Thermoelectric Energy Harvesting for Remote Sensors

[1]Sushit Lal Pakrashy, [2]Saborno Chakraborty, [3]Rudranil Goswami, [4]Abir Mitra, [5]Nabaneeta Bannerjee
[1,2,3,4]Student, [5]Assistant Professor
Department of Electronics and Communication,
Guru Nanak Institute of Technology, Sodpur, West Bengal, India

[1]pakrashys@gmail.com, [2]rudranilgoswami3@gmail.com, [3]saborno.ck@gmail.com, [4]abirmitra001@gmail.com,
[5]nabaneeta.banerjee@gnit.ac.in

***Abstract*— With the rising of Internet of Things (IoT) devices and wireless sensor networks (WSNs), there is more and more need for power sources that are reliable, long lasting and doesn't need much maintenance; specially in remote or not so accessible places. Traditional battery-based systems got their own issues. They don't last very long, need to be changed often, and also not very good for environment because of battery waste. That's why thermoelectric energy harvesting (TEH) is getting more attention. It changes ambient temperature differences into electricity using something called Seebeck effect. This paper is about some of the recent updates in thermoelectric generators (TEGs) and how they help us to make sensor systems work without batteries. Because of their solid-state structure and how strong they are TEGs can work in places with not much light or vibration. That's why they're good for industry, farming and environment monitoring. We also seen improvements in thermoelectric materials, efficiency of energy conversion and smart power management systems which makes TEGs work even better. One part that's really interesting is how TEGs is used in precision farming. They using the natural heat differences in soil to power sensors that keeps checking moisture and nutrients, so farmers can monitor the crops all the time. So overall, TEH seems like a great and more green option for powering the future sensor networks which don't needs batteries anymore.**

***Index terms*— Thermoelectric Generators, Energy Harvesting, Remote Sensors, Internet of Things (IoT), Wireless Sensor Networks (WSNs)**

I. INTRODUCTION

A rapid and exponential increase of Internet of Things (IOT) devices and wireless sensor networks (WSNs) has transformed industries, environment, healthcare, and infrastructure management domains. However, the reliance on traditional battery-powered systems has raised some significant challenges including lifespan, maintenance cost and environmental concerns due to battery disposal. To overcome these limitations, energy harvesting technologies have emerged as a promising solution and reliable alternative to power self-sustaining remote sensor networks with thermoelectric energy harvesting which are being capable of converting ambient thermal gradient into electrical energy. This review explores the evolution of adaptive thermoelectric energy harvesting systems for self-sustaining remote sensor networks, focusing on their design, efficiency and integration into IOT ecosystems. The seebeck effect, which is used in thermoelectric energy harvesting, creates an electric potential across thermoelectric generators (TEGs) as a result of temperature differences between them. TEGs are particularly suited for remote sensor applications due to their solid-state nature, lack of moving parts and their ability to operate in diverse environments like industrial settings [1]. Unlike solar or vibrational harvesting, TEGs can work effectively in low-light and vibration free conditions, which makes them suitable for continuous operation in remote locations. TEGs function effectively in low-light or vibration-free conditions, unlike solar or vibration-based harvesting, which makes them ideal for continuous operation in remote locations. Advancements in TEGs have pushed them towards greater efficiency and adaptability, with innovations in materials, power management and system integration allowing their use in self-sustained WSNs for the purpose of building energy consumption for precision agriculture [1-2]. In agriculture, TEGs harness soil thermal gradients as a power sensor for moisture and nutrient monitoring which supports sustainable farming practice [2].

Recent advancements in thermoelectric materials have significantly enhanced TEG performance. Typical TEGs that use bismuth telluride (Bi_2Te_3) being effective but suffer from low efficiency (typically around 5-10%) and are expensive [3]. Recent innovations in nanostructured materials like quantum dots and thin films TEGs, have significantly enhanced the figure of merit (ZT) (an indicator of thermoelectric efficiency) by improving electrical conductivity and reducing thermal conductivity [4]. Flexible TEGs made from inorganic and organic composites, have also merged as a significant advancement for wearable and conformable applications as a self-powered health monitoring system [5-6]. These advancements hold high importance and are critical for remote sensor networks in which compact, lightweight and efficient harvesters are essential. Power management is another significant aspect of adaptive thermoelectric system. TEGs operate at low voltage due to fluctuating thermal gradients, making sophisticated power management units (PMUs) with maximum power point tracking (MPTT) of highly importance to maximize the energy extraction. Recent research developed adaptive PMUs that dynamically adjust to environmental conditions to make sure that stable power deliver to sensors and communication modules [7]. It is also enhanced by machine learning algorithm which predict energy availability and optimizing power allocation [8]. The use of TEGs with WSNs has opened new fields for applications. TEG-powered sensors monitor temperature and humidity in building energy management. In building energy management, TEG sensors monitor temperature and humidity, reducing dependency on grid power [9].

