Long-Term Prediction Model for Forecasting Photovoltaic Production and Waste Generation Using Polynomial Regression in Machine Learning

Submitted for the Partial Fulfillments of the Requirements of the degree of

Bachelor of Technology

In

Computer Science and Engineering

By

D. Pavan Kumar - AP22110010208

Under the Supervision of

Dr. Deblina Dutta
Assistant Professor
Dept of Env. Sci. and Engg.
SRM University - AP
Mangalagiri - 522502
Andhra Pradesh

Dr. Sunil Kumar
Sr. Principal Scientist
Solid & Hazardous Waste Management
CSIR - NEERI
Nagpur - 440020, Maharashtra

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SRM UNIVERSITY - AP

JANUARY - 2025

DECLARATION

This is to Certify that work presented in the Dissertation Entitled “ **Long - Term Prediction Model for Forecasting Photovoltaic Production and Waste Generation using Polynomial Regression in Machine Learning** “ being Submitted to the “ **SRM University - Andhra Pradesh** “ for the award of Bachelor of Technology in Computer Science and Engineering is my original research work during **01 - June - 2024 to 10 - August - 2024**.

This Dissertation embodies the result of Investigation, Observation & Experiments carried out by me. I have neither Plagiarised any part of the dissertation nor have submitted same work for the award of any other Diploma / Degree / Masters / PHD anywhere.

Pavan kumar

D. Pavan Kumar.

SRM University - AP

सी.एस.आई.आर. – राष्ट्रीय पर्यावरण अभियांत्रिकी अनुसंधान संस्थान
CSIR - National Environmental Engineering Research Institute
(वैज्ञानिक तथा औद्योगिक अनुसंधान परिषद, / Council of Scientific & Industrial Research)
(वैज्ञानिक तथा औद्योगिक अनुसंधान परिषद, विज्ञान एवं प्रौद्योगिकी मंत्रालय, भारत सरकार के अंतर्गत स्वायत्त संघठन)
नीरी
NEERI

डॉ. सुनील कुमार
वरिष्ठ प्रधान वैज्ञानिक
Dr. Sunil Kumar
Sr. Principal Scientist

To Whomsoever it may concern

This is to certify that **Mr. D. Pavan Kumar** pursing the degree of Bachelor of Technology in Computer Science and Engineering at SRM University – AP, Neerukonda has carried out a project entitled " **Long-Term Prediction Model for Forecasting Photovoltaic Production and Waste Generation Using Polynomial Regression in Machine Learning** " at CSIR – National Environmental Engineering Research Institute, Nagpur under the supervision and Guidance of Dr. Sunil Kumar during June 2024 to August 2024.

(Dr. Sunil Kumar)
Senior Principal Scientist
CSIR-NEERI

नेहरु मार्ग, नागपूर - 440 020 (भारत) - Nehru Marg, Nagpur - 440 020 (INDIA)
Ph (O) : 91-712-2249885-89 (Ext.696) Fax : 2249900 Email : s_kumar@neeri.res.in
URL : www.neeri.res.in
सतत विकास की ओर / Towards Sustainable Development

ACKNOWLEDGEMENT

I would like to express my deepest gratitude to my supervisor, **Dr. Sunil Kumar**, Senior Principal Scientist at CSIR-NEERI, for his invaluable guidance, support, and encouragement throughout the course of this prediction model. His expertise and insightful feedback have greatly shaped the direction of my work. I am immensely grateful for the time and effort he invested in mentoring me. His dedication to research and his willingness to share knowledge have been a constant source of inspiration. Without his unwavering support, this prediction model would not have reached its current state of completion.

I am also profoundly grateful to **Dr. Deblina Dutta** for her continuous support and mentorship. Her guidance has been instrumental in navigating challenges and refining the quality of this prediction model. Her encouragement and constructive feedback have provided me with confidence and clarity, enabling me to overcome obstacles and make informed decisions.

A special thanks goes to **Mr. Rahul Rautela** and **Mr. Pranav Prasanth Dagwar** for their technical insights and collaborative spirit. Their contributions have been invaluable in refining the methodology and ensuring the accuracy of the results. Their support has enriched the overall quality of this work, and I deeply appreciate their critical feedback and expertise.

Lastly, I extend my sincere thanks to my parents, **Bhupathi Rao** and **Lakshmi Sujatha**, and my brother, **Venkata Gowtham**, for their unwavering love, patience, and support. Their encouragement and belief in my abilities have been a constant source of strength, motivating me to persevere during challenging times. The values they have instilled in me have been a guiding light, and their sacrifices have enabled me to focus on my academic pursuits.

Signature of the Student

Date - 02/January/2025

Place - Amaravathi

Table of Contents

S. No	Content	Page No
1	Abstract	1
2	Introduction	2 - 6
3	Methodology	7 - 9
4	Results and Discussion	10 - 22
5	Conclusion	23
6	References	24 - 28

List of Abbreviations

1. **MSE** - Mean Squared Error
2. **C++** - C++ Programming Language
3. **PV** - Photovoltaic
4. **R^2** - R-squared (Coefficient of Determination)
5. **EOL** - End of Life
6. **RE** - Rare Earth (metals)
7. **KG** - Kilogram
8. **MT** - Metric Ton
9. **%** - Percentage
10. **KT** - Kiloton
11. **MT** - Metric Ton
12. **R&D** - Research and Development
13. **AI** - Artificial Intelligence
14. **ML** - Machine Learning
15. **Al** - Aluminum
16. **Cu** - Copper
17. **Ag** - Silver
18. **Sn** - Tin
19. **Pb** - Lead
20. **Zn** - Zinc
21. **Ni** - Nickel
22. **In** - Indium
23. **Ga** - Gallium
24. **Te** - Tellurium
25. **Se** - Selenium

List of Figures

Figure - 1 - Production VS Waste Generation from 2010 to 2070

Figure - 2 - Waste Generation from 2010 to 2070

Figure - 3 - Heat map of the Predicted Data from 2010 to 2070

Long-Term Prediction Model for Forecasting Photovoltaic Production and Waste Generation Using Polynomial Regression in Machine Learning

Abstract

The prediction model that employs polynomial regression to forecast photovoltaic production and waste generation from 2024 to 2070. By fitting a third-degree polynomial to historical data, this prediction model captures complex, non-linear trends and provides accurate forecasts for future scenarios. The implementation in C++ ensures efficient calculation of polynomial coefficients from historical datasets, enabling precise predictions based on user input.

The results confirm that this prediction model effectively addresses intricate patterns within the data, with forecasts demonstrating reliable accuracy. The validation process, evidenced by a low Mean Squared Error (MSE), reinforces the model's effectiveness in aligning predictions with historical trends. These forecasts offer valuable insights for stakeholders, including policymakers, environmental agencies, and industry leaders, supporting strategic planning and informed decision-making.

Future improvements may involve integrating advanced machine learning techniques and incorporating additional factors to enhance prediction accuracy. Overall, this prediction model showcases the power of polynomial regression in predictive analytics and its potential to contribute to sustainable energy practices and efficient waste management strategies.

Keyword - Photovoltaic Waste, Prediction Model, Polynomial Regression, C++, Historical Data analysis, Machine Learning Integration

1. INTRODUCTION

1.1 Overview of Photovoltaic Waste

The global adoption of photovoltaic (PV) technology has rapidly increased as the world seeks sustainable energy solutions. Solar panels, integral to efforts aimed at combating climate change and reducing reliance on fossil fuels, have become a key component in renewable energy strategies. However, this widespread use has introduced a new environmental issue - photovoltaic waste. This type of waste includes all discarded materials from the production, use, and disposal of solar panels. As these panels typically have a lifespan of 25-30 years, their disposal contributes to the growing problem of electronic waste **(Gharaee et al., 2024).**

A thorough understanding of photovoltaic waste its composition and lifecycle is vital for developing effective waste management strategies. Solar panels are primarily made of materials such as glass, aluminium, silicon, and various metals, including silver, lead, and cadmium. While these materials have significant value, they also present considerable challenges for recycling. Without proper disposal and recycling measures, PV waste could lead to environmental contamination and resource depletion. Thus, it is crucial to implement comprehensive strategies that incorporate efficient recycling technologies and support circular economy principles.

Anticipating future PV waste generation is key to creating and executing effective waste management systems. Accurate forecasting helps policymakers and industry leaders prepare for the scale of the waste issue and allocate resources appropriately **(Maheri et al., 2023).** By using advanced mathematical models, such as polynomial regression, we can predict the volume of PV waste over time. This proactive approach ensures that the benefits of solar energy are maintained without creating additional environmental problems from panel disposal.

