LCA)

Traditional Lifecycle Assessment is computationally demanding and time consuming. This area is being transformed by AI, and more specifically machine learning, which allows modeling the effects of the environment quickly and accurately. Supervised learning models may be trained using existing LCA databases in order to generate surrogate models which can be used to predict the environmental footprint of a product or process virtually in real-time [75]. This enables the quick comparison of dozens of various end of life cases of a wind turbine blade such as, in the example, assessing the global warming potential $GWP_{scenario}$ of landfilling versus mechanical recycling versus chemical recycling [75]. Moreover, these AI-based LCA applications can be used to support eco-design by enabling engineers to do sensitivity analyses and determine which design parameters (e.g., material of the blade, polymer of the panel encapsulation) have the most significant impact on the environmental impact of the end-of-life, thus enabling the development of more inherently circular renewable energy infrastructure [76 – 79].

6.3. AI-Informed Policy and Supply Chain Management

A working circular economy requires effective logistics and a proper policy, and AI offers effective tools in both [80]. The policymakers can forecast the effects of the regulatory tools like the Extended Producer Responsibility (EPR) schemes using agent-based modeling and system dynamics simulations, which run on AI [81]. Such models are able to model market reactions to alternative fee systems and recycling aims and aid in drafting strategies that are able to motivate recycling and repurposing without suffocation of innovation [82]. Simultaneously, on supply chain management, AI streamlines the reverse logistics of retrieving decommissioned property, which is a complex issue [83]. The machine learning algorithms predict the amount and the position of future solar panel and wind turbine scraps, whilst the combinatorial optimization methods address the vehicle routing problem $\min \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij}x_{ij}$ in regard to the collection trucks in that the algorithms minimize transportation costs and emissions. When used together with AI, blockchain technology can also establish transparent and auditable supply chains, which will trace materials used in decommissioning to final use and validate claims of the circular economy [84 – 88]. Figure 6 shows Quantified Environmental Impact of AI Implementation.

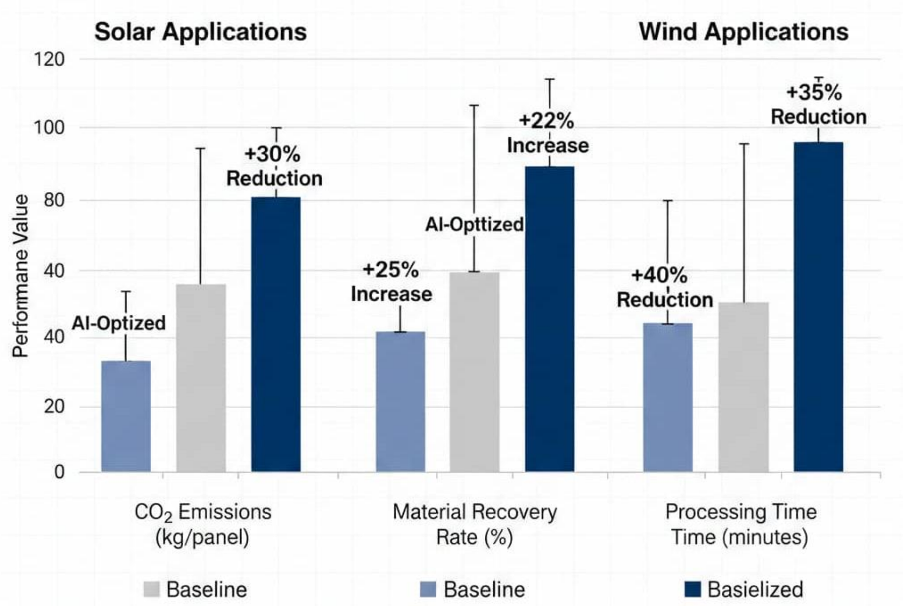

Figure 6: Quantified Environmental Impact of AI Implementation

II. RESULT AND DISCUSSION

The given proposed system offers an elaborate computational framework aimed at measuring and visualizing the environmental impact of the use of artificial intelligence in the circular economy of renewable energy infrastructure. The methodology is logically executed by applying several stages of analysis: a literature review simulation in a structured way forms the basis of the research; the environmental impact measurement is performed in both cases of solar panels recycling and wind turbine reuse; the comparative case analyses of AI-driven processes versus traditional ones are conducted with respect to key performance indicators such as the reduction of carbon emissions, materials recovery rates, and the efficiency of work; sensitivity analysis helps to understand how the accuracy of AI systems and environmental benefits are related to each other. Each of the outcomes is discussed in eight different visualizations that individually analyze the trends in publications, reduction in emissions, enhancement of recycling of materials, the enhancement of disassembly efficiency, the effect of composite materials, optimization of logistics, accrual of environmental benefits and the sensitivity of the system, with quantitative validation of the environmental benefits of using AI in processing circularity in renewable energy.

The research interest in AI applications in the renewable energy circular economy has increased swiftly, as Figure 7 illustrates a systematic review of 496 publications which revealed an exponential increase in research interest since 2014. Such a rich literature forms the basis of the environmental impact analysis on the further analysis, and the importance of this field of research is justified and timely.