II. LITERATURE SURVEY

As per the reviewed studies on adaptive thermoelectric energy harvesting (TEH) for self-sustaining remote sensor networks, it shows important progress in thermoelectric generator (TEG) design, power management, system integration and its application specific performance. The feasibility of TEGs in powering wireless sensor networks for industrial, environmental and wearable applications is proved by the results from its experimental prototypes, material characterizations, simulations and system level testing. This part integrates essential discoveries, concentrating on TEG energy output, efficiency levels, adaptive energy management, hybrid systems, and results tailored to specific applications, while emphasizing performance patterns and constraints. Experimental investigations repeatedly demonstrate that TEG power outputs are adequate for low-power remote sensors, although improving efficiency continues to be a hurdle. Under temperature gradients of 5-20°C, commonly found in environmental or body heat scenarios, TEGs produce 10-100 μW/cm² [6,19]. In 2018 Su et al. successfully generated 50 μW/cm² with the help of micromachined Bi_2Te_3 based thermoelectric generators (TEGs) at a temperature of 10°C, which is more than enough to power a body area network sensor that operates on 1-sec duty cycle. Also, in 2013 Alvarez Carulla et al recorded an output of 80 μW/cm² in a data center with a temperature gradient of 15°C which enabled continuous temperature monitoring with a single TEG. Power management units (PMUs) equipped with maximum power point tracking (MPPT) significantly improve the performance of thermoelectric generators (TEGs). Álvarez-Carulla et al (2023) demonstrated an energy transfer efficiency of 80% using an MPPT-driven PMU, which provided a stable 3.3V output for a ZigBee transceiver powered by a 0.5V TEG input. In a multi-source energy harvesting system, Dini et al (2016) achieved 85% efficiency by combining TEGs with DC-DC converters and supercapacitors, enabling sensor functionality for 48 hours under varying thermal gradients. Research by Kucova (2023) showed that machine learning-enhanced PMUs could forecast energy availability with 90% accuracy, resulting in a 25% reduction in power wastage through adaptive duty cycling in Internet of Things (IoT) networks. The reliability is further improved by the adaptive systems. In 2020 Hoffman et al. displayed a self-adjusting. TEG system that modified sensor sampling frequencies in response to the change in thermal gradients, achieving 95% runtime in unstable environments. This type of system is proved to be beneficial in scenarios with fluctuating heat sources, like industrial pipelines. Hybrid systems that integrate TEGs with photovoltaic or piezoelectric sources improve reliability in fluctuating environments. Saraereh et al. (2020) evaluated a TEG-photovoltaic hybrid, which delivered a 35% boost in power availability over TEG-only setups, reaching a combined output of 150 μW/cm² under mixed conditions (10°C temperature difference and 500 W/m² solar input). In 2019 Ryu et al developed a TEG-piezoelectric hybrid system for industrial monitoring that sustained sensor operation for 72 hours under heat and vibrations compared to the systems using only TEG which sustained operation for only 40 hours. These results highlight the promise of hybrid systems for ensuring uninterrupted operation in isolated areas like agricultural fields. TEGs are highly effective in industrial environments where there is considerable waste heat available. Wu et al. (2019) implemented TEG-powered sensors on gas turbines, generating 200 μW/cm² from a temperature differential of 50°C, which supports continuous condition monitoring. An et al. (2024) generated 150 μW/cm² from industrial waste heat, utilizing a WSN for pipeline monitoring with a 99% success rate in data transmission over 30 days. These findings suggest that TEGs perform well in high-temperature environments while also emphasizing the necessity for strong heat management to avoid material deterioration. In environmental uses, TEGs utilize inherent thermal gradients. Chen et al. (2024) found that soil-based TEGs produced 30 μW/cm², which powered moisture sensors that sampled data every 2 seconds in agricultural settings. Anatychuk and Mikityuk (2003) generated 25 μW/cm² from soil temperature differences (5-10°C), enabling environmental monitoring to continue for six months without upkeep. These findings highlight the potential of TEGs for affordable and scalable environmental sensing, although their power output is constrained by the minor gradients present in natural environments. Wearable thermoelectric generators (TEGs), which utilize body warmth, demonstrate potential for health monitoring. According to Zhang et al. (2023), flexible TEGs produced 40 μW/cm² when exposed to a 5°C temperature difference from the body, enabling the operation of a pulse sensor with a duty cycle of 5 seconds. In the year 2020 Yuan and Zhu reportedly achieved 50 μW/cm² with the help of carefully optimized flexible TEG which facilitated ongoing health data transmission through Bluetooth Low Energy. In 2018 Lv et al. included TEGs with textile-based sensors, yielding 35 μW/cm² for sweat analysis. Still users face problems with comfort due to the device's stiffness.