1.2. Photovoltaic Waste Generation in India

India has become a major player in the global solar energy sector, driven by ambitious goals to boost renewable energy capacity. The country’s solar power infrastructure has expanded significantly, with a growing number of large-scale solar farms and rooftop installations enhancing the national grid. However, this rapid expansion also presents the challenge of managing solar panel waste. While India’s solar growth is beneficial for energy security and environmental sustainability, it is anticipated to generate a considerable amount of photovoltaic (PV) waste in the coming decades **(Kanthasamy et al., 2023)**

The Indian Government has introduced various initiatives to support the adoption of solar energy including subsidies, tax incentives and renewable purchase obligations. Despite these supportive measures, the focus has been predominantly on the deployment phase, often neglecting the management of solar panels at the end of their life cycle. Consequently, there is an urgent need to develop effective frameworks for the collection, recycling, and disposal of PV waste. Existing waste management systems are not adequately equipped to handle the expected increase in decommissioned solar panels, highlighting the need for comprehensive recycling infrastructure **(Sappl et al., 2023).**

Raising awareness about PV waste among all stakeholders is also essential. Manufacturers, installers, and consumers need to be educated on the importance of responsible disposal and recycling practices. Collaborative efforts involving government bodies, industry stakeholders, and research organisations are necessary to drive advancements in recycling technologies and establish efficient PV waste management systems.

1.3. Environmental Impacts

The environmental consequences of photovoltaic waste are diverse and considerable. Discarded solar panels, if not properly managed, can contaminate land and water with dangerous compounds including lead, cadmium, and other heavy metals. These compounds have the potential to contaminate the environment, endangering human health and ecosystems. Furthermore, inappropriate rooftop solar panel recycling contributes to the rising electronic waste problem, which is already a serious environmental concern throughout the world **(Alsagri et al., 2024).**

Photovoltaic waste may be effectively recycled to reduce environmental impacts by recovering valuable materials and minimising the requirement for virgin resource extraction. Recycling techniques can recover metals, glass, and silicon from retired panels, saving natural resources and reducing environmental deterioration. However, present recycling systems encounter difficulties in successfully isolating and processing the complex components contained in solar cells. Research and development in sophisticated recycling systems is important to overcome these limitations and improve the sustainability of the solar sector.

Aside from the immediate environmental consequences, improper management of photovoltaic (PV) waste can erode public faith in renewable energy. If end-of-life difficulties with solar panels are not handled appropriately, the perception of solar energy as a clean and environmentally beneficial alternative to fossil fuels may suffer. To maintain the reputation and environmental advantages of solar energy, it is critical to create appropriate Photovoltaic waste management systems **(Massidda & Marrocu 2023).** This entails implementing suitable rules, establishing industry standards, and undertaking public education campaigns emphasising the value of recycling and proper disposal procedures.

1.4. Recycling Practices in India

Recycling practices for photovoltaic (PV) waste in India are currently underdeveloped, with limited infrastructure and regulatory support. The country encounters considerable challenges in creating effective systems for managing PV waste. This includes a shortage of specialized recycling facilities and the lack of comprehensive policies for the disposal of solar panels. At present, many decommissioned solar panels are either sent to landfills or exported for recycling, which are neither sustainable nor environmentally friendly solutions **(Manuguerra et al., 2024).**

Nevertheless, there are emerging efforts to advance PV waste recycling in India. Some private enterprises and research institutions are working on innovative recycling technologies designed to meet the specific needs of the Indian market. These technologies aim to efficiently recover valuable materials from solar panels while reducing environmental impacts. Additionally, various pilot projects and collaborations between government agencies and industry players are exploring scalable methods for managing PV waste.

Policy intervention is essential to enhance the development of recycling infrastructure and practices. The Indian government needs to establish clear regulations and guidelines for the collection, transportation, and recycling of PV waste. Providing incentives for recycling businesses and setting mandatory recycling targets for solar panel manufacturers can encourage the adoption of sustainable waste management practices. Furthermore, integrating PV waste management into broader environmental and energy policies will support a comprehensive approach to sustainable development **(Agbulut et al., 2020).**

Raising public awareness and education is also critical for promoting recycling practices. Consumers and industry stakeholders should be informed about the environmental benefits and economic potential of PV waste recycling. By cultivating a culture of responsibility and innovation, India can develop a robust system for managing PV waste that supports the growth of its solar industry while safeguarding the environment.

1.5. Importance of Polynomial Regression in Predictive Modelling

Polynomial regression is notable in data science for its capacity to forecast trends and relationships, particularly when these interactions have non-linear properties. In contrast to linear regression which fits a straight line between datapoints, polynomial Regression fits a curved line. economic development, environmental changes, and technology advancements frequently follow nonlinear trend to that traditional linear frameworks cannot represent. Polynomial regression offers a strong foundation for comprehending these complex interactions, resulting in more accurate predictions **(Yang et al., 2024).**

In this study, we use polynomial regression to anticipate solar production and waste creation between 2024 and 2070. Our model is based on historical data, which allows us to generate polynomial coefficients that reflect the underlying trends in these measurements. These coefficients are critical for making future forecasts and providing useful insights into possible scenarios. Our method is implemented as a C++ software that methodically calculates polynomial regression coefficients from historical data. This implementation demonstrates the actual use of polynomial regression in real-world data with complex patterns. By using C++, we ensure the program's efficiency and performance, making it ideal for managing massive datasets.

The polynomial regression model produces coefficients that describe the relationship between years, production, and waste. These coefficients provide the mathematical basis for making predictions. By fitting a polynomial curve to historical data, the model captures the nuances and differences that occur over time. We picked a polynomial of degree three to strike a balance between model complexity and generalisability beyond training data. A higher-degree polynomial may overfit the data, collecting noise rather than the underlying trend, whereas a lower-degree polynomial may overlook key details. The precise choice of polynomial degree is critical to ensure the model's robustness and reliability **(Wansasueb et al., 2024).**

1.5.1. Implementing the Polynomial Regression Model

The program allows users to input a year between 2024 and 2070 to predict production and waste for that specific year. This feature highlights the model's ability to generate tailored predictions, making it a valuable asset for planning and forecasting. Accurate predictions are essential for various stakeholders, including policymakers, environmental agencies, and industries. They can guide decision-making processes, support efficient resource allocation, aid in future production planning, and enhance waste management strategies. Making data-driven decisions based on precise predictions significantly improves strategic planning and operational effectiveness across these sectors **(Shomope et al., 2025).**

Handling real-world data comes with its own set of challenges, such as missing values, outliers, and non-linear patterns. The C++ program addresses these challenges by incorporating robust data preprocessing techniques. This ensures that missing values and outliers are managed effectively, allowing the model to be trained on clean, high-quality data. By utilizing polynomial regression, the model captures complex relationships within the data, improving the accuracy of predictions **(Bian et al., 2025)**

Updating the model with new data is crucial for maintaining the accuracy of forecasts. Polynomial regression models can recalibrate with the latest data to refine predictions and ensure they remain relevant. This ongoing update process is key to preserving the model's effectiveness in a dynamic environment. As new data becomes available, recalculating the model's coefficients helps reflect the most current trends and patterns, thereby enhancing predictive accuracy and ensuring that predictions stay useful for stakeholders.

1.5.2. Environmental and Economic Implications of Accurate Forecasting

Accurate forecasting of trash generation is critical to promoting environmental sustainability. By forecasting future waste volumes, measures can be established to reduce waste, increase recycling efforts, and lessen the environmental effect of manufacturing activities. Economically, recognising production trends is critical for both firms and governments. Reliable forecasts guide economic policies, affect market strategies, and aid long-term planning. Our approach, with accurate predictions, can lead to more effective and sustainable production and waste management procedures, ultimately benefiting society **(Palaniyappan & Vinopraba 2024).**

Although polynomial regression is a useful tool, it has limitations. The model's accuracy depends greatly on the quality and scope of the historical data used. Furthermore, external influences that were not captured in previous data can influence future developments. To confirm the model's robustness, we validate its predictions against actual historical data. This validation assists in identifying any biases or inaccuracies, allowing us to develop the model and improve its performance **(Al-Rbaihat et al., 2023).**

Future enhancements may include incorporating more predictive approaches, such as machine learning algorithms, to capture more complicated patterns and interactions in the data. For example, machine learning approaches such as neural networks can detect complex linkages and dependencies that classic regression models may miss. A hybrid method could improve the accuracy and dependability of predictions, delivering even more relevant insights for successful decision-making **(Sodhi.T.I 2023).**

2. Methodology

2.1. Data Collection and Preparation

The first step of the project is focused to collecting precise and comprehensive historical data on photovoltaic production and trash generation. This information is critical for creating a reliable predictive model and is often gathered from reputable databases and industry records. It is critical that the data span multiple years to provide a comprehensive picture of trends. Every data point must be verified for accuracy, completeness, and relevancy. This method frequently involves cross-referencing numerous sources to validate the information, which improves the dataset's dependability. Proper data collection is critical since it directly influences the model's validity and the quality of the insights produced from it **(He et al., 2025).**

