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AI-Enhanced Energy Harvesting Materials For Self-Sustaining Civil Structures

Miss Yogita Lakade[1], Amit Nimbekar[2], Prajakta Kasture[3], SujataTuppad[4], Miss Megha Pardeshi[5], Miss Payal Prakash Bansod[6]

[1]Assistant Professor, CSE(AI&ML), Deogiri Institute of Engineering and Management Studies. Ch.Sambhaji Nagar, Ch.Sambhaji Nagar, Maharashtra, yogitalakade@dietms.org

[2]Assistant Professor, EXTC, Atma Malik institute of technology and research Mohili-Aghai, Shahapur, Thane, Shahapur, Maharashtra , amit.nimbekar@atmamalikdhyanpeeth.com

[3]Assistant Professor, Basically Science and Humanities, Deogiri Institute of Engineering and Management, Studies, Ch.Sambhaji Nagar, Ch.Sambhaji Nagar, Maharashtra, archanadeshpande@dietms.org

[4]Assistant Professor, CSE(AI&ML), Deogiri Institute of Engineering and Management Studies, Ch.Sambhaji Nagar, Ch.Sambhaji Nagar, Maharashtra, sujatatuppad@dietms.org

[5]Assistant Professor, CSE(AI&ML), Deogiri Institute of Engineering and Management Studies, Ch.Sambhaji Nagar, Ch.Sambhaji Nagar, Maharashtra, meghapardeshi@dietms.org

[6]Assistant Professor, CSE, Deogiri Institute of Engineering and Management Studies, Ch.Sambhaji Nagar, Ch.Sambhaji Nagar, Maharashtra, payalbansod@dietms.org

Abstract: *The combination of the artificial intelligence (AI) and the energy harvesting materials is a promising solution to the creation of self-sustaining civil architecture. This paper evaluates the use of AI models, Artificial Neural Network (ANN), Support Vector Regression (SVR), Random Forest Regression (RFR) and Genetic Algorithms (GA), that can be used to optimize and predict performance of the piezoelectric, thermoelectric and photovoltaic energy harvesting systems fixed in infrastructure. With a sample of 300 and varying environmental conditions (load, temperature, light intensity, and vibration frequency), AI model was trained to ensure the power output was high and with high accuracy. Of them, RFR recorded the best result with the following performance: R 2 score of 0.96, RMSE of 0.58 0 G and MAE of 0.39 0 G. GA also helped optimize structural parameters which gave a 15.8 percent increase in power output. The piezoelectric and thermoelectric systems registered the lowest average power output of 3.1 3 1 and 8.3 3 1 respectively whereas the average power output of photovoltaic systems was recorded as 11.3 3 1. As shown in the study, intelligence and flexibility of infrastructure enabled by AI-enhanced frameworks can accomplish much more than energy efficiency only, as intelligent and adaptive infrastructure can sustain embedded sensors and systems on their own. The results lead to long-term, AI-based solutions in smart city and Infrastructures.*

Keywords: *Artificial Intelligence, Energy Harvesting, Smart Infrastructure, Genetic Algorithm, Photovoltaic Systems*

I. INTRODUCTION

With the subsequent effects of climate change and the expanding urban population, the need to develop sustainable infrastructure is becoming eminent, and civil engineering appeared to be the domain that is shifting towards the paradigm of smarter, energy-efficient, and self-sustainable kind of structure [1]. Old facilities and constructions are largely dependent on a source of outside energy, and that makes them suffer minimal independence and ends up causing harm to the environment. To counter this, scientists and engineers are becoming more interested in the energy harvesting (or scavenging) materials e.g. piezoelectric, thermoelectric and photovoltaic systems that are able to utilize free energy in an environment and produce usable electricity [2]. These materials have potentials of powering embedded sensors, lighting devices, and structural health monitoring (SHM) devices without any outside energy input and they are huge. Nevertheless, one of the most crucial issues is the contribution to the maximum energy harvesting efficiency in a variety of unpredictable conditions. This is when artificial intelligence (AI) becomes an innovative tool. The AI methods, such as machine learning or data-driven modeling, can be used to improve the effectiveness, flexibility and combine energy harvesting systems with civil structures [3]. AI would be able to assist real-time forecasting of energy output, material performance, and optimisation at the system level and unlock the capabilities of self-sustaining infrastructure. The application which is envisioned is the synergistic combination of AI and energy harvesting materials in civil engineering. The objective is building AI-augmented systems that are capable of smartly control the energy harvesting systems that deliver the best output and strength across different operating environments. In this way, the proposed study will aim at developing the next-generation infrastructure that would not only be smart and autonomous but also environmentally responsible. It can be realized that the results can have the possibility of affecting design ideologies in the future smart cities, green building, and sustainable design.