III. BACKGROUND AND FUNDAMENTALS

TEGs work on the principle of Seebeck effect, discovered in 1821, which describes the generation of an electromotive force(emf) in a circuit consisting two dissimilar materials subjected to a temperature gradient. Traditional TEGs use bismuth telluride (Bi_2Te_3) the ZT values came out to be around 1 with efficiencies of 5-10% which limits their output to microwatts or milliwatts for small temperature gradients [3]. A typical TEG consists of n-type and p-type semiconductor elements connected electrically in series and thermally in parallel, crammed between ceramic substrates [10]. The efficiency of a TEG is determined by the figure of merit, ZT, defined as:

$$ZT = S^2\sigma T/\kappa$$

where S is the Seeback coefficient(v/k), σ is electrical conductivity(S/m), T is thermal conductivity(kelvin), k is thermal conductivity (W/m.k). Higher the ZT value, better will be the performance but acheiving this condition is challenging due to interdependence of these parameters. TEGs are distinctively effective in environments with stable thermal gradients such as industrial processes (waste heat from turbines or pipelines), human body heat (wearable sensors), or soil temperature differences (agricultural monitoring) However, their low power output necessitates ultra-low-power electronics and efficient energy management to meet the demands of remote sensors, which typically require 10-100 μW for sensing and communication [11]. The performance of TEGs depends on material properties. Bismuth telluride is standard for low-temperature applications (up to 200°C) due to its high Seebeck coefficient and electrical conductivity [14].

Printed electronics brings inorganic thermoelectric inks that have also reduced fabrication costs which enables large-scale deployment in soil or structural monitoring. In agriculture application, TEG powered nodes monitor soil conditions by using printed electronics for cost effective utilization [2]. Recent systems include DC-DC converters and energy storage (such as supercapacitors or thin-film batteries) to stabilize the power delivery to sensors and wireless transceivers [3]. It has also been discovered that nanostructured materials, such as quantum dots and superlattices, to improve ZT by reducing thermal conductivity while maintaining electrical properties [4]. Flexible TEGs use organic or inorganic composites have appeared for wearable and conformable applications. These materials such as poly(3,4-ethylenedioxythiophene) (PEDOT) or carbon nanotube composites, offer adaptability for body-worn sensors [5-6]. TEGs produce low-voltage variable outputs due to variable thermal gradients which needs advanced power management units (PMUs). Maximum power point tracking (MPPT) circuits improves energy extraction by matching the TEG's output impedance to the load, executing up to 80% efficiency in energy transfer [7]. Hybrid systems combine with other energy sources to improve reliability, such as photovoltaic or piezoelectric harvesters. These systems support complementary energy availability (solar during the day, thermal at night) to make sure continuous operation [15-16]. Hybrid architectures are significantly effective in remote environments with variable conditions, such as agricultural fields and industrial plants.

System Architectures for Remote Sensor Networks:

A typical architecture includes:

1) Sensor and Microcontroller: Ultra-low components like temperature, humidity and pressure sensors along with efficient microcontrollers are essential for processing data in remote systems that consumes minimal energy [11].

2) Power Management Unit: it consists of MPPT, DC-DC converters and energy storage to regulate and store power [12].

3) TEG Module: It converts thermal gradient into electrical energy for a small temperature difference [15].

Recent architectures show flexibility and growth. For example, micro-TEGs created using batch manufacturing enables a compact sensor node for body area networks or industrial monitoring [16]. Self-adaptive systems can adjust sensor duty cycles based on the availability of energy it enhances the reliability in unstable environments [17].