After the data collecting is completed, the next step is data preparation, Which entails transforming raw data into a clean, structured format suitable for analysis. This begins with data cleaning, which involves correcting or removing entries that are missing, incorrect, or irrelevant. Effective data cleansing is required to avoid biases or mistakes that may affect the results. Normalisation is another important stage that involves scaling data to a homogenous range to improve model performance. Detecting and managing outliers is particularly critical because extreme values might bias outcomes. Having no such outliers helps to build a strong model that accurately reflects underlying patterns **(Qadeer et al., 2021).**

The final step in data preparation is feature engineering, which involves developing new variables from current data to increase the model's prediction capabilities. This includes identifying relevant features that have a major impact on the outcome, altering variables to better capture underlying patterns, and even combining features to generate more informative variables. Feature engineering necessitates knowledge and a complete grasp of the data, as feature selection and transformation have a significant impact on model correctness. By carefully designing features, the model's ability to learn from data is improved, resulting in more accurate and dependable predictions. This extensive approach to data collecting and preparation lays the groundwork for creating an effective polynomial regression model for estimating photovoltaic production and waste creation **(Cetina et al., 2023)**

2.2. Data Analysis

During the data analysis phase, attention shifts to feature selection, which entails determining which key variables to include in the polynomial regression model. The primary characteristics of this project are the years (the independent variable) and the related production and waste figures. This selection process is critical for ensuring that the chosen characteristics adequately represent the trends in the data. Each feature is evaluated for relevance and contribution to the model, ensuring that the final dataset appropriately reflects historical production and waste patterns.

The polynomial regression model is constructed when the necessary features have been selected. This procedure entails generating a design matrix that includes the powers of the independent variable (years) and calculating the polynomial coefficients **(Dan et al., 2024).** The model's performance is measured by how well it matches past data and how accurate it makes forecasts. Effective data analysis ensures that the model is constructed on a solid foundation of essential features, resulting in more accurate and reliable forecasts of future trends in photovoltaic production and waste.

In addition, comprehensive statistical approaches are used to validate the model's performance. This includes evaluating the quality of fit with measurements such as R-squared values, performing residual analysis to find any patterns that the model did not capture, and utilising cross-validation to assess the model's robustness. By carefully analysing the data and testing the model, we may find possible areas for improvement and make the necessary changes. This meticulous approach to data analysis not only improves the model's prediction skills but also increases its reliability, making it an invaluable tool for accurately estimating photovoltaic production and waste **(Can et al., 2022).**

Finally, the data analysis phase examines external elements that may have an impact on photovoltaic production and waste generation. These reasons could include regulatory changes, technical breakthroughs, or economic adjustments. Incorporating these variables into the study enables for model revisions to account for future uncertainty, enhancing long-term predicted accuracy. This thorough methodology ensures that the polynomial regression model can produce accurate forecasts, allowing stakeholders to make educated decisions **(Manivannan 2024).**

2.3. Polynomial Regression

The polynomial regression model is employed to understand the complex relationships between years and photovoltaic production and waste generation. This type of regression is particularly useful when the data exhibits non-linear trends that simple linear models cannot capture. By fitting a polynomial curve to the historical data, the model can accurately represent the intricate patterns and variations over time **(Junior et al., 2024).** The coefficients of the polynomial regression model are derived from historical data using statistical methods that minimise the differences between observed and predicted values. This ensures that the model aligns closely with past trends, providing a reliable foundation for making future predictions. By leveraging the power of polynomial regression, the project aims to generate accurate forecasts for photovoltaic production and waste generation, aiding in effective planning and decision-making **(Kashyap et al., 2024).** This model is employed to understand the complex relationships between years and photovoltaic production and waste generation. For a third-degree polynomial regression, the equation used is

$$\boldsymbol{Y = a_0 + a_1x + a_2x^2 + a_3x^3}$$

Here, y is the predicted value (either production or waste), x represents the input year, and $a0$,$a1$, $a2$, $a3$ are the coefficients derived from historical data. These coefficients are calculated using the least squares method which minimises the sum of the squared difference between the observed and predicted values. The matrix form of the polynomial regression equation is

$$\mathbf{Y = X \,.\, A}$$

Where Y is the vector of observed values, X is the design matrix containing the powers of X and A is the vector of coefficients. Solving for A involves

$$\mathbf{Y = (((X^T X^{-1}) ^{-1}) X^T) Y}$$

This formula ensures that the polynomial regression model fits the historical data as accurately as possible, providing a robust basis for future predictions

2.4. Continuous Model Improvement

A major feature of the process is the continuous improvement of the prediction model to ensure its accuracy and relevance over time. This development process begins with the regular incorporation of fresh data, which allows the model to keep up with the newest trends and patterns in PV production and waste management. The model's parameters and predictions are fine-tuned by incorporating new data. This continuous update is critical for detecting shifts in trends and identifying developing patterns that may not be obvious in earlier data. Such iterative modifications enable the model to adapt to changing situations, hence increasing prediction accuracy and reliability **(Demirci et al., 2021).**

Another important factor in refining the predictive model is the use of advanced techniques. For example, integrating machine learning algorithms can help in identifying complex patterns and interactions within the data that simpler models might overlook. These algorithms can reveal subtle relationships between variables, leading to more precise forecasts. Additionally, including extra features, such as economic indicators or technological advancements, can enrich the model's understanding of the factors influencing photovoltaic production and waste. Expanding the model to encompass these additional variables results in a more detailed and accurate predictive tool that considers a broader range of influences.

Consistent updates and changes keep the model current with shifting patterns, ensuring its usefulness over time. This iterative technique improves the model's accuracy while also providing useful insights for long-term planning and decision-making. By continuously updating the model, stakeholders can utilise it to make strategic decisions about PV production and waste management. This proactive model improves resource allocation, policy formation, and operational planning, resulting in more sustainable and efficient operations. As a result, constant refinement of the predictive model is critical to its success, assuring its sustained usefulness as a forecasting and planning tool in the dynamic field of solar technology **(Wen et al., 2023).**

3. Results and Discussion

3.1. Overview of Data Characterisation

Characterising data for projecting solar production and waste generation necessitates a thorough examination of previous data and patterns. This procedure begins with obtaining large datasets spanning several years. Such datasets provide essential information on production levels, waste amounts, and their changing dynamics over time. Examining these data reveals tremendous expansion in photovoltaic manufacturing, which is frequently connected to increased waste generation. This extensive examination is critical for identifying patterns, seasonal changes, and abnormalities that may affect projections. A thorough understanding of historical data enables better model revisions, ensuring that previous trends are appropriately mirrored in future forecasts. The data collection process is comprehensive, generally requiring several sources to check the data's correctness and consistency, which is critical for building reliable predictive models **(Zheng et al., 2023).**

Evaluating historical patterns in photovoltaic production and waste creation indicates not just general increase, but also the factors that influence these changes. Seasonal patterns may suggest times of increased or decreased activity, whereas anomalies may reflect unusual events or shifts in technology and policy. Recognising these elements is critical for creating forecasting models that can handle a variety of scenarios. This approach also helps to understand the long-term environmental and economic consequences of solar waste. By recording and understanding historical trends, researchers can develop models that provide more exact future estimates as well as significant insights for policymaking and strategic planning. This level of information guarantees that the models remain relevant and reliable, providing a comprehensive picture of current and future photovoltaic waste patterns **(Tan et al., 2023).**

Accurate and thorough data collection and verification are essential for accurate forecasting. Ensuring that datasets are both broad and exact enables researchers to develop strong models that appropriately reflect historical patterns. This rigorous approach helps to avoid errors or biases that could affect forecasts. Thus, well-executed data characterisation serves as the foundation of effective forecasting, enabling the development of models that are both accurate and flexible to future changes. This first stage is critical for any predictive model, setting the foundations for accurate assessments and projections **(Chaudhry et al., 2024).**

3.2. Historical Data Trends and Patterns

Historical data show a consistent increase in photovoltaic production, owing mostly to technological breakthroughs and increased acceptance of solar energy. This growth in production is coupled by an increase in waste generation, highlighting the importance of appropriate management systems. By evaluating these trends, researchers can identify notable periods of development or decline that are affected by technology advancements, legislative changes, and market dynamics. Understanding these historical patterns provides essential insights into the complex link between production and waste creation, which is necessary for constructing models capable of reliably forecasting future trends based on previous performance and projected changes **(Rodriguez et al., 2021).**