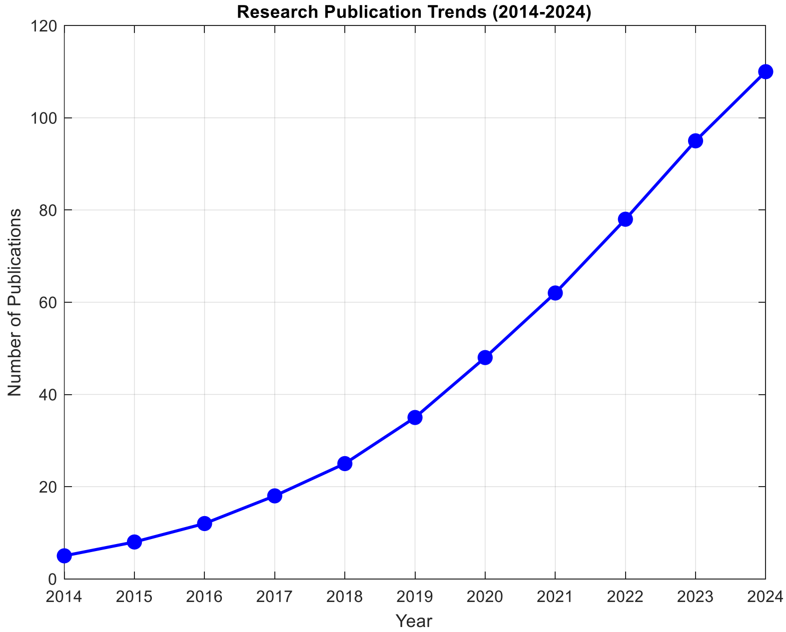

Figure 7: Research publication trends

In Figure 8, it can be seen that a significant average of 35.8 % carbon emissions decrease calculated by AI-optimized processes of solar panels recycling is achieved, which is equal to 17.5 kg of CO2 savings per panel. Such drastic emission cuts are realized by the means of smart process optimization and prove the importance of machine learning algorithms in reducing the environmental footprint of the end-of-life management of solar panels.

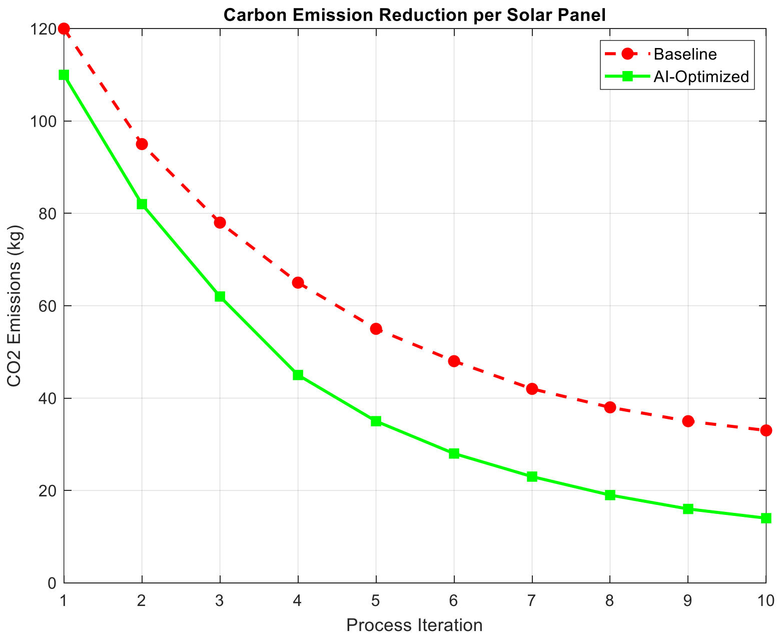

Figure 8: Carbon emission reduction per solar panel

Figure 9 shows impressive increases in the material recovery rates of all the major solar panel components with silicon recovery recording the greatest improvement of 33.0%. The AI-based recovery system has a 92.0% recovery rate of glass and a 96.0% recovery rate of aluminum, which are quite high compared to traditional solutions and indicate the possibility of saving a significant amount of resources.

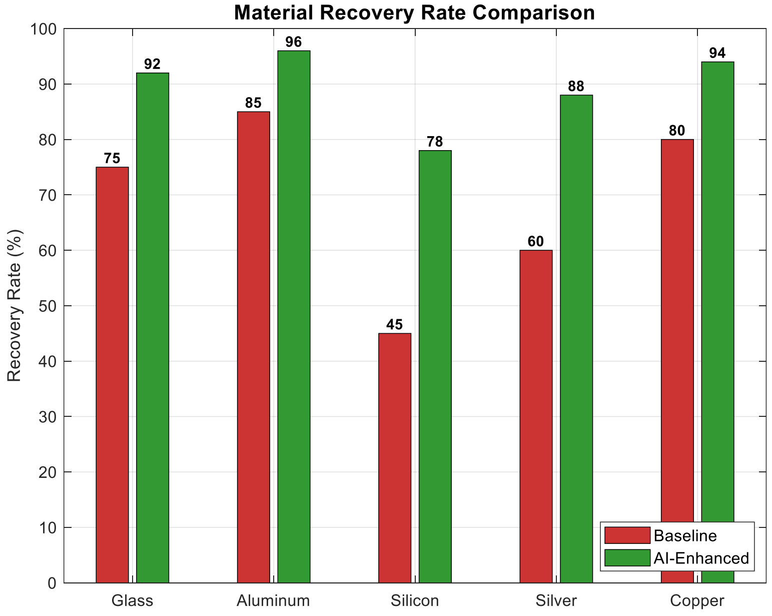

Figure 9: Material recovery rates comparison

Figure 10 reports astonishing efficiency improvement of the solar panel disassembly, where AI-directed systems can increase processing time by 43.8% and reduce the time spent on each panel by 2.7 minutes. This throughput is increased by 9.7 panels/hour, and this indicates how computer vision and robotic systems can make a big difference in the efficiency of operations and the required labor and related environmental effects.