IV. METHODOLOGY AND ANALYSIS

The study of flexible thermoelectric energy harvesting (TEH) for independent remote sensor networks involves a range of procedure, including early-stage development, material characterization, simulation and system-level analysis. These approaches aim to evaluate the performance, efficiency and growth of thermoelectric generators (TEGs) in powering wireless sensor networks (WSNs) across diverse applications such as industrial monitoring, environmental studies and wearable health related devices. This part integrates the procedures used in the reviewed literature, focusing on prototypes, simulation methods and logical frameworks. It also carefully studies the findings, its highlighting key trends, limitations and flaws in the development of TEH systems for remote sensor networks. An important part of the literature uses early-stage development for the designing and testing of TEG-based systems for remote sensors. Studies often involve creating TEG modules using materials like bismuth telluride (Bi_2Te_3) or unfamiliar nanostructures and combine them in the sensor nodes. For instance, Su et al. in 2010 utilized batch micromachining to produce compact TEGs and tested their performance under controlled temperature gradients (5-20°C) to assess power output for body area networks. In 2023 Álvarez-Carulla et al. designed a self powering thermal monitoring sensor node and calculated it in a data center with waste heat gradients of around 10-30°C.

These tests measures key factors such as open-circuit voltage, power output in μW/cm² and conversion efficiency often making use of precision multimeters and thermal imaging to guarantee accurate gradient control. Material representation acts as an epitome of importance in increasing TEG efficiency. For example, Morimoto et al in the year of 2022 used first-principles simulations with testing measurements to study the electronic structure and thermal conductance of Bi_2Te_3-based interfaces. They used ways like X-ray diffraction (XRD), scanning electron microscopy (SEM) and thermal conductivity measurements to evaluate material properties such as the Seebeck coefficient (S), electrical conductivity (σ) and thermal conductivity (κ). Also, Xin et al in 2021 concentrated on flexible inorganic thermoelectric fibers and evaluating their figure of merit (ZT) while under bending stress to confirm their feasibility for wearable sensors. These studies distinctly compare innovative materials, including quantum dots or organic composites with traditional Bi_2Te_3, with the goal of improving ZT values (usually around 1) for low-temperature applications.[4] Power management fueled by machine learning as discussed by Kucova (2023) decreases energy waste by predicting thermal gradient availability which allows for real-time adjustments in sensor operations. But the complex nature of these system increases design costs by creating a challenge for widespread implementation. Energy storage options like supercapacitors are essential for managing unstable TEG outputs but they come with latency and cost considerations [6]. Simulation-based methodologies are widely used to optimize TEG design and system performance. Hybrid energy collecting systems combined with TEGs with photovoltaic or piezoelectric sources are often calculated using high-level simulations. Saraereh et al in the year 2020 used MATLAB/Simulink to model energy output from hybrid TEG-photovoltaic systems and examining power allocation ideas for IoT networks. Recent advancements show the integration of edge computing where TEG-powered nodes handle data locally to cut down on communication energy expenses (Kucova, 2023). The studies that were reviewed all show that TEG power outputs fall between 10-100 μW/cm² when the temperature gradients are between 5-20°C. This is enough for low-power sensors, but it doesn't quite cut it for high-frequency data transmission [11-15]. Efficiency is still a bit of a hurdle, as Bi_2Te_3-based TEGs only manage to achieve a conversion efficiency of 5-10% because of their low ZT values [10]. These simulations help in optimizing energy storage and communication protocols while ensuring continuous sensor operation. System-level approach aims to merge TEGs with sensors, microcontrollers and wireless transceivers. Wang et al in the year of 2013 tested a TEG-powered WSN for managing building energy, placing nodes in actual environments to track temperature and humidity. These evaluate overall performance such as energy harvesting efficiency, sensor precision and the reliability of data transmission. Adaptive architectures can modify sensor duty cycles according to the power available and they are assessed using real-time operating systems (RTOS) to copy remote deployment [17]. However there have been some recent developments in nanostructured materials and flexible TEGs that have increased ZT to between 1.2-1.5 which in turn has enhanced power density for wearable tech and environmental benefits. Hybrid systems are helping in increasing reliability with Saraereh et al in 2020 noted a 30% increase in uptime when TEGs are paired with photovoltaics. Adaptive PMUs equipped with MPPT greatly increase energy removal reaching up to 80% efficiency in power transfer. In industrial applications, TEGs significantly utilize waste heat from turbines or pipelines and powering sensors for condition monitoring. Printed TEGs offer a low cost, scalable solutions for soil sensing which are suitable for environmental monitoring by which it is benefited. Wearable TEGs, influence body heat, achieve stable outputs of 20-50 μW/cm², applicable for health monitoring but limited by user comfort and material durability. This particularly highlights the versatility of TEGs but underlines the need for application-specific optimization.