A thorough examination of historical data might identify certain time periods during which solar production and trash creation changed significantly. Technological innovations frequently result in greater output, whereas market conditions and regulatory frameworks can either encourage or impede this expansion. Identifying these patterns helps to clarify the forces driving changes in the photovoltaic sector. This complete approach is required for developing forecasting models that deliver accurate future estimates, ensuring that they remain relevant and credible. Furthermore, understanding the historical relationship between production and waste generation is critical for developing effective waste management methods and informing policy decisions. This extensive analysis not only improves model accuracy, but also assures that it is practical and relevant in real-world circumstances, thereby aiding the photovoltaic industry's long-term development **(Byun et al., 2021).**

An understanding of the intricate relationship between waste generation and production can be gained by analysing historical data. Recognising the elements that influence these trends enables the creation of more accurate forecasting models that predict future changes. This emphasises the importance of continually updating and refining models to incorporate new data and evolving patterns. Furthermore, it emphasises the significance of historical data in defining strategic decisions and policymaking, laying the groundwork for long-term practices in the photovoltaic business. This strategy ensures that models remain precise and adaptive to changing situations, increasing forecast accuracy and practical use **(Patty & Malakar 2024).**

Table – 1 – Historical data of the Production and Waste Generation from 2010 to 2023

Year	Production (MT)	Waste Generated (MT)
2010	748.00	29.92
2011	927.00	43.41
2012	1189.54	56.46
2013	1486.25	67.25
2014	1798.11	81.57
2015	2153.83	101.82
2016	2603.12	121.16
2017	2928.00	133.78
2018	3279.36	156.52
2019	3606.92	186.52
2020	2910.12	213.378
2021	3105.92	245.23
2022	3663.98	281.75
2023	4021.76	321.54

3.3. Recovery Potential of Photovoltaic Waste

The potential for recovering valuable materials from photovoltaic (PV) waste is a crucial aspect of managing panels that have reached the end of their lifecycle. PV waste includes materials such as silicon, silver, and rare earth metals that can be reclaimed using advanced recycling methods. A thorough analysis of the material composition in PV waste is essential for identifying which elements can be effectively recovered. This process is fundamental for crafting recycling strategies aimed at maximising the retrieval of these important resources. By examining the composition in detail, researchers can pinpoint the most efficient extraction techniques, ensuring the recycling process is both effective and economical. Proper recovery practices not only reduce the environmental impact of PV waste but also contribute to resources conservation helping to preserve natural materials **(Wu et al., 2024).**

Assessing the recovery potential highlights the necessity of developing and adopting technologies that can effectively extract valuable materials from PV waste. Identifying key components such as silicon, silver, and rare earth metals drives innovation in recycling technology. These innovations are critical for boosting the sustainability of PV systems. Effective recovery technologies support a circular economy by continuously reusing materials, which reduces the need for new resources. Furthermore, the successful recovery of valuable materials makes recycling initiatives more financially viable, attracting interest from investors and policymakers. This comprehensive approach to PV waste management enhances both environmental sustainability and the long-term economic stability of the industry **(Prinsloo et al., 2023).**

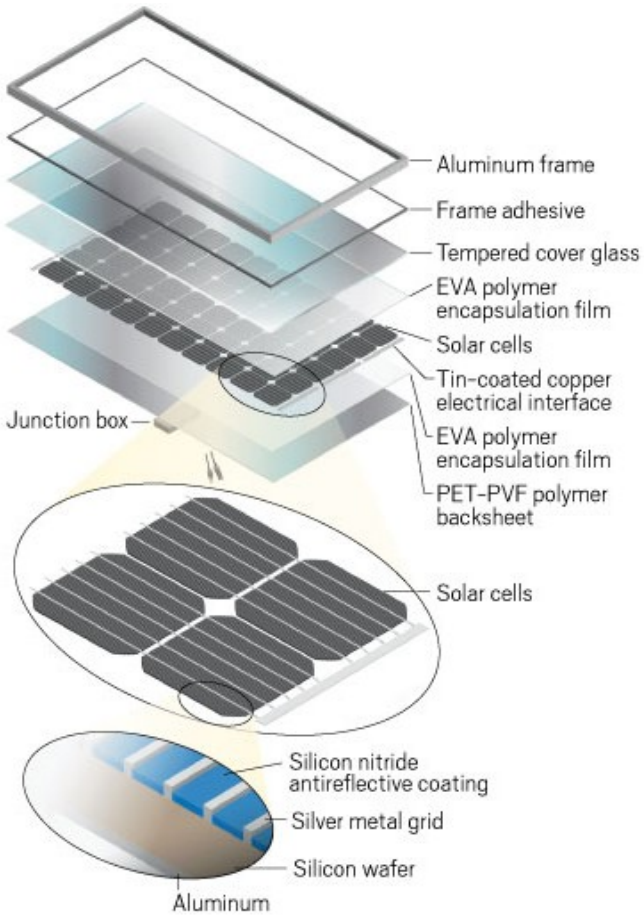
Creating effective recycling strategies based on a detailed analysis of material composition is vital for optimizing the recovery of valuable resources. This strategy involves determining the most efficient methods for extracting each material, ensuring that the recycling process remains both cost-effective and environmentally sound. By focusing on the specific properties of each material, researchers can develop tailored processes for their recovery. This focused approach improves the efficiency of recycling efforts and supports the principles of a circular economy, where resources are perpetually reused, minimising the need for fresh raw materials. Overall, this methodical approach to managing PV waste delivers significant environmental and economic benefits **(Wu et al., 2023).**

3.4. Material Composition and its Implementations

Glass, aluminium, silicon, and copper are among the components that make up photovoltaic waste. Glass accounts for the biggest part of this waste, followed by aluminium and silicon. Understanding the composition of solar waste is critical for developing efficient recycling technologies that separate and recover these elements. A thorough investigation of material composition aids in determining the most efficient techniques for recycling each component. Glass and aluminium, for example, are very easy to recycle using current methods, whereas silicon and rare earth metals require specialised techniques. Knowing the composition of materials helps to build tailored recycling programs that maximise resource recovery. By focussing on the unique properties of each material, researchers can develop procedures that are both efficient and environmentally beneficial **(Wang et al., 2023).**

The material composition of photovoltaic waste has important consequences for both environmental management and economic recovery. Proper treatment and recycling of these items can yield significant benefits, including reduced environmental impact and natural resource conservation. Glass and aluminium recycling that is done correctly not only minimises waste volume but also recovers resources that can be reused in the manufacturing process. Recovery of silicon and rare earth metals, on the other hand, is more complex but critical to the long-term viability of solar technology. These materials are critical for the production of new solar panels, and successful reclamation can reduce reliance on virgin resource mining and extraction. By emphasising tailored recycling solutions, this methodology ensures that solar waste management maximises both environmental and economic benefits, contributing to overall sustainability of the solar industry **(Askari et al., 2022).**

A thorough grasp of material composition is required when building recycling procedures that maximise the recovery of precious materials. Analysing material composition assists in determining the most efficient techniques for separating and reclaiming each component, ensuring that recycling procedures are both economically and environmentally sustainable. Researchers can design focused solutions that improve recycling efficiency and support the concepts of a circular economy by focussing on the individual properties of each material. This holistic approach ensures that photovoltaic waste management maximises environmental and economic benefits, thereby contributing to the photovoltaic industry's overall sustainability **(Socci et al., 2024).**



3.5. Metal Composition Analysis

Photovoltaic waste contains essential elements like aluminium, copper, silver, and lead. Each metal has varied recovery potential and recycling needs. Aluminium and copper are reasonably abundant materials that can be recycled effectively using current technologies. Silver and lead, on the other hand, require more complex recovery processes due to their distinct chemical and physical properties. Understanding the metal composition is critical for determining the economic worth of waste and developing targeted recycling programs. A thorough examination of these metals aids in selecting the most effective recovery strategies, ensuring that recycling procedures are both efficient and economically viable. Researchers can build more refined and successful recycling processes by determining each metal's particular features and recovery potential **(Shaik et al., 2022).**

Effectively recovering metals such as aluminium, copper, silver, and lead from solar waste helps to conserve resources and decreases the environmental impact of photovoltaic technology. Aluminium and copper are easier to recycle and may be processed using existing technology, reducing the demand for new raw materials. On the other hand, retrieving silver and lead, albeit more difficult, is critical because to their great economic worth and significant environmental risks. Analysing the metal composition reveals not only the economic benefits of recycling, but also the importance of establishing specialised procedures to solve the distinct issues connected with each metal. This comprehensive approach guarantees that recycling programs are customised to maximise the recovery of valuable materials while minimising environmental effect, therefore improving the sustainability of the photovoltaic industry **(Wei et al., 2022).**