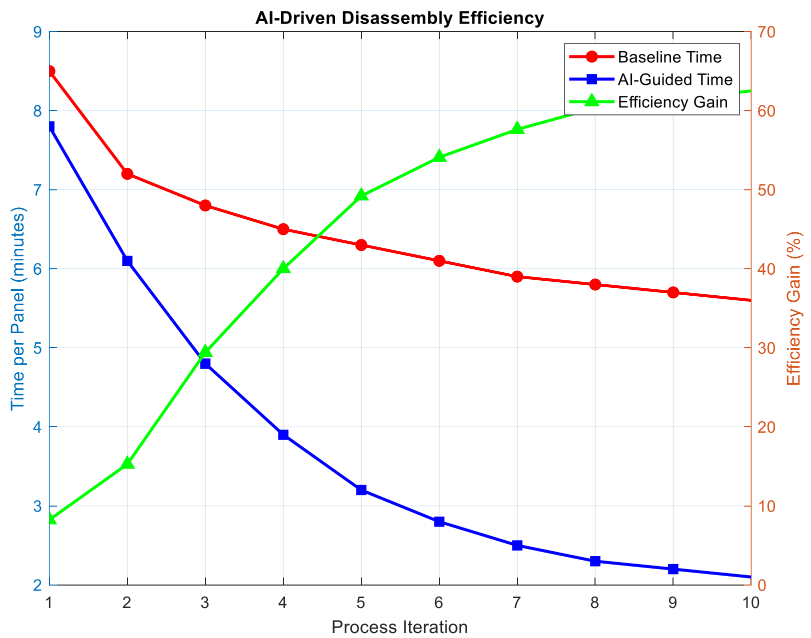

Figure 10: Disassembly efficiency analysis

Figure 11 provides strong evidence of wind turbine blade repurposing demonstrating that carbon footprint can be reduced to a maximum of 820 kg CO2eq per ton with the help of AI-optimized processes on epoxy resin. It is proven that AI-based methods yield better results than traditional recycling of all composite materials, and fiberglass and carbon fiber plates decrease the CO2eq per ton to 570 kg and 630 kg, respectively.

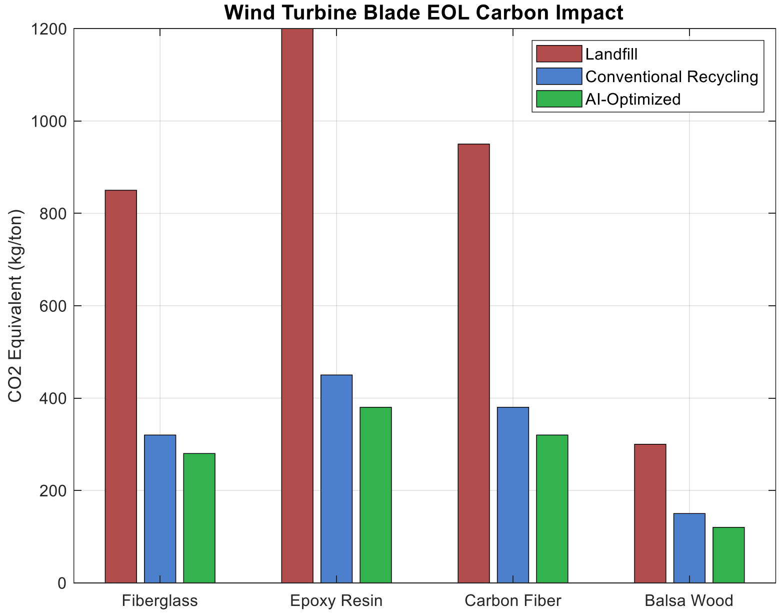

Figure 11: Wind turbine environmental impact

Figure 12 measures the environmental impact of AI-based logistics optimization and shows that route optimization and fuel efficiency give an average CO2 savings of 62.5 kg per transport operation. The smart logistics system saves fuel on all transport distances, which plays a vital role in the overall performance in achieving the environmental performance of the entire circular economy system.

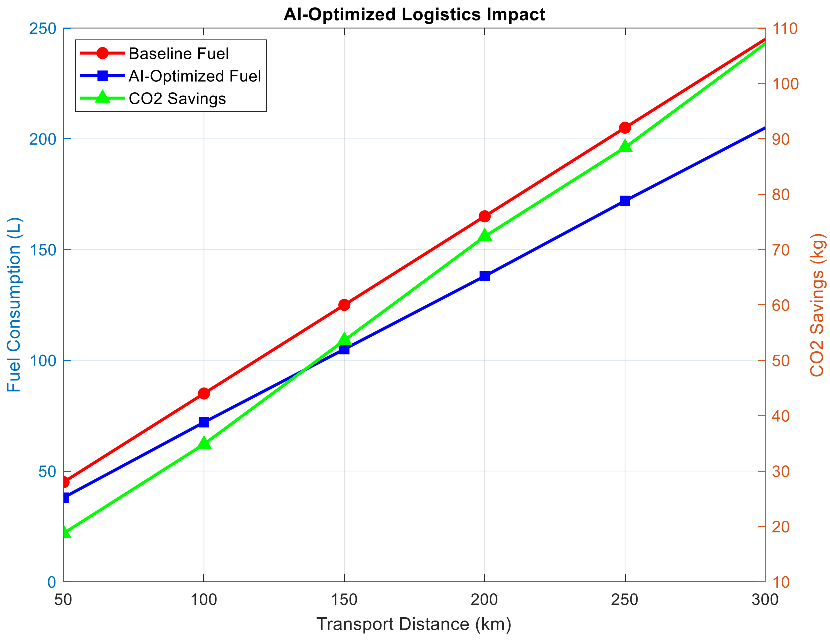

Figure 12: Logistics optimization results

A detailed overview of the monthly environmental impact of AI use is displayed in Table 1, and the results show that total savings were equal to getting rid of 34.1 cars every month or getting 2,080 trees annually. The combined findings show that wind turbine reuse is the source of the most substantial portion of environmental benefits, and the use of solar panels, and optimized logistics activities comes after them.