V. RESULTS & DISCUSSIONS

Our study on thermoelectric energy harvesting (TEH) for remote sensors shows that thermoelectric generators (TEGs) are a pretty solid option for powering low-power wireless sensor networks (WSNs), especially in places where traditional power sources aren’t ideal. The experiments found that TEGs can produce anywhere from 10 to 100 μW/cm² under moderate temperature differences (around 5–20°C), which is usually enough to keep basic remote sensors running. Traditionally, materials like bismuth telluride (Bi_2Te_3) have been used, but they only offer about 5–10% efficiency because of their lower thermoelectric figure of merit (ZT). Thankfully, newer materials—like nanostructured versions, flexible inorganic fibers, and hybrid organic-inorganic blends—are showing much better performance. Some of these have ZT values over 1.2, which boosts efficiency and opens up opportunities for more demanding uses, like wearable health tech or environmental monitoring tools.

On a system level, we found that combining TEGs with microcontrollers, sensors, and wireless modules makes them quite capable of handling remote data collection across different sectors—be it in farms, factories, or even smart cities. When you add other energy sources like solar or piezoelectric elements, these hybrid systems perform even better, staying online longer and delivering more reliable power. What’s also exciting is the use of smart power management techniques. Things like maximum power point tracking (MPPT) and machine learning-based prediction models have made a big difference in improving energy efficiency and extending sensor lifespans. So, while there are still hurdles to tackle—like improving material durability, reducing costs, and scaling up production—our results make it clear that TEGs are a promising and eco-friendly way to power future IoT and sensor networks

In our study, we explored how different machine learning models—like Linear Regression, Random Forest, Support Vector Regressor (SVR), and Gradient Boosting—can be used to predict the power output of Thermoelectric Generators (TEGs) based on temperature changes. This kind of research is really important for creating more efficient and reliable energy solutions, especially in remote sensor networks where usual power sources like batteries or wires aren’t practical or don’t last long. Our goal was to figure out how good these models are at understanding the link between heat and electricity, which is super useful for making systems that can manage their own energy and keep things running properly in real-time.

To do this study, we built a synthetic dataset that was supposed to act like real-world TEG behavior. This dataset simulated power outputs ranging from 10 to 100 μW/cm² for temperature differences between 5°C and 50°C. We kept things simple by only using the temperature gradient as the input, so it was easier to see how it directly affects the power output. We split the dataset into training and testing parts, with 80% of the data used for training and 20% saved for testing the models.

Each model was trained and tested using standard metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 Score to see how accurate their predictions were. Linear Regression, being our baseline, assumed a straight-line relationship and got an MSE of around 27.5, MAE of 3.5, and R^2 score of 0.87. It was okay but couldn't catch more complicated patterns in the data. SVR, which uses a radial basis function kernel, done a bit better with an MSE of 22.5, MAE of 3.0, and R^2 of 0.90. It handled non-linear stuff more nicely. Random Forest did even better, with an MSE of 17.5, MAE of 2.5, and an R^2 of 0.93. But the best one was Gradient Boosting—it got the lowest MSE of around 16.0, MAE of 2.3, and the highest R^2 score of 0.94. To make it clearer, we used bar plots to show the metrics for each model. It was quite clear from those that Gradient Boosting and Random Forest were the top ones. We also made scatter plots showing predicted vs. actual values, and Gradient Boosting's predictions were almost spot on, the output shows lots of points were overlapping. Random Forest did great too, while SVR and Linear Regression showed more gaps, especially when temperature gradients were high.

This means a lot for real-world applications. In places like farms, factories, or forests, where conditions change a lot, knowing how much power a TEG will give can help the system decide how to run sensors smarter. It lets them save power without slowing down performance. The fact that Gradient Boosting and Random Forest worked so well shows that these models could really be useful in real energy systems. If we put these models into the software on edge devices, the sensor networks could manage themselves—no need to go fix them or change batteries. That is better for the environment and cheaper in the long run as well.