Developing specific recycling plans based on a thorough examination of metal composition is critical for maximising the recovery of precious resources. This strategy entails determining the most efficient ways for extracting each metal, ensuring that the recycling process is both commercially viable and environmentally sustainable. Researchers can create techniques that address the unique recovery needs of each metal by focussing on its specific features. This targeted strategy not only increases the effectiveness of recycling operations, but it also promotes the concepts of a circular economy, in which resources are continuously reused, reducing the need for new raw materials. This comprehensive plan guarantees that solar waste is managed in a way that maximises environmental and economic benefits, thereby contributing to the photovoltaic industry's overall sustainability **(Sun et al., 2025)**

Table - 2 - Metal Composition of Photovoltaic Waste

METAL	PERCENTAGE	QUANTITY
Aluminium	5 – 15	50 – 150
Copper	1 – 2	10 – 20
Silver	0.05 – 0.1	0.5 - 1
Tin	0.05 – 0.1	0.5 - 1
Lead	0.05 – 0.1	0.5 - 1
Zinc	0.01 – 0.05	0.1 – 0.5
Nickel	0.01 – 0.05	0.1 – 0.5

3.6. Rare Earth MetalAnalysis

Photovoltaic waste also contains rare earth metals such as gallium, indium, and selenium, which are essential for the functionality of solar panels. Recovering these rare earth metals presents unique challenges due to the complexity & specificity of the required extraction process. Although these metals are present in smaller quantities compared to other materials, they hold significant economic value and are crucial for producing high-efficiency solar panels. Understanding the composition and distribution of rare earth metals in photovoltaic waste is key to developing effective recycling techniques that can recover these valuable resources. Detailed analysis helps researchers identify the most suitable methods for their extraction, ensuring that the recycling process is both efficient and economically viable. By focusing on the specific characteristics of rare earth metals, researchers can develop targeted strategies that maximise their recovery while minimising environmental impact **(Iqbal et al., 2024)**

The ability to effectively recover rare earth metals from solar waste has significant ramifications. These metals are essential for a variety of high-tech applications, and efficient reclamation can reduce reliance on new resource mining, which frequently has severe environmental and social effects. Furthermore, the commercial importance of rare earth metals makes their recovery financially appealing, bolstering the overall viability of recycling efforts. Creating specialised techniques for extracting these metals requires the use of modern technologies such as hydrometallurgy and pyrometallurgy, which are tailored to their specific qualities. This holistic method ensures that rare earth metals are recovered in a way that promotes both environmental and economic sustainability, so contributing to the photovoltaic industry's long-term viability (**Li et al., 2022)**

To develop targeted recycling techniques for rare earth metals, a full understanding of their composition and properties is required. By determining the most efficient extraction methods, researchers can develop systems that are both economically and environmentally sustainable. This method employs modern technologies and novel methodologies to effectively separate and recover rare earth metals from photovoltaic waste. Researchers can develop techniques to improve recycling efficiency and support the concepts of a circular economy by focussing on the specific properties of these metals. This comprehensive plan guarantees that rare earth metals are managed in a way that maximises both environmental and economic benefits, therefore contributing to the overall sustainability of the solar industry **(Egeland & Sartori 2024)**

Table - 3 - Rare Earth Metal Composition of Photovoltaic Waste

RARE EARTH METALS	PERCENTAGE (%)	QUANTITY
Indium	0.01 – 0.05	0.1 – 0.5
Gallium	0.01 – 0.05	0.1 – 0.5
Tellurium	0.01 – 0.05	0.1 – 0.5
Selenium	0.01 – 0.05	0.1 – 0.5

3.7. Economic Value of Recovered Materials

The economic value of materials recovered from photovoltaic (PV) waste is critical in creating effective recycling techniques. PV panels contain valuable substances such as silicon, silver, aluminium, and rare earth metals, all of which have high market value. To assess the economic potential of these resources, it is necessary to examine market prices, demand, and recovery costs. This research helps to establish whether recycling activities are both environmentally and economically viable. By focussing on the financial value of recovered materials, researchers can create recycling systems that maximise financial returns while minimising environmental damage **(De et al., 2023).**

Understanding the economic potential of elements like silicon, silver, and rare earth metals is critical for promoting recycling activities. The high market value of these materials provides a significant financial incentive, encouraging investment in improved recycling technology. This investment encourages the development of efficient techniques for retrieving these rich materials, as well as the construction of long-term business strategies. Highlighting the financial benefits of recycling PV waste can enhance industry and government support, so contributing to the PV industry's long-term viability **(Han et al., 2023).**

A detailed understanding of the economic value of recovered materials greatly increases the viability of recycling initiatives. Detailed economic analysis contributes in developing viable and sustainable business models, assuring the long-term success of recycling initiatives. The emphasis on the economic potential of minerals such as silicon, silver, and rare earth metals aids in the development of methods that provide significant financial returns while adhering to circular economy principles. This method ensures that PV waste management maximises both environmental and economic benefits, strengthening PV technology's overall sustainability and increasing support for recycling activities **(Zhao et al., 2024).**

3.8 Methodological Advances in Recycling Processes

Advances in recycling techniques are critical for increasing the recovery of valuable elements from solar waste. Emerging techniques including hydrometallurgy, pyrometallurgy, and sophisticated sorting technologies have considerably improved the efficiency and effectiveness of recycling processes. These approaches enable the accurate separation and extraction of valuable elements while reducing their environmental impact. By combining these novel technologies, researchers can create recycling systems that are both commercially viable and environmentally sustainable. Continuous advancement in recycling technology is critical for dealing with the expanding amounts of solar waste and ensuring that valuable resources are recovered properly (**Parrado et al., 2024).**

To tackle the specific challenges associated with photovoltaic waste, the development of advanced recycling methods is essential. Hydrometallurgy involves using aqueous solutions to dissolve and separate metals, while pyrometallurgy uses high-temperature processes for the extraction of valuable components. These modern techniques offer superior efficiency and lower environmental impact compared to traditional methods. Through continuous refinement of these processes, researchers can improve material recovery, reduce the environmental impact of recycling operations, and support the sustainability of the photovoltaic industry. Embracing these innovative techniques is crucial for managing increasing volumes of photovoltaic waste and optimizing resource recovery (**Mirzaee et al., 2023).**

Sustained innovation in recycling methods is required to improve material recovery from solar waste. Researchers can build effective and sustainable recycling systems by incorporating cutting-edge technologies and enhancing existing processes. These innovations address the specific issues of managing photovoltaic waste, ensuring that valuable components are recovered with minimal environmental impact. Continuous improvement in recycling methods is critical for handling the growing volume of solar waste, promoting a circular economy, and reaping environmental and economic benefits. This holistic approach is critical to promoting the photovoltaic industry's long-term viability **(Yang & Xiong 2024).**

3.9. Future Trends in Photovoltaic Waste Management

To predict future trends in solar waste management, present approaches, developing technologies, and evolving regulations must all be thoroughly evaluated. The amount of pv waste is predicted to increase significantly as solar energy usage grows. This predicted increase emphasises the need for novel recycling and waste management technologies to efficiently address the expanding waste volume. Advances in recycling technology, tougher regulatory frameworks, and increased industry cooperation are all likely to affect future trends in this area. By evaluating these factors, researchers can design models for forecasting future events and developing effective waste management techniques **(Nie et al., 2022).**

Several critical aspects will shape the future of solar waste management. Improvements in recycling technologies are projected to improve material recovery while reducing the environmental impact of solar waste. Increasing regulatory pressure is anticipated to lead to stricter waste management practices and the development of sustainable alternatives. Furthermore, collaboration between industries and increasing investment in research and development are critical for expanding recycling technology and supporting a circular economy. Understanding these patterns will assist academics in developing methods that address future issues while capitalising on opportunities, ensuring that photovoltaic waste is managed sustainably and efficiently **(Banjhadid et al., 2024).**

Preparing for future advances in solar waste management is critical for developing effective and sustainable methods. Researchers can create predictive models and lead the development of innovative waste management solutions by examining current practices, technology improvements, and regulatory changes. This proactive approach guarantees that the photovoltaic sector is prepared to handle growing waste quantities, maximise material recovery, and reduce environmental impact. Focussing on future trends allows researchers to develop comprehensive plans that support the concepts of a circular economy while also improving the overall sustainability of the photovoltaic industry **(Chen et al., 2023)**

Table – 4 – Predicted Production, Predicted Waste Generation, Total Value Recovered from the Photovoltaic Waste