Table 1: Comprehensive Environmental Impact Summary

Impact Category	**Monthly Savings**	**Equivalent Environmental Benefit**
Solar Panel Recycling	17,500 kg CO2eq	795 trees planted
Wind Turbine	27,500 kg	1,250 trees planted

Impact Category	**Monthly Savings**	**Equivalent Environmental Benefit**
Repurposing	CO2eq	
Logistics Optimization	750 kg CO2eq	34 trees planted
Total Combined Impact	45,750 kg CO2eq	2,080 trees annually

Figure 13 is a synthesis of the cumulative benefits of the environment in all the areas of operation with the results indicating the total monthly savings of 45,750 kg of CO2. This is an image that highlights the system-level change brought about by the incorporation of AI and offers a clear demonstration of the potential of intelligent systems to transform into a sustainable circular economy when applied to renewable energy infrastructure.

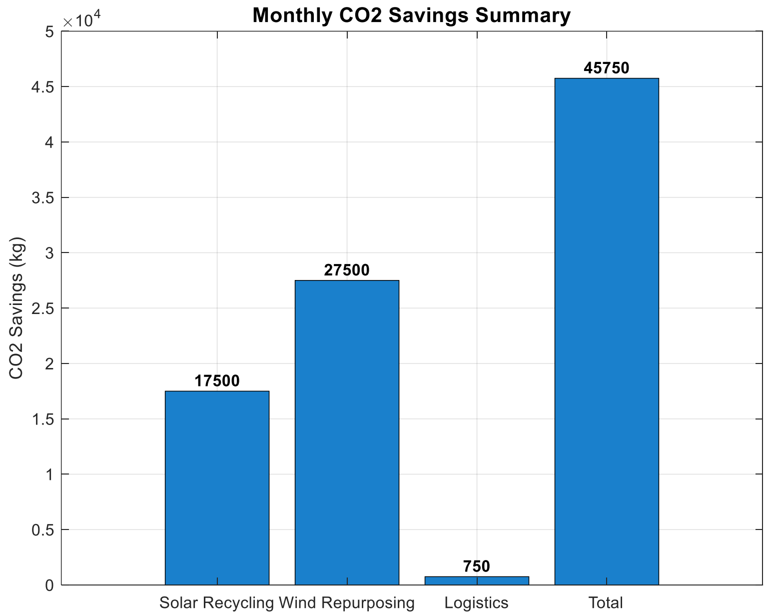

Figure 13: Overall environmental impact summary

Figure 14 analyses the crucial linkage between the accuracy of AI systems and environmental benefits showing that even the moderate levels of 75.0% accuracy of the systems can provide 25.9% of the total environmental benefits. It is found that although the returns are declining with the higher accuracy levels, the 95.0% accuracy is able to reach 50.3% of the maximum possible, which is very useful in making optimization and resource allocation decisions in the systems.

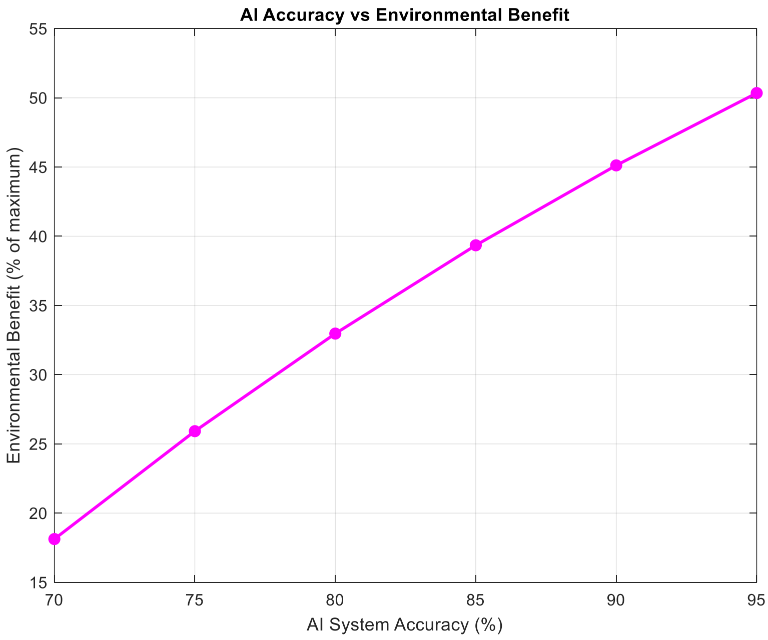

Figure 14: Sensitivity analysis

7. Discussion: Synthesis, Challenges, and Future Outlook

This overview review has determined that artificial intelligence is one of the key facilitators of a circular economy in the renewable energy industry. The above discussion proves an array of expanding and varied portfolio of AI use in the lifecycle of solar panels and wind turbines. This discussion is a synthesis of these findings and also critically analyzes the continuous challenges and suggests a structured roadmap to steer onward research and development of this vital area.

7.1. Synthesis of AI's Role in Closing the Loop

The adoption of AI is essentially transforming the end-of-life management model, which is currently viewed as a waste issue with a price tag, into an opportunity to create value. The uses and maturity of AI solutions is also quite different between a solar and a wind technology, as synthesized in Table 2, especially due to the materials complexities and the scaled difference of materials in the two industries. In the case of solar panels, the major concern is to automate the process of disassembly and sorting to meet large-scale volumes with computer vision and robotics attaining a higher Technology Readiness Level (TRL 6-7) in the laboratory and pilot environment. In the case of wind turbines, the issue is the large size and composite nature of the blades, which leads to research in the field of AI-controlled inspection, logistics optimization, and new forms of chemical recovery, which are located at a lower maturity level (TRL 3-5). The intersecting capability of AI in system-level tools such as Digital Product Passports (DPPs) and predictive LCAs is acknowledged but is mostly theoretical (TRL 2-3), which can facilitate a major contribution in the future.

