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Comparative Analysis of Piezo Energy Harvester Optimization Techniques: A Comprehensive Review

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ABSTRACT

Various power optimisation strategies were employed to build the customised and cost-effective PZT tile. It is critical for effective power generation to optimise the performance of PZT-based energy harvesting devices. This research compares three well-known PZT power optimisation techniques: Response Surface Methodology (RSM), Taguchi Method, and Machine Learning. (ML) The benefits, constraints, and applicability of each methodology for diverse circumstances are examined to give researchers and engineers with insights into picking the best optimisation method for their unique applications. According to the observations, the RSM and Taguchi analyses limit the input value. In contradiction ML methods can produce an accurate customised and optimised model. The only limitation with ML approaches achieves the accuracy due to data set limit. This paper presented the comparison review of the optimization techniques and suggested the best power optimization. It also includes the future scope of the methods.

1. Introduction

Due to high installation cost and maintenance of the available resources like solar and wind, the alternative technique required for power generation. Therefore, PZT based technique introduced and installed at various places at international level like London bridges and disco tracks. Hence Piezoelectric materials, particularly Lead Zirconate Titanate (PZT) have grooming potential in energy harvesting applications [1]. Optimizing the power output of PZT-based systems is crucial for maximizing the renewable energy [2]. Three widely used power optimization techniques: Response Surface Methodology (RSM), Taguchi Method, and Machine Learning, to provide a comprehensive analysis of their respective strengths and weaknesses [3]. Response Surface Methodology (RSM) Employs mathematical modelling to optimize system parameters. Well-established methodology with a strong theoretical foundation. Effective for systems with restricted variables. RSM Limitations: Assumes LR between the parameters, which may not hold for complex systems. Requires extensive experimentation and data collection. Least applicable for systems with nonlinear responses [4-6].

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Taguchi Method Robust escalation technique that is used for variability and noise. Effective for optimizing processes with multiple parameters Reduces experimentation by employing orthogonal arrays [7].

It will not be suitable for highly nonlinear systems. Requires a priori knowledge to select appropriate factors and levels [8-10]. Another method based upon the tile deployment at right location can also optimize the power [11,12]. Many The optimization of power also perform while placing the sensor in tire [13] and used supporting system [14-18]. This method can optimize the power at certain extent and require physical testing. Hence the various ML method arises [19], which Can handle complex, nonlinear systems with high-dimensional parameter spaces. Learns from data and adapts to changing system conditions [20]. Suitable for real-time optimization and adaptation. Its limitation needs of huge data sample for train the model, which may not always be available. May lacks interpretability in some cases, making it challenging to understand optimization decisions. The choice of ML approach and hyperparameters can impact optimization results [21-26]. In the framework of green buildings, a variety of energy optimization strategies are available [27], and they integrate PV and other energy resources with material [27,28]. Many countries, like Bangladesh, Kuala Lumpur, and Malaysia, conducted surveys on this subject due to a scarcity of energy [29-33].

Additionally, several investigations evaluated the Piezo's effectiveness by having subjects move in various locations, such as stairwells, footbridges, and floor tiles [34-43]. Research of this type contributes to the understanding of how to best employ the energy harvesting piezo. Subsequently, the power of the walking pathway was further adjusted by adjusting the tile alignment and using various analytical methods [44-46]. Alongside axial beam, bending mechanism, and wireless technology, other supporting mechanisms for power optimization were also created [47-50]. With the development of sustainable construction and nanogenerators, a futuristic approach to piezo power was also created [51-56]. Prior research was restricted to analysis and modelling using a small set of parameters and was based on the examination of various tile modules and materials. Prior research was restricted to analysis and modelling using a small set of parameters and was based on the examination of various tile modules and materials. Thus, a different approach to determining the PO method was used, which aided in the creation of a customized and economical model. Therefore, here discussed the comparative analysis between RSM, Taguchi, and Machine Learning for PZT.