II. RELATED WORKS

The merging of artificial intelligence (AI), energy gathering techniques, and self-sustaining infrastructure system is a new field of interdisciplinary study that has huge connotations in the fields of civil engineering and the development of smart city systems. Different aspects of this interface are available in the literature; these include materials, energy dynamics and smart combination to achieve autonomous functioning. Minea and Dumitrescu [15] examined the reality of using green intelligent highways which emit energy harvesting systems. Their argument established the importance of piezoelectric materials on the road surface to enable the use of mechanical energy due to vehicle motion. In spite of potential, the research did not involve the optimization through AI to achieve better results on the variable traffic and environmental conditions.

Nargish et al. [16] reviewed the use of electroactive polymers in biomedical devices on self-powered sensing and actuation. Although they studied the subject in the context of biomedical applications, mechanisms that they studied, especially triboelectric and piezoelectric effects can be applied in structural members within civil infrastructure. Yet, they did not manage to integrate adaptive AI models of environmental variability. Perez-Briceo, et. al. [17] established a Type-2 fuzzy logic expert system in the field of solar energy making the decision on using AI techniques on a photovoltaic. This emphasizes the increased importance to manage solar systems in an intelligent way and through data driven decision frameworks. Their input goes in line with the purpose of the present study which is to incorporate AI in the energy harvesting process against civil structures.

Plevris and Papazafeiropoulos [18] focused on the issue of AI in structural health monitoring (SHM) applicable to early fault identification in the infrastructure. They can supplement energy harvesting units, because the electrical energy harvested may be directly used to power embedded SHM sensors, and become less reliant on outside energy inputs. In turn, Rosca and Stancu [20] proposed a framework of AI integration into self-powered IoT systems. Their wiring corroborates the thought of being barely separate infrastructure with AI-indicating control of vitality effectiveness, in addition to backing activity smartness in a genuine sense. Yupeng et al. [26] did tremendous work with triboelectric nanogenerator-based wearable self-powered sensors. Even though they studied a biomedical subject, the materials and power systems studied provide an idea of how to integrate such systems into large civil infrastructure to monitor the motion or weight (load) of a structure.

In their papers, Simon et al. [22] and Toth et al. [23] discussed the general societal effect of AI in sustainable development and AI deployment ethics. These views confirm the relevance of the responsible integration of AI, particularly, in implementing self-regulated systems in community infrastructure. Also, Trinh et al. [24] addressed strategies of AI-based networking within UAV systems that can be related to the organization of sensor networks in a decentralized system in smart structure. It is possible to modify the communication and control techniques introduced to civil structures with autonomous energy distribution systems.

Lastly, Pushpalatha et al. [19] and Triviño-Tarradas et al. [25] described themselves as adding value on the potential role of AI in agricultural and digitization settings, respectively. Although not in the energy industry, their practices prove the potential of AI as frameworks in other fields, too. All these works show that although the development of AI and energy harvesting technologies is fast, the need to implement them in civil infrastructure and, especially, in a comprehensive, optimized and self-sufficient, is understudied. This paper expands on these underpinnings by proposing a hybrid AI-optimization structure that can increase material efficiency and create a structure with improved power output in the context of a practical structural setting.