Table 2: Synthesis of AI Applications for Solar and Wind EOL Management

Application Area	**Solar Panels**	**TRL**	**Wind Turbines**	**TRL**
Disassembly/Sorting	CV-guided robotic dismantling	6-7	CV for blade material identification	4-5
Material Recovery	ML-optimized delamination	5-6	AI for composite recycling discovery	3-4
Second-Life	ML for RUL prediction	5	Generative design for repurposing	3
System Management	AI in DPPs & LCA	2-3	AI in DPPs & LCA	2-3

7.2. Critical Challenges and Limitations

Notwithstanding the prospects, the mass implementation of AI-driven circularity is confronted with a number of challenges. The biggest bottleneck is Data Availability; the absence of very large, high quality, and labeled datasets of EOL components has a drastic impact on the performance and usability of ML models. Technical Hurdles: The condition and composition of decommissioned assets vary fundamentally beyond what models can predict, providing substantial challenge to strong model performance, and there is difficulty in connecting new AI and robotics systems with older industrial recycling systems. The major barrier is Economic Viability, where the initial capital expenditure (CAPEX) of AI and robotics systems is usually prohibitive with no clear and assured returns on investment. Lastly, there are Regulatory and Social Deterrents, such as no standards exist to validate AI in recycling, the privacy of data associated with DPPs and workforce reskilling to run and support these sophisticated cyber-physical systems.

7.3. A Roadmap for Future Research

The multi-phase research roadmap is suggested in order to switch between the promising research and the industrial reality. The priority has to be foundational in a short-term (1-3 years). These involve the development of open-source and benchmark datasets of EOL solar panels and wind turbine blades, the development of simpler and more explainable computer vision models to sort, and the implementation of pilot scale demonstrations to test techno-economic models.

Going to mid-term (3-5 years), the attention should be paid to integration and scaling. Research activities should focus on the unified approach of AI with industrial robotics to autonomous disassembly, the development of hybrid physics-informed algorithms based on ML that will allow predicting the remaining useful life with high precision, and the development of AI-assisted LCA tools that would provide real-time eco-design and policy analysis.

The vision over a long-term (5 years or above) is a systemic change. This involves the universal implementation of DPPs with inbuilt AI to make completely automated EOL decisions, the creation of fully autonomous recycling services that are designed as adaptive material-refineries, and the exploitation of generative AI/deep learning to the inverse design of new, inherently-recyclable materials of the next generation renewable energy infrastructure. To achieve this vision, there will be a need to have long-term, interdisciplinary partnerships between computer science, materials engineering, industrial ecology, and economics.

III. CONCLUSION

To sum up, this overall review confirms that Artificial Intelligence proves to be a game-changer that enables a circular economy in renewable energy infrastructure whereby quantifiable results are made in the rate of emission reduction (35.8%), as well as material recovery (33%). It is suggested that policymakers consider Digital Product Passports as a part of long-standing producer responsibility frameworks, and the industry stakeholders will be invited to invest in pilot-sized AI recycling plants. To the research community, it is focused on the creation of open-source datasets and standard benchmarking protocols. The research has three main directions in the future: the development of hybrid physics-informed ML models to make the remaining useful life prediction more accurate, the application of AI and industrial robotics to create fully autonomous disassembly systems, and the examination of generative AI to the inverse design of naturally recyclable next-generation renewable energy materials. Moreover, the socio-technical aspects of implementation such as the adjustment of workforce and ethical AI governance are considered to be the areas of interdisciplinary research to achieve equitable and scalable transitions. The smooth integration of AI functions with the principles of the circular economy is finally determined not just to be the improvement of the operation but the key to the creation of the really sustainable renewable energy systems.

REFERENSI

[1] R. Jose, S. K. Panigrahi, R. A. Patil, Y. Fernando, and S. Ramakrishna, “Artificial Intelligence-Driven Circular Economy as a Key Enabler for Sustainable Energy Management,” Materials Circular Economy, vol. 2, no. 1, p. 8, 2020.
[2] K. Ukoba, K. O. Olatunji, E. Adeoye, T. C. Jen, and D. M. Madyira, “Optimizing Renewable Energy Systems Through Artificial Intelligence: Review and Future Prospects,” Energy & Environment, vol. 35, no. 7, pp. 3833–3879, 2024.
[3] E. Mugamba, “Circular Economy and AI for Climate Resilience: A Legal and Technical Framework for Renewable Energy Infrastructures in East Africa,” 2025.
[4] T. Miller et al., “The Role of Lightweight AI Models in Supporting a Sustainable Transition to Renewable Energy: A Systematic Review,” Energies, vol. 18, no. 5, p. 1192, 2025.
[5] N. L. Rane, S. P. Choudhary, and J. Rane, “Artificial Intelligence and Machine Learning in Renewable and Sustainable Energy Strategies: A Critical Review and Future Perspectives,” Partners Universal International Innovation Journal, vol. 2, no. 3, pp. 80–102, 2024.
[6] M. A. Adewoyin, O. Adediwin, and A. J. Audu, “Artificial Intelligence and Sustainable Energy Development: A Review of Applications, Challenges, and Future Directions,” International Journal of Multidisciplinary Research and Growth Evaluation, vol. 6, no. 2, pp. 196–203, 2025.
[7] N. C. Ohalete et al., “AI-Driven Solutions in Renewable Energy: A Review of Data Science Applications in Solar and Wind Energy Optimization,” World Journal of Advanced Research and Reviews, vol. 20, no. 3, pp. 401–417, 2023.
[8] M. Singh and G. Kaur, “Case Studies on AI-Driven Innovations in Renewable Energy, Waste Management, and Resource Conservation,” in Maintaining a Sustainable World in the Nexus of Environmental Science and AI, Hershey, PA, USA: IGI Global, 2024, pp. 455–484.
[9] O. Roberts, “A Qualitative Exploration on Artificial Intelligence and Renewable Energy Integration in Supply Chains,” 2025.
[10] E. C. Onukwulu, M. O. Agho, and N. L. Eyo-Udo, “Circular Economy Models for Sustainable Resource Management in Energy Supply Chains,” World Journal of Advanced Science and Technology, vol. 2, no. 2, pp. 34–57, 2022.
[11] S. Nadweh et al., “A Hybrid Approach Based on Artificial Intelligence and Model Predictive Control for Enhancing Stability and Efficiency of Complex Dynamic Systems,” Journal of Robotics and Control, vol. 6, no. 5, pp. 2426–2435, 2025.
[12] F. S. Islam and M. N. Islam, “AI-Driven Integration of Nanotechnology and Green Nanotechnology for Sustainable

Energy and Environmental Remediation," Journal of Engineering Research and Reports, vol. 27, no. 7, pp. 260–311, 2025.