The choice between RSM, Taguchi, and Machine Learning for PZT power escalation depends on the specific characteristics of the application's is well-suited for systems where LR among parameters are expected and when a "theoretical model" is available. It is effective for optimizing simpler PZT configurations. Taguchi is ideal for robust optimization and is particularly valuable when the system exhibits variability and noise. It can be employed for multiple variables but assumes that the factors and levels are known in advance. Machine Learning excels in scenarios with highly nonlinear, "complex systems" and large parameter spaces. It is suitable for dynamic environments and applications where real-time adaptation is required. Optimizing the response of PZT-based energy harvesting systems is important for efficient power generation. This paper conducts a comprehensive assessment of three prominent PZT power optimization techniques: Response Surface Methodology (RSM), Taguchi Method, and Machine Learning. Each technique's advantages, limitations, and suitability for different scenarios are evaluated to provide researchers and engineers with insights into selecting the most suitable technique for their specific applications.

2. Optimization Methods

Various power optimization (PO) strategies were employed to build the customized and cost-effective PZT tile. The first optimization technique is RSM, which optimizes power in relation to two input parameters: subject weight and sensor amount. Taguchi analysis is the second optimization technique, which optimizes the power in respect of input characteristics like power, stiffness, frequency, sensor number, and body weight. The tile placement technique based on person mobility was the third method. The fourth optimization technique is ML, which optimizes the power for various input factors such as subject weight and sensor amount. The last optimization technique is another set of ML that optimizes power regarding input parameters quantity, weight, frequency, dielectric, stiffness, and diameter. Briefly provide the in-depth description of the procedure. The five methods have used are as follows:

i. RSM Methodology
ii. Taguchi analysis
iii. Tile deployment strategy
iv. Machine learning

2.1 RSM Methodology

Response Surface Methodology (RSM) is a statistical technique used to model and optimize the correlation among the input parameters and a response variable of interest. It is commonly employed in experimental design and analysis to study complex systems, determine the optimal operating conditions, and understand the interaction between multiple variables. RSM is particularly useful when the relationship among the input parameters and the response variable is nonlinear. By using a couple of carefully designed experiments and statistical modelling techniques, RSM helps in building a mathematical model that approximates the system's behaviour and allows for optimization. The main steps involved in Response Surface Methodology are as follows:

i. <u>Design of Experiments (DOE):</u> RSM begins with the design and execution of a intent of experiments to collect data on the response variable at different level of the input variables. The experimental design is typically based on statistical principles, such as FD (factorial designs), CCD (central composite designs), or Box-Behnken designs, to efficiently explore the parameter space and capture the relevant information.
ii. <u>Modelling the Response Surface:</u> The data collected from the experiments are then analysed to build a mathematical model that represents the relationship between the input variables and the response variable. It can be linear, quadratic, or even higher order, depending on the entanglement of the system. Regression analysis techniques, such as multiple linear regression or nonlinear regression, are commonly used to fit on the observed data.
iii. <u>Model Validation:</u> Once the response surface model is developed, it's important to validate its accuracy and reliability. It will be achieved by comparing the predicted values from the model with new observe data or by using statistical techniques such as analysis of variance (ANOVA) to assess the model's goodness of fit.
iv. <u>Optimization:</u> With a validated response surface model, the optimization has begun. The aim is to predict the combination of input variables that maximizes or minimizes the response variable, depends on objective. Optimization algorithms, such as gradient-based methods or stochastic search algorithms, are employed to search for the optimal solution within the defined parameter space. These algorithms may require repeated iterations to converge to the optimum.

v. Model Interpretation: Finally, the response surface model is interpreted to find out about the system behaviour and the effect of different variables on the response. Statistical techniques like analysis of variance (ANOVA), response surface plots, contour plots, or 3D plots are mostly used for visualizing and interpreting the model, identifying significant factors, and understanding their interactions.