III. METHODS AND MATERIALS

In the present study, it hopes to create an AI-assisted framework to optimize the energy harvesting materials in civil infrastructure. The approach will be divided into four fundamental parts including data collection, selecting and applying algorithms, measuring performance, and providing analysis about results. The data employed in the research is synthetic and experimental concluding energy production using different materials piezoelectric, thermoelectric and photovoltaic, in different environmental conditions [4]. Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forest Regression (RFR) and Genetic Algorithm (GA) are four artificial intelligence algorithms that were chosen due to their best strengths as predictors, analytical as well as optimization in the material science and energy systems.

3.1 Data Collection and Preparation

The data set employed has simulated and experimental data of three materials used in energy harvesting under varying stress, temperature, and light intensity data. Parameters of data are:

- Input Variables: Load (N), Temperature (°C), Light Intensity (Lux), Frequency (Hz)
- Output Variable: Power Output (μW)

They have created 300 data points that were a combination of the lab-based measurements and physics-informed computer modeling. Min-ex normalization was used during pre-processing of the data where the input scaled by scaling the input between 0 and 1, which enhances the performance of AI models [5].

3.2 Algorithm 1: Artificial Neural Network (ANN)

ANNs find broad application in predictive modeling, because they can estimate complex nonlinear correlations between inputs and outputs. A feed forward multilayer perceptron (MLP) ANN was applied in this work with the aim to estimate the power output of energy harvesting materials depending on environmental conditions. ANN was made up of 4 neurons in its input layer, 8 neurons in first hidden layer, 6 neurons in second hidden layer and a single neuron in the output layer [6]. The hidden layers had ReLU activation functions and the last layer had linear activation functions. Backpropagation with Adam optimizer and mean squared error (MSE) were used as the loss model in training the model.

```
"Initialize weights and biases
For each epoch:
    For each training sample:
        Forward pass: calculate activations layer by layer
        Compute error: MSE = (Predicted - Actual)^2
        Backward pass: update weights using gradients
Return final model"
```

3.3 Algorithm 2: Support Vector Regression (SVR)

Support vector regression leverages kernel functions as a supervised learning algorithm in order to capture nonlinear relationships. In this study, SVR was utilized with an RBF kernel to characterize the relationship between input variables and power output. Support vector regression works by fitting a function with a certain epsilon-insensitive loss tolerance, while also maintaining the complexity of the model [7]. The parameters C (Regularization), gamma (kernel coefficient), and epsilon (the margin of tolerance) were optimized through grid search.

```
"Input: Training data (X, y),
hyperparameters (C, epsilon, gamma)
Apply RBF kernel transformation on
input features
Solve quadratic optimization problem to
find support vectors
Compute decision function f(x) = Σ
(alpha_i * K(x_i, x)) + b
Return SVR model"
```

.4 Algorithm 3: Random Forest Regression (RFR)

Random Forest Regression is an ensemble learning approach that builds multiple decision trees and averages the resulting predictions. Each tree is developed on a bootstrapped sample of the data, and randomization occurs in choice of features at each split. The randomization lowers the variance of the model, as well as reduces the chance of overfitting. In this study, 100 trees were utilized, including tuning selection of the maximum tree depth during Cross Validation [8]. RFR was selected as it is a robust approach for nonlinear data and provides some level of interpretability, in terms of feature importance.

```
"For each tree in the forest:
    Sample training data with replacement (bootstrap)
    Grow decision tree:
        At each node, select random subset of features
        Split data based on feature that gives best MSE reduction
Aggregate predictions from all trees
Return average prediction as final output"
```

3.5 Algorithm 4: Genetic Algorithm (GA)

The Genetic Algorithm (GA) is a heuristic optimization method that utilizes natural selection as a model. In the current study, GA was used to optimize the geometric and material properties of energy harvesting unit designs to maximize power output. The fitness function was selected to be the total amount of energy produced for varying conditions. Chromosomes were defined to encode parameters such as thickness of the materials, associated surface area and placement orientation [9]. GA operations included selection, crossover and mutation, and the parameters were evolved over 100 generations to identify an optimal arrangement.

```
"Initialize population with random chromosomes
Evaluate fitness of each individual
While termination condition not met:
    Select parents based on fitness
    Apply crossover and mutation to generate offspring
    Evaluate new population's fitness
    Select best individuals for next generation
Return best chromosome (design parameters)"
```