Year	Production (MT)	Waste Generated (MT)	Total Value Recovered (USD)
2010	748	29.92	64,725.97
2011	927	43.41	93,886.45
2012	1189.54	56.46	122,123.01
2013	1486.25	67.25	145,468.71
2014	1798.11	81.57	176,411.56
2015	2153.83	101.82	220,229.90
2016	2603.12	121.16	262,045.16
2017	2928	133.78	289,319.66
2018	3279.36	156.74	338,941.20
2019	3606.925	186.52	403,416.37
2020	2910.12	213.378	461,476.47
2021	3105.92	245.23	530,382.98
2022	3663.98	281.75	609,374.41
2023	4021.76	321.54	695,415.37
2024	5553.14	777.92	1,682,480.92
2025	7084.52	1000.93	2,164,800.61
2026	8615.9	1214.92	2,627,578.16
2027	10147.28	1445.31	3,125,879.80
2028	11678.66	1741.49	3,765,469.07
2029	13210.04	2081.2	4,501,284.42
2030	14741.41	2603.12	5,629,976.02
2031	16272.79	2928	6,332,602.27

2032	17804.17	3279.36	7,092,518.01
2033	19335.55	3606.93	7,800,980.82
2034	20866.93	2910.12	6,293,938.80
2035	22398.31	3105.92	6,716,928.65
2036	23929.69	3663.98	7,926,909.15
2037	25461.07	4021.76	8,698,161.43
2038	26992.45	5553.14	12,013,754.18
2039	28523.83	7084.52	15,322,231.43
2040	30055.21	8615.9	18,637,018.50
2041	31586.59	10147.28	21,919,335.75
2042	33117.97	11678.66	25,246,264.05
2043	34649.35	13210.04	28,577,650.28
2044	36180.72	14741.41	31,881,628.61
2045	37712.1	16272.79	35,196,419.30
2046	39243.48	17804.17	38,503,625.67
2047	40774.86	19335.55	41,816,977.04
2048	42306.24	20866.93	45,130,215.06
2049	43837.62	22398.31	48,434,785.17
2050	45369	23929.69	51,752,985.43
2051	49636.6	25461.07	55,066,533.82
2052	53904.2	26992.45	58,384,085.56
2053	58171.8	28523.83	61,689,025.62
2054	62439.4	30055.21	65,003,192.83
2055	66707	31586.59	68,320,669.06
2056	70974.6	33117.97	71,623,209.62

2057	75242.2	34649.35	74,953,101.25
2058	79509.8	36180.72	78,252,006.44
2059	83777.4	37712.1	81,562,093.06
2060	88045	39243.48	84,875,399.63
2061	92312.6	40774.86	88,187,795.60
2062	96580.2	42306.24	91,491,205.59
2063	100847.8	43837.62	94,459,949.75
2064	105115.4	45369	98,121,354.57
2065	109383	49636.6	107,353,042.00
2066	113650.6	53904.2	116,578,647.40
2067	117918.2	58171.8	125,552,192.20
2068	122185.8	62439.4	135,050,501.70
2069	126453.4	66707	144,268,280.40
2070	130721	70974.6	153,491,824.60

Figure - 1 - Production VS Waste Generation from 2010 to 2070

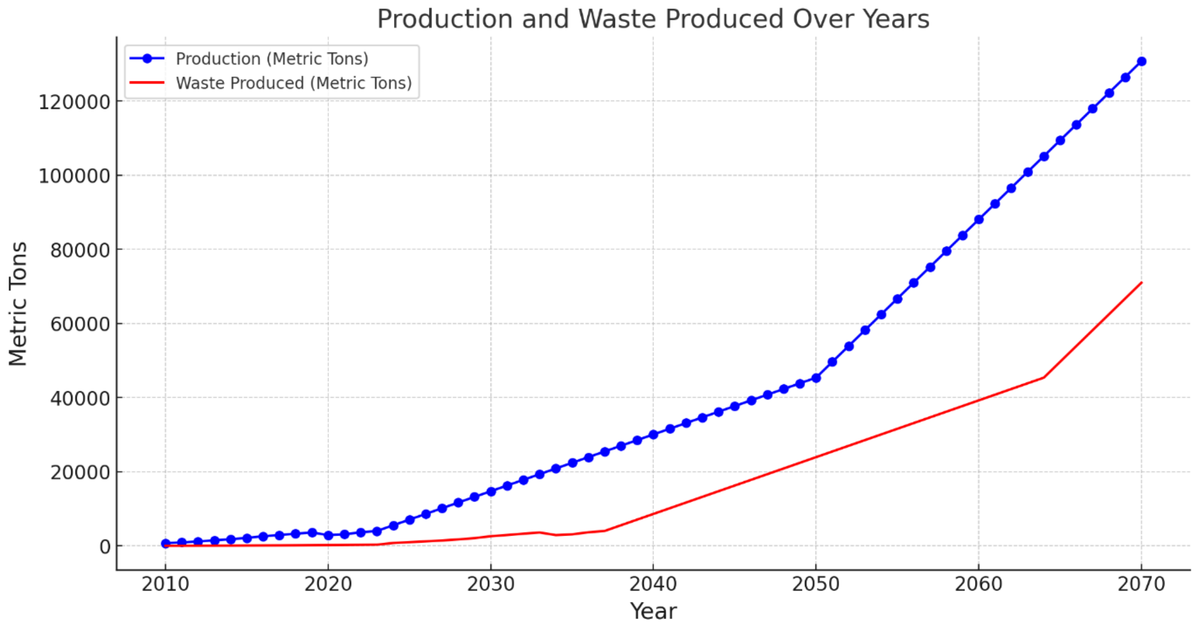


Figure - 2 - Waste Generation from 2010 to 2070

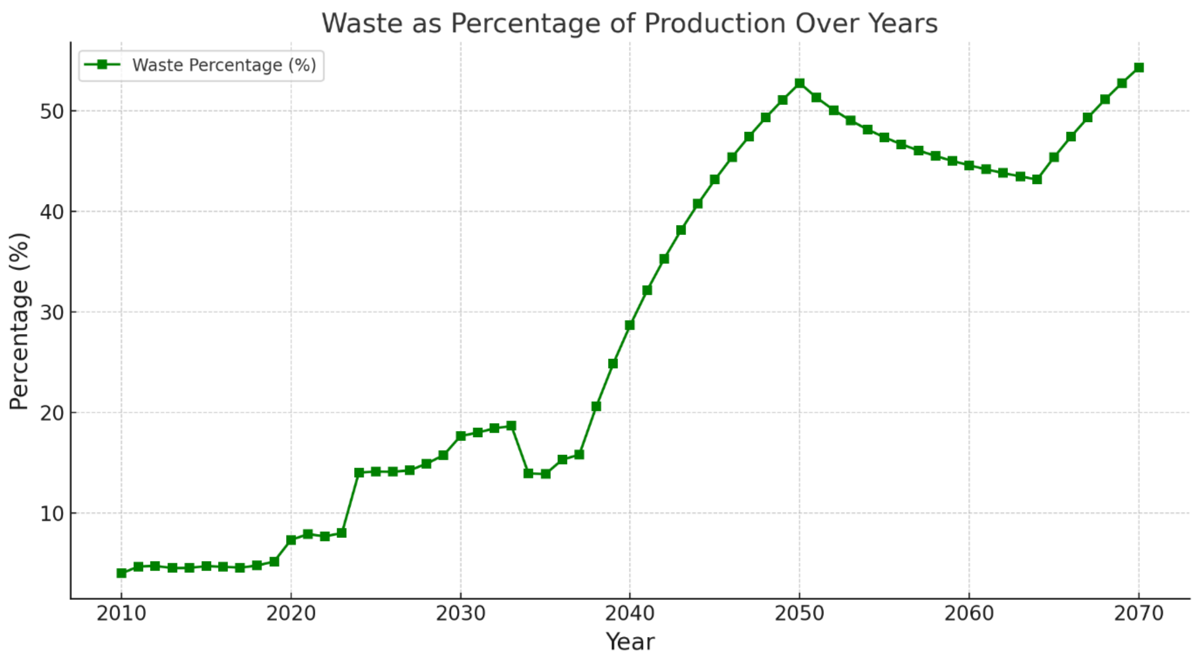
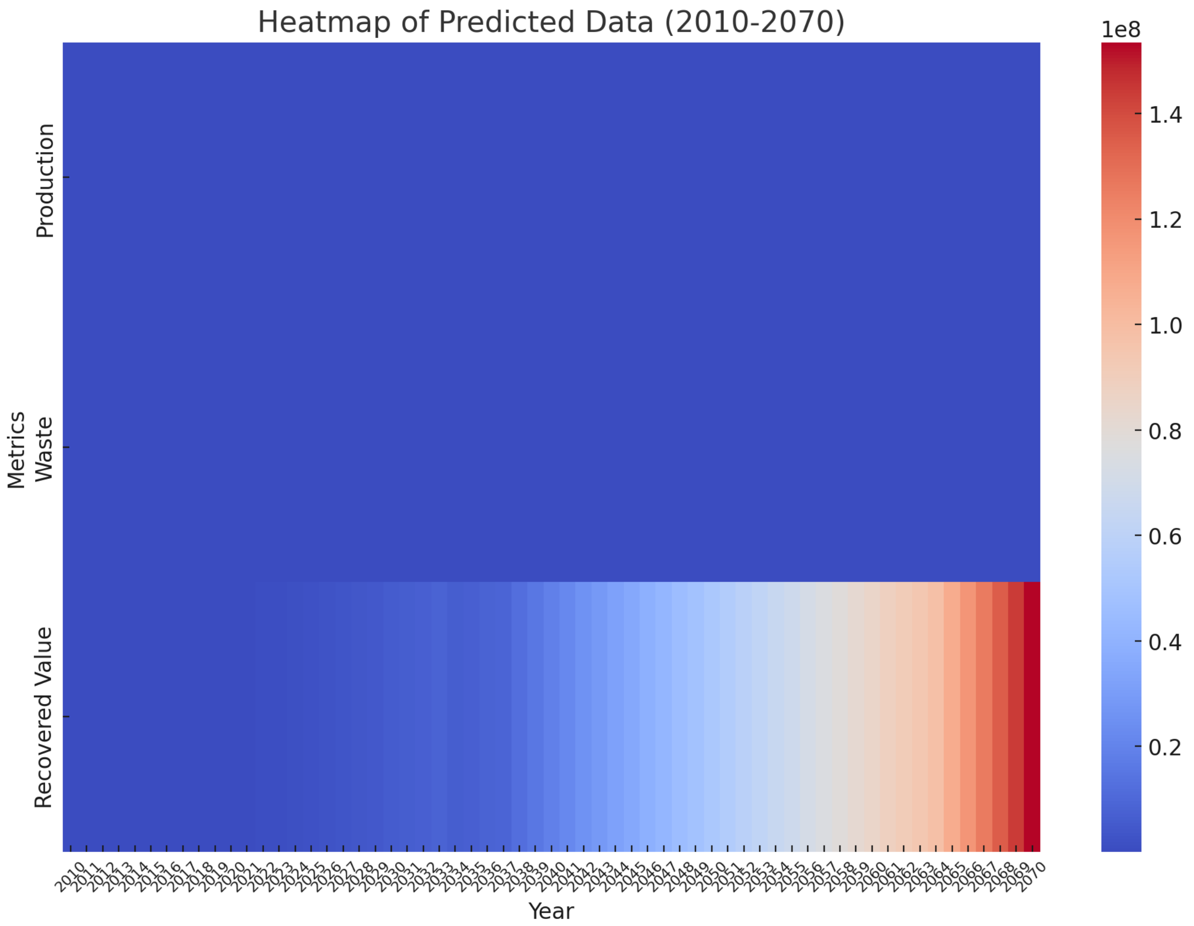