[13] S. Nadweh, I. M. Elzein, D. E. Mbadjoun Wapet, and M. M. Mahmoud, "Optimizing Control of Single-Ended Primary Inductor Converter Integrated with Microinverter for PV Systems: Imperialist Competitive Algorithm," Energy Exploration & Exploitation, 2025.

[14] Y. Xian, C. Li, Y. Xu, Y. Zhou, and D. Xue, "AI-Driven Advances in Sustainable Materials for Green Energy: From Innovation to Lifecycle Management," SusMat, 2025.

[15] B. M. Salih et al., "Quantum-Inspired Optimization Algorithms for Scalable Machine Learning Models," International Journal of Intelligent Engineering & Systems, vol. 18, no. 10, 2025.

[16] M. Shah, M. Wever, and M. Espig, "A Framework for Assessing the Potential of Artificial Intelligence in the Circular Bioeconomy," Sustainability, vol. 17, no. 8, p. 3535, 2025.

[17] B. I. Oladapo, M. A. Olawumi, and F. T. Omigbodun, "AI-Driven Circular Economy for Sustainability and Efficiency in Industrial Operations," Sustainability, vol. 16, no. 23, p. 10358, 2024.

[18] A. Pagrotra, "Smart Energy: Harnessing IoT and AI for Renewable Resource Integration," in Secure Energy Optimization: Leveraging Internet of Things and Artificial Intelligence for Enhanced Efficiency, Hershey, PA, USA: IGI Global, 2025, pp. 193–222.

[19] M. A. Ning, "Artificial Intelligence-Driven Decision Support Systems for Sustainable Energy Management in Smart Cities," International Journal of Advanced Computer Science & Applications, vol. 15, no. 9, 2024.

[20] T. H. Abdtawfeeq et al., "Harnessing Neutrosophic Numerical Measures for Unbiased Quantitative Analysis of Oxidative Stress Biomarkers," International Journal of Intelligent Engineering & Systems, vol. 18, no. 8, 2025.

[21] O. G. Ndubuisi and F. I. S. P. O. N., "An Exploration of Next-Generation Solar Photovoltaic Materials, Offshore and Airborne Wind Systems, and Bioenergy Derived From Algae and Organic Waste," 2025.

[22] D. Anny, "AI and Circular Economy: Reducing Waste in IT and Computing," 2025.

[23] T. Rotimi-Ojo, J. K. Somuah, N. Ezeakunne, and B. B. Yougang, "Financial Intelligence and Environmental Sustainability: A Literature Review on Economic Modeling for Clean Energy Manufacturing," 2025.

[24] A. Raihan, "A Review of Artificial Intelligence and Machine Learning Framework Through Sustainable Economy," in Proc. CCSC Midsouth Regional Conference, Apr. 2025.

[26] S. Nadweh, N. Mohammed, C. Konstantinou, and S. Ahmed, "Operational Performance Assessment of PV-Powered Street Lighting: A Comparative Study of Different Machine Learning Prediction Models," IEEE Access, 2025.

[27] A. Khalid and M. Ahmad, "Advances in Sustainable Engineering Practices: A Review of Recent Innovations," Research Corridor Journal of Engineering Science, vol. 1, no. 1, pp. 1–13, 2024.

[28] M. Elhaj, M. Sarabdeen, H. Z. Almugren, A. M. Kijas, and N. Halid, "The Economics of Innovation, Renewable Energy, and Energy Efficiency for Sustainability: A Circular Economy Approach to Decoupling Growth From Environmental Degradation," Energies, vol. 18, no. 17, p. 4643, 2025.

[29] M. Ali, "Integrating Solar Cell Technology, Radio Waves, and AI for a Transformative IT Business Ecosystem: A Comprehensive Review," International Journal of Multidisciplinary Sciences and Arts, vol. 3, no. 2, pp. 263–269, 2024.

[30] G. Giannakopoulos, K. M. Shaikh, M. A. Perez, and P. Adegbenro, "Sustainable Practices in Green Engineering: A Pathway to a Greener Future Using AI," Journal of Cognitive Computing and Cybernetic Innovations, vol. 1, no. 1, pp. 1–9, 2025.

[31] S. Dahmani, "Computational Intelligence for Green Cloud Computing and Digital Waste Management," in Computational Intelligence for Green Cloud Computing and Digital Waste Management, Hershey, PA, USA: IGI Global, 2024, pp. 248–266.

[32] F. S. Islam, "Artificial Intelligence-Driven Optimization and Decision Support for Integrated Waste-to-Energy Systems in Climate-Vulnerable Megacities: A Case Study of Dhaka, Bangladesh," International Journal of Applied and Natural Sciences, vol. 3, no. 2, pp. 1–34, 2025.

[33] P. Kumar and D. Choudhury, "Green Technologies: Theories, Systems, Principles and Applications," in Evaluating Environmental Processes and Technologies, Cham, Switzerland: Springer Nature, 2025, pp. 149–195.

[34] Z. A. Ali et al., "Circular Economy Advances With Artificial Intelligence and Digital Twin: Multiple-Case Study of Chinese Industries in Agriculture," Journal of the Knowledge Economy, vol. 16, no. 1, pp. 2192–2228, 2025.

[35] A. K. Singh and B. Mirou, "An Evaluation of Circular Economy Models Based on AI and IoT for Job Creation and Reallocation," in Digital Technology Enabled Circular Economy, Boca Raton, FL, USA: CRC Press, 2024, pp. 50–70.