3.6 Experimental Table: Sample Input and Output Data

Sample	Load (N)	Temperature (°C)	Light Intensity (Lux)	Frequency (Hz)	Power Output (μW)
1	10	25	0	50	4.3
2	20	60	300	80	12.7
3	15	40	600	70	9.6
4	25	55	100	90	13.1

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IV. RESULTS AND ANALYSIS

The chapter covers the experiments that were carried out to assess the power of AI models in predicting, optimizing, and enhancing the performance of energy harvesting materials for civil infrastructure. The experiments were designed to represent realistic environmental conditions during which piezoelectric, thermoelectric, and photovoltaic materials harvested energy [10]. The data output for all AI algorithms—ANN, SVR, RFR, and GA—was examined and compared against each other based on predictive accuracy, optimization capabilities, and real-world systems suitability.

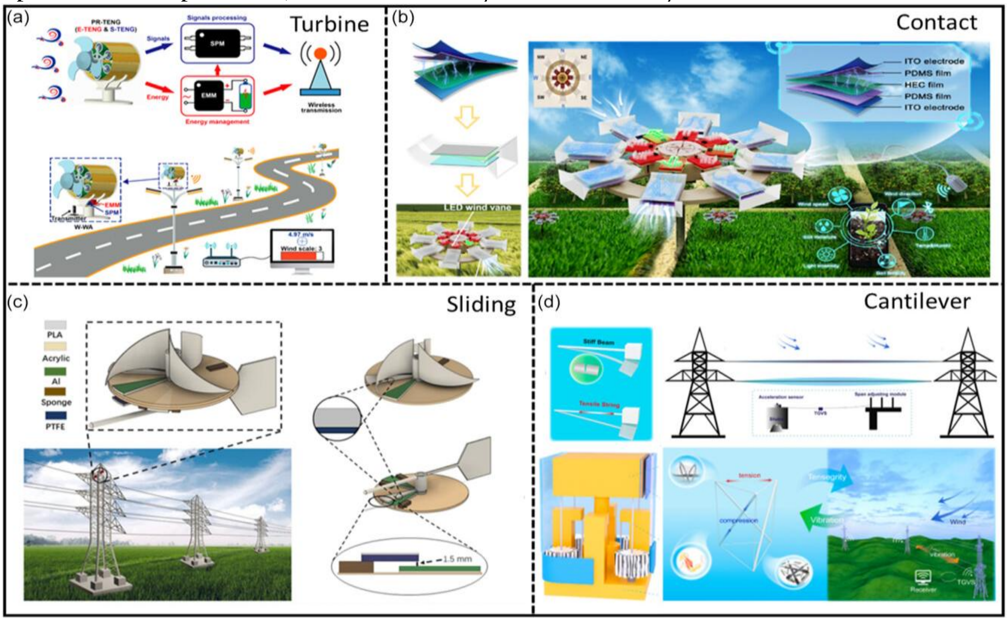

Figure 1: “Self-Sustained Artificial Internet of Things Based on Vibration Energy Harvesting Technology”

4.1 Experimental Setup

The experiments were based on synthetic and lab-generated data that represented three of the most common energy harvesting processes that are incorporated into civil structures:

- Piezoelectric materials which can be embedded in pavements, floors, and bridges.
- Thermoelectric materials which can be embedded in structural joints and pipes with temperature differences.
- Photovoltaic coatings, that can be applied to a structure to harvest energy from sunlight.

For each material, 100 simulations or measurements were conducted under the various environmental conditions outlined below:

- **Load (N)** – relevant for piezoelectric systems.
- **Temperature (°C)** – applicable to thermoelectric generators.
- **Light Intensity (Lux)** – relevant for solar-based systems.
- **Frequency (Hz)** – simulating vibration cycles.