Figure - 3 - Heatmap of the Predicted Data from 2010 to 2070



Conclusion -

The polynomial regression model offers valuable insights into photovoltaic production and waste generation, proving essential for forecasting and strategic planning. By thoroughly analysing historical data, material compositions, and recovery potentials, this model delivers accurate predictions about future trends in the lifecycle management of photovoltaic panels. This precision is crucial for optimizing production capacities and managing waste effectively. The model's ability to capture intricate non-linear patterns and provide dependable forecasts enables stakeholders to make informed decisions about production strategies, waste management, and recycling investments. This proactive approach ensures more efficient resource allocation, fostering sustainability within the industry. As a result, polynomial regression becomes a fundamental tool for strategic planning, helping stakeholders anticipate and address potential issues before they escalate.

The model's impact extends to policy development, where its predictive power can inform regulations and standards for photovoltaic waste management. Accurate forecasts empower policymakers to craft and implement effective regulations that promote sustainable practices and optimize resource management. By integrating the model's insights, regulations can be better tailored to meet both environmental and economic goals, addressing the specific requirements of the industry. This tailored approach supports the development of policies that enhance waste management and resource recovery, aiding the industry's shift toward more sustainable practices. Consequently, incorporating forecasting insights into policy-making not only improves environmental stewardship but also supports the industry's long-term viability and adaptability to emerging challenges.

On the economic front, the polynomial regression model significantly influences financial planning and investment strategies within the photovoltaic sector. By offering a clearer understanding of future trends, the model enables stakeholders to evaluate the economic benefits of recycling and resource recovery more accurately. This informed outlook supports strategic investment decisions, enhancing the financial feasibility of recycling initiatives and sustainable practices. The model's forecasts highlight its role in driving efficient resource management, contributing to the sector's economic growth and sustainability. As stakeholders leverage these insights for financial planning and investment, they are better positioned to advance a more economically and environmentally sustainable photovoltaic industry, ensuring continued progress and development in both technology and waste management practices.

References -

1. Gharaee, H., Erfanimatin, M., & Bahman, A. M. (2024). Machine learning development to predict the electrical efficiency of photovoltaic-thermal (PVT) collector systems. *Energy Conversion and Management*, *315*, 118808.

2. Maheri, M., Bazan, C., Zendehboudi, S., & Usefi, H. (2023). Machine learning to assess CO2 adsorption by biomass waste. *Journal of CO2 Utilization*, *76*, 102590.

3. Kanthasamy, R., Almatrafi, E., Ali, I., Sait, H. H., Zwawi, M., Abnisa, F., ... & Ayodele, B. V. (2023). Biochar production from valorization of agricultural Wastes: Data-Driven modelling using Machine learning algorithms. *Fuel*, *351*, 128948.

4. Sappl, J., Harders, M., & Rauch, W. (2023). Machine learning for quantile regression of biogas production rates in anaerobic digesters. *Science of the Total Environment*, *872*, 161923.

5. Alsagri, A. S., & Alrobaian, A. A. (2024). Analysis and performance prediction of a building integrated photovoltaic thermal system with and without phase change material. *Energy*, *310*, 133249.

6. Massidda, L., & Marrocu, M. (2023). Total and thermal load forecasting in residential communities through probabilistic methods and causal machine learning. *Applied Energy*, *351*, 121783.

7. Manuguerra, L., Cappelletti, F., & Germani, M. (2024). A machine learning based method for parametric environmental impact model for electric vehicles. *Journal of Cleaner Production*, *454*, 142308.

8. Ağbulut, Ü., Gürel, A. E., Ergün, A., & Ceylan, İ. (2020). Performance assessment of a V-trough photovoltaic system and prediction of power output with different machine learning algorithms. *Journal of Cleaner Production*, *268*, 122269.

9. Yang, Q., Zhao, L., Xiao, J., Wen, R., Zhang, F., & Zhang, D. (2024). Machine learning-assisted prediction and optimization of solid oxide electrolysis cell for green hydrogen production. *Green Chemical Engineering*.

10. Wansasueb, K., Promthaisong, P., Bubphachot, B., Pattiya, A., Chompookham, T., Rittidech, S., & Siriwan, N. (2024). Applied machine learning: Performance prediction of heat pipe with mesh wick. *Case Studies in Thermal Engineering*, *63*, 105307.

11. Shomope, I., Al-Othman, A., Tawalbeh, M., Alshraideh, H., & Almomani, F. (2025). Machine learning in PEM water electrolysis: A study of hydrogen production and operating parameters. *Computers & Chemical Engineering*, *194*, 108954.

12. Bian, C., Cheung, K. L., Chen, X., & Lee, C. C. (2025). Integrating microclimate modelling with building energy simulation and solar photovoltaic potential estimation: The parametric analysis and optimization of urban design. *Applied Energy*, *380*, 125062.

13. Palaniyappan, B., & Vinopraba, T. (2024). Dynamic pricing for load shifting: Reducing electric vehicle charging impacts on the grid through machine learning-based demand response. *Sustainable Cities and Society*, *103*, 105256.

14. Al-Rbaihat, R., Alahmer, H., Alahmer, A., Altork, Y., Al-Manea, A., & Awwad, K. E. (2023). Energy and exergy analysis of a subfreezing evaporator environment ammonia-water absorption refrigeration cycle: Machine learning and parametric optimization. *International Journal of Refrigeration*, *154*, 182-204.

15. Zohdi, T. I. (2023). A machine-learning digital-twin for rapid large-scale solar-thermal energy system design. *Computer Methods in Applied Mechanics and Engineering*, *412*, 115991.

16. He, J., Tan, Q., & Lv, H. (2025). Data-driven climate resilience assessment for distributed energy systems using diffusion transformer and polynomial expansions. *Applied Energy*, *380*, 124957.

17. Qadeer, K., Ahmad, A., Qyyum, M. A., Nizami, A. S., & Lee, M. (2021). Developing machine learning models for relative humidity prediction in air-based energy systems and environmental management applications. *Journal of Environmental Management*, *292*, 112736.