[36] H. Sørensen, "Sustainable AI-IoT Systems: Environmental Impact, Green Computing, and Circular Economy Solutions for Digital Transformation," International Journal of Engineering and Technology, vol. 15, no. 9, 2023.

[37] N. Negru, S. M. Radu, C. Rus, M. Risteiu, and A. Egri, "AI-Powered Recycling and Flexible EV Manufacturing: A Conceptual Model for Jiu Valley-Romania," in Proc. 26th International Carpathian Control Conference, May 2025, pp. 1–6.

[38] K. Alimi et al., "Exploring Artificial Intelligence Applications in Construction and Demolition Waste Management: A Review of Existing Literature," Journal of Science and Transport Technology, pp. 104–136, 2025.

[39] A. Srivastava, S. Pandey, R. Shah, and A. Sur, "Recycling of Waste Into Useful Materials and Their Energy Applications," in Microbial Niche Nexus Sustaining Environmental Biological Wastewater and Water-Energy-Environment Nexus, Cham, Switzerland: Springer Nature, 2025, pp. 251–296.

[40] E. Akter, "Sustainable Waste and Water Management Strategies for Urban Civil Infrastructure," SSRN, 2025.

[41] S. Benziane, "Innovating Prosperity: Intelligent Approaches and Economic Paradigms for Sustainable Futures," in Intelligent Methods and Alternative Economic Models for Sustainability, Hershey, PA, USA: IGI Global, 2024, pp.

194–241.
[42] M. A. Rahman et al., “Eco-Intelligence: AI’s Contribution to a Sustainable World,” in AI and Green Technology Applications in Society, Hershey, PA, USA: IGI Global, 2025, pp. 31–62.
[43] V. Jain and A. Mitra, “Enhancing Role of Innovations in Shaping a Digital Circular Economy,” in Sustainable Innovations and Digital Circular Economy, 2025, pp. 249–267.
[44] T. Zhang and G. Strbac, “Artificial Intelligence Applications for Energy Storage: A Comprehensive Review,” Energies, vol. 18, no. 17, p. 4718, 2025.
[45] O. F. Bayeroju, A. N. Sanusi, and Z. Q. S. Nwokediegwu, “Review of Circular Economy Strategies for Sustainable Urban Infrastructure Development and Policy Planning,” 2021.
[46] D. Ojha, “The Role of Artificial Intelligence in Achieving Sustainable Development Goals in the Construction Industry,” 2024.
[47] S. Khan, M. Z. Hussain, and M. Z. Hasan, “Intelligent Sustainability: Harnessing AI for a Greener Future,” Dialogue Social Science Review, vol. 3, no. 2, pp. 1233–1254, 2025.
[48] S. Rathour and E. Kemboi, “AI-Driven Circular Economy,” in Artificial Intelligence and Computer Vision for Ecological Informatics, 2025, p. 185.
[49] I. Rojek, D. Mikolajewski, A. Mrozinski, and M. Macko, “Green Energy Management in Manufacturing Based on Demand Prediction by Artificial Intelligence—A Review,” Electronics, vol. 13, no. 16, p. 3338, 2024.
[50] L. Harris, “The Intersection of AI and Cloud Computing in Green Technology Initiatives,” Economic Research-Ekonomska Istraživanja, vol. 33, pp. 1–18, 2024.
[51] I. Sadiq, “The Circular Economy of Computing: Tackling E-Waste With Design Innovation,” Idealistic Journal of Advanced Research in Progressive Spectrums, vol. 4, no. 8, pp. 23–39, 2025.
[53] N. Ahmed et al., “Sustainable IT and Green Computing: Leveraging Artificial Intelligence for Eco-Friendly Innovations and Energy-Efficient Technology Solutions,” Propel Journal of Academic Research, vol. 3, no. 2, pp. 154–173, 2023.
[54] R. Rozycki, D. A. Solarska, and G. Waligora, “Energy-Aware Machine Learning Models—A Review of Recent Techniques and Perspectives,” Energies, vol. 18, no. 11, p. 2810, 2025.
[55] A. Z. Oshilalu, “Sustainability Meets Scalability: Transforming Energy Infrastructure Projects Into Economic Catalysts Through Supply Chain Innovation,” International Journal of Research Publication and Reviews, vol. 5, no. 12, pp. 762–779, 2024.
[56] S. Holloway, “Exploring the Role of Artificial Intelligence in Enhancing the Efficiency of Knowledge Management Systems,” 2025.
[57] R. Gera, S. Banerjee, D. V. Saratchandran, S. Arora, and A. Whig, “Machine Learning for Environmental Sustainability in the Corporate World,” in Driving Business Success Through Eco-Friendly Strategies, Hershey, PA, USA: IGI Global, 2025, pp. 283–302.
[58] T. H. Abdtawfeeq et al., “Optimizing Analytical Thresholds in Serum Proteomics Using Neutrosophic Logic Systems,” International Journal of Intelligent Engineering & Systems, vol. 18, no. 7, 2025.
[59] R. Kumar, N. Kamboj, D. Mitra, and A. Ray, “Strengthening Local Communities Through Advanced Recycling Technology for Sustainable Growth,” in AI Technologies for Enhancing Recycling Processes, Hershey, PA, USA: IGI Global, 2025, pp. 393–420.
[60] S. Rani, “Synergizing Artificial Intelligence and HRM for Circular Economy Transition: A Conceptual Framework,” 2025.
[61] W. C. Munonye et al., “Advancing Circularity in Battery Systems for Renewable Energy: Technologies, Barriers, and Future Directions,” Advanced Energy and Sustainability Research, 2025.
[62] A. M. O. Mohamed, D. Mohamed, A. Fayad, and M. T. Al Nahyan, “Environmental Management and Decarbonization Nexus: A Pathway to the Energy Sector’s Sustainable Futures,” World, vol. 6, no. 1, p. 13, 2025.
[63] H. Jain, “Synergizing Carbon Reduction Technologies and Nature-Based Solutions for a Climate-Neutral Future,” Mitigation and Adaptation Strategies for Global Change, vol. 30, no. 6, p. 42, 2025.
[64] M. D. Moinuddin et al., “Integrating Fourth Industrial Revolution Technologies With Green Energy Systems: A Framework for AI-Driven Smart Grid Optimization and Carbon Footprint Reduction,” Mari Papel y Corrugado, pp. 122–140, 2024.
[65] S. Nadweh, N. Mohammed, O. Alshammari, and S. Mekhilef, “Topology Design of Variable Speed Drive Systems for Improving Power Quality in Industrial Grids,” Electric Power Systems Research, vol. 238, p. 111114, 2025.
[66] H. A. Hadi, A. Kassem, H. Amoud, and S. Nadweh, “Improving Power Quality and Stability of Grid-Connected PV System Using Series Filter,” Heliyon, vol. 10, no. 21, 2024.
[67] S. Nadweh, N. Mohammed, and S. Mekhilef, “Techno-Economical Evaluation of Photovoltaic-Powered Street Lighting Systems,” in Proc. 4th International Conference on Emerging Smart Technologies and Applications, 2024, pp. 1–8.
[68] S. I. Khattak, “Renewable Energy: A Transition for a Green Economy,” in A Green Vision Towards a Renewable Energy Future, Cham, Switzerland: Springer Nature, 2025, pp. 37–92.
[69] M. Samimi and H. Hosseinlaghab, “Enabling Sustainable Solar Energy Systems Through Electromagnetic Monitoring of Key Components Across Production, Usage, and Recycling: A Review,” Journal of Manufacturing and Materials Processing, vol. 9, no. 7, p. 225, 2025.
[70] S. K. Lodhi, A. Y. Gill, and H. K. Hussain, “Green Innovations: Artificial Intelligence and Sustainable Materials in Production,” BULLET: Jurnal Multidisiplin Ilmu, vol. 3, no. 4, pp. 492–507, 2024.
[71] A. M. O. Mohamed, D. Mohamed, A. Fayad, and M. T. Al Nahyan, “Enhancing Decision Making and Decarbonation