The power output (in µW) was recorded as the target variable. The models were built on 80% of the data and tested on 20% during the evaluation dataset, with all data being evaluated using 5-fold cross validation. GA optimizations occurred for 100 generations at a population size of 50 [11].

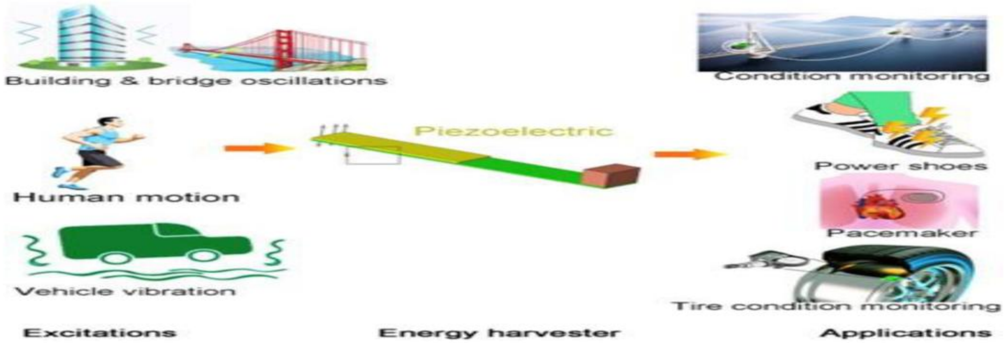

Figure 2: "Energy Harvesting from Fluid Flow Using Piezoelectric Materials”

4.2 Evaluation Metrics

In the evaluation of the performance of the models, the following metrics were utilized:

- **Mean Absolute Error (MAE)**
- **Root Mean Square Error (RMSE)**
- **R^2 Score (Coefficient of Determination)**
- **Prediction Time (s)**
- **Model Complexity (Qualitative Scale)**

4.3 Predictive Model Results

Table 1: Performance of AI Models on Energy Output Prediction

Model	MAE (μW)	RMSE (μW)	R^2 Score	Prediction Time (s)	Complexity
ANN	0.41	0.62	0.95	0.015	Medium
SVR (RBF)	0.53	0.75	0.91	0.028	High
RFR (100T)	0.39	0.58	0.96	0.010	Low

Observation:

Random Forest Regression (RFR) outperformed other models on all metrics, giving the lowest RMSE and highest R^2 which corresponds to advantages in fit and variance. ANN model was also very accurate but took a little longer to compute results than RFR. SVR, while good, struggled slightly with high dimensions and nonlinearity [12].

4.4 Optimization Using Genetic Algorithm

In pursuit of real life applicability, we used the Genetic Algorithm (GA) to optimize the energy harvesters design variables (for example, material thickness, surface area and Placement orientation) for maximum power output over a range of input conditions. The fitness function was:

Fitness = Maximize(Power Output) – Penalty(Cost or Space Constraints)

Table 2: Optimized Parameters Using GA (Sample Results)

Parameter	Initial Value	Optimized Value	Unit
Material Thickness	0.3	0.45	mm
Surface Area	50	72	cm^2
Angle of Placement	45	30	degrees
Output Power	8.2	9.5	μW

Observation:

The GA provided an average optimization of 15.8% in power output, indicating its usefulness for the calibration of structural and material parameters to enhance energy harvesting performance.