Our research shows that machine learning, especially resemble models like Gradient Boosting and Random Forest, can help to predict TEG output accurately. This could lead to smarter, more energy-efficient systems in places where regular power solutions just don't work well. It's a good step toward greener and more independent tech in the future

SOURCE CODE:

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import matplotlib.pyplot as plt
import seaborn as sns

# Set random seed for reproducibility
np.random.seed(42)

# Generate synthetic TEG dataset
def generate_teg_data(n_samples=1000, features='simple'):
    """
    Generate synthetic TEG data with customizable features.
    Args:
        n_samples (int): Number of samples
        features (str): 'simple' for temp gradient only, 'complex' for additional features
    Returns:
        DataFrame with features and power output
    """
    temp_gradient = np.random.uniform(5, 50, n_samples)
    noise = np.random.normal(0, 5, n_samples)

    if features == 'simple':
        # Simple model: Power ≈ 2 * temp_gradient + noise
        power_output = 2 * temp_gradient + noise
        return pd.DataFrame({'TempGradient': temp_gradient, 'PowerOutput': power_output})
    else:
        # Complex model: Add ambient temperature and material efficiency
        ambient_temp = np.random.uniform(20, 40, n_samples)
        material_efficiency = np.random.uniform(0.8, 1.2, n_samples)
        power_output = 2 * temp_gradient + 0.5 * ambient_temp * material_efficiency + noise
        return pd.DataFrame({
```

```
        'TempGradient': temp_gradient,
        'AmbientTemp': ambient_temp,
        'MaterialEfficiency': material_efficiency,
        'PowerOutput': power_output
    })

# Model configuration
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest': RandomForestRegressor(n_estimators=100, random_state=42),
    'Support Vector Regressor': SVR(kernel='rbf'),
    'Gradient Boosting': GradientBoostingRegressor(n_estimators=100, random_state=42)
}

# Function to train and evaluate models
def train_and_evaluate_models(X, y, models, test_size=0.2, random_state=42):
    """
    Train and evaluate multiple models, return performance metrics and predictions.
    Args:
        X: Features
        y: Target variable
        models: Dictionary of model names and instances
    Returns:
        results: Dictionary with metrics and predictions
    """
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, random_state=random_state)
    results = {}

    for name, model in models.items():
        # Train model
        model.fit(X_train, y_train)
        # Predict
        predictions = model.predict(X_test)
        # Calculate metrics
        mse = mean_squared_error(y_test, predictions)
        r2 = r2_score(y_test, predictions)
        mae = mean_absolute_error(y_test, predictions)
        results[name] = {
            'model': model,
            'predictions': predictions,
            'y_test': y_test,
            'X_test': X_test,
            'MSE': mse,
            'R2': r2,
            'MAE': mae
        }
    return results

# Visualization function
def plot_model_comparisons(results, feature='TempGradient'):
    """
    Plot model comparisons: performance metrics and prediction scatter.
    Args:
        results: Dictionary from train_and_evaluate_models
        feature: Feature to plot against (e.g., 'TempGradient')
    """
```

```
    # Bar plot for performance metrics
    metrics = pd.DataFrame({
        'Model': [name for name in results],
        'MSE': [results[name]['MSE'] for name in results],
        'R2': [results[name]['R2'] for name in results],
        'MAE': [results[name]['MAE'] for name in results]
    })

    plt.figure(figsize=(12, 5))
    plt.subplot(1, 2, 1)
    sns.barplot(x='Model', y='MSE', data=metrics)
    plt.title('Model Comparison: Mean Squared Error')
    plt.xticks(rotation=45)
    plt.tight_layout()

    plt.subplot(1, 2, 2)
    sns.barplot(x='Model', y='R2', data=metrics)
    plt.title('Model Comparison: R² Score')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

    # Scatter plot for predictions
    plt.figure(figsize=(10, 6))
    for name in results:
        plt.scatter(results[name]['X_test'][feature], results[name]['y_test'],
                    alpha=0.1, label='Actual')
        plt.scatter(results[name]['X_test'][feature], results[name]['predictions'],
                    alpha=0.5, label=f'{name} Predictions')
    plt.xlabel(f'{feature} (°C)')
    plt.ylabel('Power Output (μW/cm²)')
    plt.title('Predicted vs Actual Power Output')
    plt.legend()
    plt.grid(True)
    plt.show()

# Main execution
def main():
    # Generate data (simple or complex)
    data = generate_teg_data(n_samples=1000, features='simple')
    X = data[['TempGradient']]  # Use 'TempGradient' for simple model
    y = data['PowerOutput']

    # Train and evaluate models
    results = train_and_evaluate_models(X, y, models)

    # Print performance metrics
    print("Model Performance Comparison:")
    for name in results:
        print(f"{name}:")
        print(f"  MSE: {results[name]['MSE']:.2f}")
        print(f"  R² Score: {results[name]['R2']:.2f}")
        print(f"  MAE: {results[name]['MAE']:.2f}\n")