18. Cetina-Quiñones, A. J., Santamaria-Bonfil, G., Medina-Esquivel, R. A., & Bassam, A. (2023). Techno-economic analysis of an indirect solar dryer with thermal energy storage: An approach with machine learning algorithms for decision making. *Thermal Science and Engineering Progress*, *45*, 102131.

19. Dan, Z., Song, A., Yu, X., & Zhou, Y. (2024). Electrification-driven circular economy with machine learning-based multi-scale and cross-scale modelling approach. *Energy*, *299*, 131469.

20. Cai, Q., Luo, X., Wang, P., Gao, C., & Zhao, P. (2022). Hybrid model-driven and data-driven control method based on machine learning algorithm in energy hub and application. *Applied Energy*, *305*, 117913.

21. Manivannan, R. (2024). Research on IoT-based hybrid electrical vehicles energy management systems using machine learning-based algorithm. *Sustainable Computing: Informatics and Systems*, *41*, 100943.

22. Junior, M. Y., Freire, R. Z., Seman, L. O., Stefenon, S. F., Mariani, V. C., & dos Santos Coelho, L. (2024). Optimized hybrid ensemble learning approaches applied to very short-term load forecasting. *International Journal of Electrical Power & Energy Systems*, *155*, 109579.

23. Kashyap, P. K., Dohare, U., Kumar, M., & Kumar, S. (2024). Blockchain and Quantum Machine Learning Driven Energy Trading for Electric Vehicles. *Ad Hoc Networks*, *165*, 103632.

24. Demirci, M. Y., Beşli, N., & Gümüşçü, A. (2021). Efficient deep feature extraction and classification for identifying defective photovoltaic module cells in Electroluminescence images. *Expert Systems with Applications*, *175*, 114810.

25. Wen, Y., Lau, S. K., Leng, J., & Liu, K. (2023). Sustainable underground environment integrating hybrid ventilation, photovoltaic thermal and ground source heat pump. *Sustainable Cities and Society*, *90*, 104383.

26. Zheng, X., Zhou, S., & Jin, T. (2023). A new machine learning-based approach for cross-region coupled wind-storage integrated systems identification considering electricity demand response and data integration: A new provincial perspective of China. *Energy*, *283*, 129141.

27. Tan, Y., Peng, J., Luo, Y., Li, H., Wang, M., Zhang, F., ... & Song, A. (2023). Daylight-electrical-thermal coupling model for real-time zero-energy potential analysis of vacuum-photovoltaic glazing. *Renewable Energy*, *205*, 1040-1056.

28. Chaudhry, A. M., Ghorbaniasl, G., Hachez, J., Chicherin, S., & Bram, S. (2024). Improving the potential of fifth-generation district heating and cooling networks through robust design and operational optimization under future energy market and demand uncertainties. *Energy and Buildings*, *325*, 114998.

29. Rodríguez, F., Genn, M., Fontán, L., & Galarza, A. (2021). Very short-term temperature forecaster using MLP and N-nearest stations for calculating key control parameters in solar photovoltaic generation. *Sustainable Energy Technologies and Assessments*, *45*, 101085.

30. Byun, M., Lee, H., Choe, C., Cheon, S., & Lim, H. (2021). Machine learning based predictive model for methanol steam reforming with technical, environmental, and economic perspectives. *Chemical Engineering Journal*, *426*, 131639.

31. Patty, S., & Malakar, T. (2024). Performance analysis of machine learning based prediction models in assessing optimal operation of microgrid under uncertainty. *Results in Control and Optimization*, *15*, 100407.

32. Wu, Z., Kang, J., Mosteiro-Romero, M., Bartolini, A., Ng, T. S., & Su, B. (2024). A distributionally robust optimization model for building-integrated photovoltaic system expansion planning under demand and irradiance uncertainties. *Applied Energy*, *372*, 123740.

33. Prinsloo, F. C., Schmitz, P., & Lombard, A. (2023). System dynamics characterisation and synthesis of floating photovoltaics in terms of energy, environmental and economic parameters with WELF nexus sustainability features. *Sustainable Energy Technologies and Assessments*, *55*, 102901.

34. Wu, W., Hu, Y., & Wu, Q. (2023). Subsidies and tax incentives-Does it make a difference on TFP? Evidences from China's photovoltaic and wind listed companies. *Renewable Energy*, *208*, 645-656.

35. Wang, P., Li, C., Hossain, M. N., Yoon, S., Zhao, L., Liang, R., & Guan, H. (2023). Research on designated calibration method of fault sensor in photovoltaic thermal heat

pump system based on fault detection and virtual calibration. *Journal of Building Engineering*, *76*, 107237.

36. Askari, I. B., Shahsavar, A., Jamei, M., Calise, F., & Karbasi, M. (2022). A parametric assessing and intelligent forecasting of the energy and exergy performances of a dish concentrating photovoltaic/thermal collector considering six different nanofluids and applying two meticulous soft computing paradigms. *Renewable Energy*, *193*, 149-166.
37. Socci, L., Rocchetti, A., Verzino, A., Zini, A., & Talluri, L. (2024). Enhancing Third-Generation District Heating Networks with Data Centre Waste Heat Recovery: Analysis of a Case Study in Italy. *Energy*, 134013.
38. Shaik, N. B., Inayat, M., Benjapolakul, W., Bakthavatchalam, B., Barewar, S. D., Asdornwised, W., & Chaitusaney, S. (2022). Artificial neural network modeling and optimization of thermophysical behavior of MXene Ionanofluids for hybrid solar photovoltaic and thermal systems. *Thermal Science and Engineering Progress*, *33*, 101391.
39. Wei, Y., Han, T., Wang, S., Qin, Y., Lu, L., Han, X., & Ouyang, M. (2022). An efficient data-driven optimal sizing framework for photovoltaics-battery-based electric vehicle charging microgrid. *Journal of Energy Storage*, *55*, 105670.
40. Sun, Y., Du, R., & Chen, H. (2025). Energy transition and policy perception acuity: An analysis of 335 high-energy-consuming enterprises in China. *Applied Energy*, *377*, 124627.
41. Iqbal, M. S., Adnan, M., Mohamed, S. E. G., & Tariq, M. (2024). A hybrid deep learning framework for short-term load forecasting with improved data cleansing and preprocessing techniques. *Results in Engineering*, *24*, 103560.
42. Li, Z., Tian, Y., Sun, J., Lu, X., & Kan, Y. (2022). Simulation-based optimization of large-scale dedicated bus lanes allocation: Using efficient machine learning models as surrogates. *Transportation Research Part C: Emerging Technologies*, *143*, 103827.
43. Egeland-Eriksen, T., & Sartori, S. (2024). Techno-economic analysis of the effect of a novel price-based control system on the hydrogen production for an offshore 1.5 GW wind-hydrogen system. *Energy Reports*, *11*, 2633-2655
44. de Lima Nogueira, S. C., Och, S. H., Moura, L. M., Domingues, E., dos Santos Coelho, L., & Mariani, V. C. (2023). Prediction of the NOx and CO2 emissions from an experimental dual fuel engine using optimized random forest combined with feature engineering. *Energy*, *280*, 128066.
45. Han, J. M., Lim, S., Malkawi, A., Han, X., Chen, E. X., Salimi, S., ... & Edwards, K. (2023). Data-informed building energy management (DiBEM) towards ultra-low energy buildings. *Energy and Buildings*, *281*, 112761.
46. Zhao, J., Chang, H., & Tu, Z. (2024). A novel hydrogen translation compensation method for hydrogen-heat-electric coupling system based on daily load prediction. *International Journal of Hydrogen Energy*.

47. Parrado-Hernando, G., Herc, L., Feijoo, F., & Capellán-Pérez, I. (2024). Capturing features of hourly-resolution energy models in an integrated assessment model: An application to the EU27 region. *Energy*, *304*, 131903.

48. Mirzaee, P., Salami, P., Akhijahani, H. S., & Zareei, S. (2023). Life cycle assessment, energy and exergy analysis in an indirect cabinet solar dryer equipped with phase change materials. *Journal of Energy Storage*, *61*, 106760.

49. Yang, F., & Xiong, X. (2024). Carbon emissions, wastewater treatment and aquatic ecosystems. *Science of The Total Environment*, *921*, 171138.

50. Nie, P., Roccotelli, M., Fanti, M. P., & Li, Z. (2022). Fuzzy rule-based models for home energy consumption prediction. *Energy Reports*, *8*, 9279-9289.

51. Banihabib, R., Fadnes, F. S., & Assadi, M. (2024). Techno-economic optimization of microgrid operation with integration of renewable energy, hydrogen storage, and micro gas turbine. *Renewable Energy*, *237*, 121708.

52. Chen, S., Wong, N. H., Zhang, W., & Ignatius, M. (2023). The impact of urban morphology on the spatiotemporal dimension of estate-level air temperature: A case study in the tropics. *Building and Environment*, *228*, 109843.