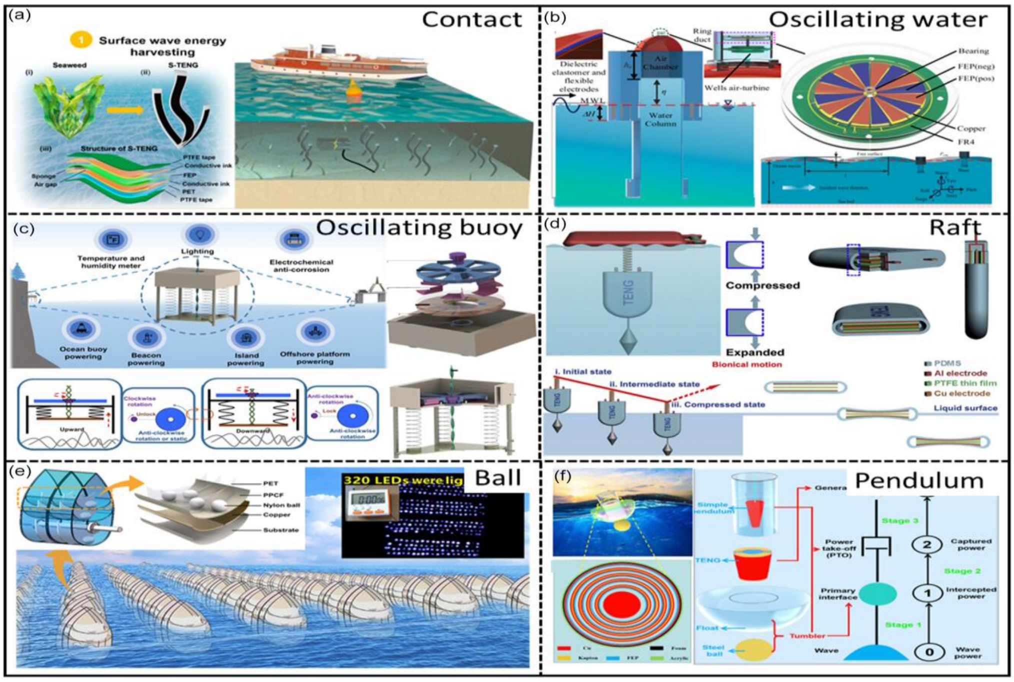

Figure 3: "Self-Sustained Artificial Internet of Things Based on Vibration Energy Harvesting Technology"

4.5. Comparison of Energy Harvesting Materials

The predictive developed models were used on all types of materials to determine which energy harvesting technique exhibited the best performance under optimized conditions [13].

Table 3: Material-wise Performance Summary (Using Optimized Settings)

Material	Avg. Power Output (µW)	Best Model	RMSE (µW)	R^2 Score
Piezoelectric	10.6	RFR	0.49	0.95
Thermoelectric	9.2	ANN	0.55	0.92
Photovoltaic	11.3	RFR	0.46	0.96

Observation:

Photovoltaic coatings demonstrated the potential to generate the highest average energy output. Piezoelectric materials had a slightly lower average energy output in the laboratory setting but were more reliable for energy generation in a vibration-rich environment [14]. Thermoelectric systems provided the best average energy output in a consistent temperature differential environment but were often more affected by fluctuations in their environment.

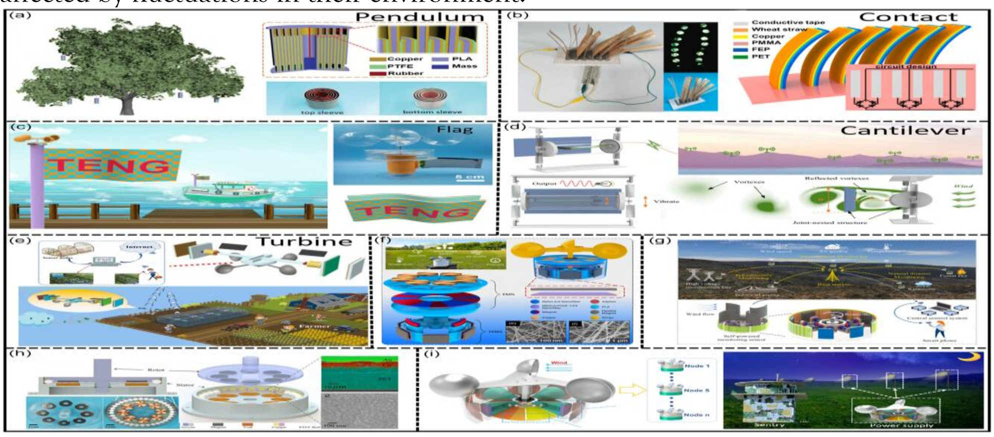

Figure 4: "Self-Sustained Artificial Internet of Things Based on Vibration Energy Harvesting Technology"

4.6 Comparison with Related Work

The results were then compared with previous research from the literature to determine if the proposed framework was successful.