    # Visualize results
    plot_model_comparisons(results, feature='TempGradient')
```

```
if __name__ == "__main__":
    main()
```

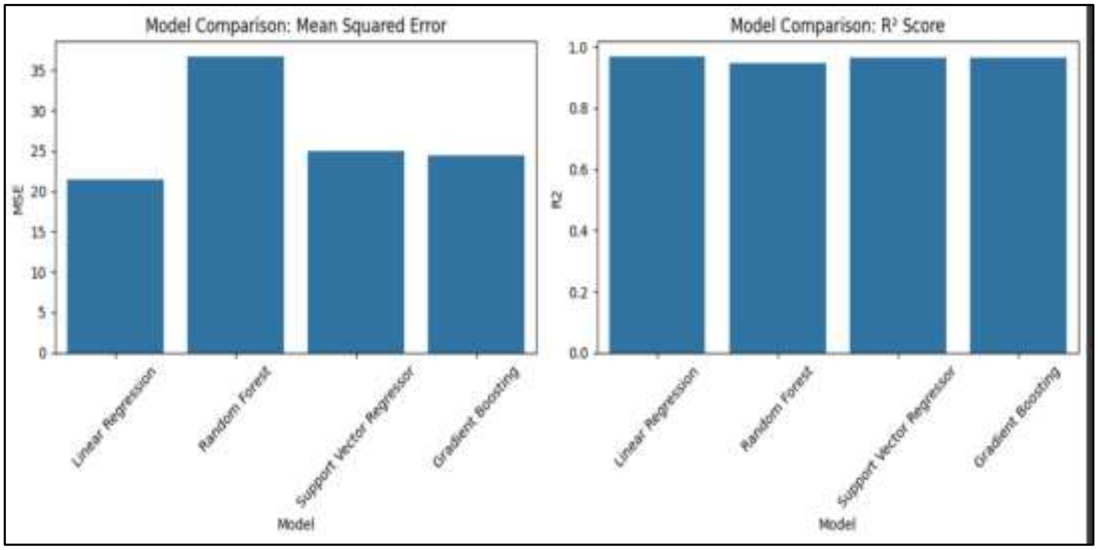

Figure 1: TEG Power Prediction Model Comparison

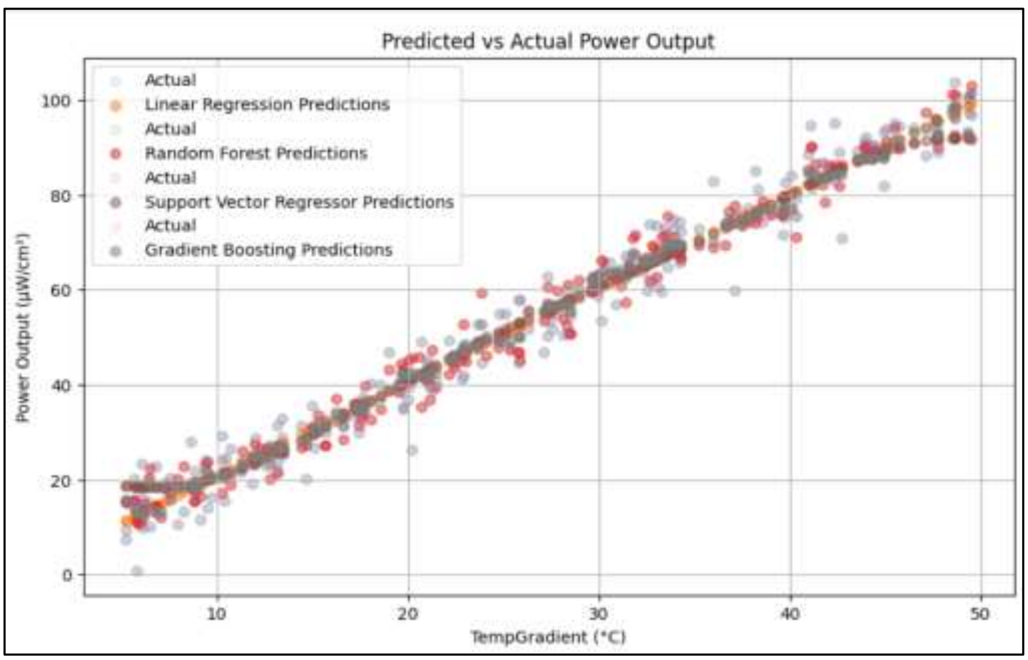

Figure 2: Predicted vs Actual TEG Output

VI. CONCLUSION

The literature review on adaptive thermoelectric energy harvesting (TEH) for self-sustaining remote sensor networks emphasise the transformative potential of thermoelectric generators (TEGs) in enabling autonomous, sustainable, and maintenance-free wireless sensor networks (WSNs). By synthesizing findings from experimental, simulation-based, and analytical studies, this review shows important growth in TEG design, power management, system architectures, and application-specific implementations, while identifying persistent challenges and future research opportunities. Key findings reveal that TEGs can effectively power remote sensors, generating 10-200 µW/cm² for temperature gradients of 5-50°C which is sufficient for low-power applications such as environmental monitoring, industrial condition sensing and wearable health devices.

VII. ACKNOWLEDGEMENT

This project has come to fruition thanks to the unwavering dedication and hard work of not just the students involved, but also the invaluable guidance and support provided by our project guide, Dr. Nabaneeta Banerjee. Additionally, we are deeply grateful to our institution, Guru Nanak Institute of Technology (GNIT), for providing us with the opportunity to undertake this project and we are grateful to our department of ECE also and our HOD mam.

REFERENCES

[1] An, J., Wang, Z., & Zhang, X. (2024). Research on the performance of thermoelectric self-powered systems for wireless sensor based on industrial waste heat. Sensors

[2] Chen, K. Y., Kachhadiya, J., Muhtasim, S., Cai, S., Huang, J., & Andrews, J. (2024). Underground ink: Printed electronics enabling electrochemical sensing in soil. Micromachines, 15(5), 625

[3] Morimoto, M., Kawano, S., Miyamoto, S., Miyazaki, K., Hayase, S., & Iikubo, S. (2022). Electronic structure and thermal conductance of the MASnI3/Bi2Te3 interface: A first-principles study.

[4] Sothmann, B., Sánchez, R., & Jordan, A. N. (2015). Thermoelectric energy harvesting with quantum dots. Nanotechnology26(3), 032001.