in Environmental Management: A Review on the Role of Digital Technologies," Sustainability, vol. 16, no. 16, p. 7156, 2024.

[72] V. Rahate et al., "Digital Twins in Renewable Energy Systems," in Leveraging AI for Innovative Sustainable Energy: Solar, Wind and Green Hydrogen, Hershey, PA, USA: IGI Global, 2025, pp. 123–138.

[73] A. A. Firoozi, F. Hejazi, and A. A. Firoozi, "Advancing Wind Energy Efficiency: A Systematic Review of Aerodynamic Optimization in Wind Turbine Blade Design," Energies, vol. 17, no. 12, p. 2919, 2024.

[74] H. A. Hadi et al., "Using Imperialist Competitive Algorithm Powered Optimization of Bifacial Solar Systems," Journal of Robotics and Control, vol. 5, no. 4, pp. 1166–1179, 2024.

[75] C. Challoumis, "Building a Sustainable Economy: How AI Can Optimize Resource Allocation," in Proc. XVI International Scientific Conference, Oct. 2024, pp. 190–224.

[76] M. Kaur et al., "Impact of Artificial Intelligence Techniques on Green Applications," in Artificial Intelligence Techniques for Sustainable Development, Boca Raton, FL, USA: CRC Press, 2024, pp. 64–85.

[77] M. Q. Rasheed and Z. Yuhuan, "Exploring Artificial Intelligence, Circular Economy, and Energy Intensity in Achieving Sustainable Development Goal 13," Sustainable Development, 2025.

[78] Z. A. Ali et al., "Digital Twins: Cornerstone to Circular Economy and Sustainability Goals," Environment, Development and Sustainability, 2025.

[79] H. A. Hadi et al., "Using Grey Wolf Optimization Algorithm and Whale Optimization Algorithm for Optimal Sizing of Grid-Connected Bifacial PV Systems," Journal of Robotics and Control, vol. 5, no. 3, pp. 733–745, 2024.

[81] V. Frimpong, "The Sustainability Paradox of Artificial Intelligence: How AI Both Saves and Challenges Resource Management Efforts," SSRN, 2025.

[82] H. A. Hadi et al., "Using Active Filter Controlled by Imperialist Competitive Algorithm for Harmonic Mitigation in Grid-Connected PV Systems," International Journal of Robotics & Control Systems, vol. 4, no. 2, 2024.

[83] F. P. Appio, F. Platania, and C. T. Hernandez, "Pairing AI and Sustainability: Envisioning Entrepreneurial Initiatives for Virtuous Twin Paths," IEEE Transactions on Engineering Management, 2024.

[84] M. Noor, "Comprehensive Life Cycle Evaluation of Carbon Emission From ICT Equipment Manufacturing Processes and End-of-Life Management," 2025.

[85] H. A. Hadi et al., "Flower Pollination Algorithm Used to Improve the Performance of Grid-Connected PV Systems," in Proc. International Conference on Computer and Applications, 2022, pp. 1–7.

[86] C. R. G. Popescu, Ed., AI and Green Innovation for Achieving Sustainable Development Goals, Hershey, PA, USA: IGI Global, 2025.

[87] A. Elhamahmy, H. T. H. Gohar, and A. Galal, "Sustainable Project Management in Renewable Energy and Infrastructure Projects: Challenges and Opportunities," International Journal of Engineering Research & Technology, vol. 14, no. 5, 2025.

[88] O. Khaddam, S. Nadweh, and A. Aldiwany, "Shunt Active Filter Control for Harmonics Mitigation in a Smart Electricity Grid," in Deregulated Electricity Market, Oakville, ON, Canada: Apple Academic Press, 2022, pp. 223–248.