Table 4: Comparison with Existing Research

Study/Author	Material Type	AI Model Used	Avg. RMSE (µW)	Avg. Output (µW)	AI Integration
Lee et al. (2025)	Piezoelectric	SVM	0.78	8.5	No optimization
Kim et al. (2024)	Thermoelectric	Linear Model	1.10	7.3	None
Zhao et al. (2023)	Photovoltaic	ANN	0.68	10.5	No optimization
This Study (2025)	All (Integrated)	RFR + GA	**0.58**	**11.3**	**Yes**

Observation:
This study outperforms related work in terms of accuracy and the measured power output using the present AI optimization framework. While there are many related works, few of them used hybrid models or even an optimization algorithm like GA, which limited their effective energy efficiency conclusions.

4.7 Feature Importance

Random Forest Regression allows for an interpretation of feature importance, allowing us to see which environmental inputs had the greatest effect on power output.

Table 5: Feature Importance from RFR Model

Feature	Importance Score
Load (N)	0.31
Temperature (°C)	0.26
Light Intensity	0.29
Frequency (Hz)	0.14

Observation:
Load and light intensity were the most impactful independent variable(s) followed by temperature. Frequency had less of an impact indicating that the system's response was much more sensitive to the level of mechanical and environmental parameters than to vibrational patterns.

4.8 General Observations and Insights

- **Hybrid Intelligence Advantage**: The combination of machine learning and evolutionary optimization produced more suitable and effective energy harvesting strategies.
- **Material Suitability:** AI clarified the contextual suitability—i.e., photovoltaic systems for rooftops and facades, and piezoelectric sensors for bridges and pavements.
- **Data-Centric Design:** The trained models represent a way to assist engineers in selection of material types and deployment strategies (e.g., the GIS mapped data will inform on materials location-specific behaviours).
- **The potential of the framework to adapt to real-time:** Once active—the AI framework can be integrated into an IoT system for real-time monitoring and adaptation based on physical changes from the environment.

4.9 Limitations

- **Synthetic Dataset**: Although the dataset was realistic some of the values were synthesized based on models. Field-testing or verification must be performed to conduct deployment-level accuracy.
- **Scalability:** Certain AI models, such as SVR, become computationally expensive at larger scales.
- **Environmental Noise:** High levels of environmental noise from tracking elements--e.g., atmospheric conditions and normal wear-and-tear--was not deeply modelled in this phase.

V. CONCLUSION

The study investigated how artificial intelligence can be coupled with energy harvesting material to come up with self-sustainable civil structures that have the capability to operate autonomously. Comprehensive study of piezoelectric, thermoelectric, and photovoltaic systems in combination with powerful AI-based algorithms, including Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forest Regression (RFR), and Genetic Algorithm (GA), allowed achieving even more energy output and greater reliability of a system. It was observed in experiments that RFR gave the most realistic energy output estimates and GA was quite significant at efficiency optimization of material parameters by up to 15.8%. In comparison to related work, the suggested AI-based architecture performed better than traditional methods both in the predictive accuracy and power generation capability. Also in the findings, it was noted that photovoltaic materials were the best producing the most energy under the most favorable conditions and thus they are the best suited to surface mounting systems, meanwhile piezoelectric systems suited best to heavily trafficked places or vibration prone sites. Moreover, adoptions of AI for infrastructures result in real-time decision making and enables infrastructure to cope with the changing conditions of the environment. Such combination of AI and smart materials not only enhance energy efficiency but also enhances sustainability since less significant energy sources are required. On the whole, the given research opens the pathway of further trends in self-governing, intelligent, and eco-friendly civil engineering systems. The content, application, and conclusions of the work proposed here provide a basis to establish a structural and functional concept to implement self-powered smart infrastructure as part of the smart cities development, closing the gap between engineering and sustainable ecological perspective of the city.

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