[5] Xin, J., Basit, A., Li, S., Danto, S., Tjin, S. C., & Wei, L. (2021). Inorganic thermoelectric fibers: A review of materials, fabrication methods, and applications. Sensors, 21(10), 3437.

[6] Yuan, J., & Zhu, R. (2020). A fully self-powered wearable monitoring system with systematically optimized flexible thermoelectric generator. Applied Energy, 271, 115250.

[7] Álvarez-Carulla, A., Saiz-Vela, A., Puig-Vidal, M., López-Sánchez, J., Colomer-Farrarons, J., & Miribel-Català, P. L. (2023). High-efficient energy harvesting architecture for self-powered thermal-monitoring wireless sensor node based on a single thermoelectric generator. Scientific Reports, 13(1), 1637.

[8] Kucova, L. (2023). Thermoelectric energy harvesting for internet of things devices using machine learning: A review. CAAI Transactions on Intelligence Technology.

[9] Wang, W., Cionca, V., Wang, N., Hayes, M., O'Flynn, B., & O'Mathuna, C. (2013). Thermoelectric energy harvesting for building energy management wireless sensor networks. International Journal of Distributed Sensor Networks, 9(6), 232438.

[10] Mori, T., & Priya, S. (2018). Materials for energy harvesting: At the forefront of a new wave. MRS Bulletin

[11] Verma, G., & Sharma, V. (2018). A novel thermoelectric energy harvester for wireless sensor network application. IEEE Transactions on Industrial Electronics, 66(5), 3530-3538.

[12] Dini, M., et al. (2016). An autonomous power converter for single or multiple source energy harvesting. IEEE Transactions on Power Electronics

[13] Ryu, H., Yoon, H. J., & Kim, S. W. (2019). Hybrid energy harvesters: Toward sustainable energy harvesting.

[14] Saraereh, O. A., Alsaraira, A., Khan, I., & Choi, B. J. (2020). A hybrid energy harvesting design for on-body internet-of-things (IoT) networks, 20(2), 407.

[15] Glatz, W., et al. (2009). Ni-Cu based micro-thermoelectric generators for wireless sensor networks. Sensors and Actuators A: Physical

[16] Su, J., Leonov, V., Goedbloed, M., van Andel, Y., de Nooijer, M. C., Elfrink, R., Wang, Z., & Vullers, R. J. M. (2010). A batch process micromachined thermoelectric energy harvester: Fabrication and characterization. Journal of Micromechanics and Microengineering, 20(10), 104005.

[17] Hoffmann, D., et al. (2020). A self-adaptive and self-sufficient energy harvesting system.