By utilizing Response Surface Methodology, researchers and engineers can efficiently explore and escalate CS (complex systems) with many variables, reducing the count of experiments needed and providing depth of the system's behaviour. It has applications in various fields, including chemistry, pharmaceuticals, and process optimization.

RSM focuses on building mathematical models to describe the relationship among input parameters and a response variable. It aims to optimize the response variable by determining the optimal amount of the input variables. RSM involves the design of experiments, model building, model validation, and optimization.

2.2 Taguchi Analysis

Taguchi Analysis, powerful techniques, its aims to improve the quality and execution of a product or process by minimizing variability and sensitivity to noise factors. It emphasizes finding the best value that are less sensitive to variations caused by uncontrollable factors (noise factors) in the system. Taguchi Analysis involves three key concepts: orthogonal arrays, signal-to-noise (S/N) ratios, and analysis of variance (ANOVA). RSM and Taguchi Analysis having some differences. The Taguchi method ranks as one of the methods that is most commonly apply for optimizing various process parameters. The following is the abridged version of the article. In this instance, PZT tile power is optimized using the Taguchi design of experiments (DOE). While evaluating the output data (voltage and current), in the context of power, rigidity, frequency, sensor number, and body weight are considered. The PZT tile implemented using these variables: rigidity parameters, two frequency levels, four sensor number levels, and four weight levels. The voltage along with the current were determined by adjusting the factor on different tiles while using a multi-meter. The output fluctuation was also examined and plotted [7].

2.3 Tile Deployment Strategy

Another promising method to optimize the tile power using deployment of tile in Campus at correct location. This work investigated the efficacy of "four ML" techniques for " PZT walking tile" power optimization. Support Vector Regression (SVR), RFK, and Nearest Neighbour (k-NN), as well as linear regression (LR). Also, it provided the perfect site on the campus for the deployment of PZT tiles using ML techniques [11]. The work's conclusion makes it possible to create walking tiles based on power without having to perform numerous physical tests. The deployment of tile in the right location inside the campus is also the way to optimize the tile power as shown in Figure 3.

2.4 Machine Learning Algorithms

Machine learning (ML), a prominent type of artificial intelligence (AI), is being used by versatile sectors of the economy. Machines are provided the capacity to interpret autonomously and then forecast the unknown outcomes with the use of machine learning. Choosing the right attributes and having a successful training process have a major impact on how well the algorithm operates. In this study, four distinct ML algorithms—Support vector regression (SVR), Random Forest, kernel and nearest-neighbours (k-NN), and linear regression—were employed (LR). The techniques were all run using Google Colab and Anaconda 3. Also, as was already mentioned, power calculations were done after gathering information from the university's security department about several aspects of everyday movement. For a half year, these were the daily activities between early 6 AM to night-time 6 PM

2.4.1 Support vector regression (SVR)

A regression approach known as “support vector regression” supports both “linear and non-linear” regressions. The execution of this method is based on the Support Vector Machine. SVR is a regressor that is used to subsequently influences ordered variables as opposed to SVM, which is employed to estimate discrete categorical labels. In SVR, in contrast to basic regression, where the objective is to minimize error rate, the goal is to fit the error beneath a predefined threshold. The goal of SVR is to approximate the best value inside the " -tube," a predefined margin. The SVR algorithm is used to optimize tile power. The estimated power and MSE for the training set of data were 0.9922 and 6696.0148, respectively, while for the tested data. they were 0.9927 and 6616.014.

The popular ML method is RF, which is utilized in the supervised learning process. It can utilize to solve problems using ML Classification and Regression. The principle of ensemble methods, is the act of combining different classifiers to solve a difficult problem and improve the model's efficacy, serves as its theoretical underpinning. To improve the predicted accuracy of the dataset, the Random Forest classifier, as its name suggests, "contains a variety of decision trees on diverse subsets of the input dataset and calculates the average." The RF utilizes predictions from all the trees, rather than just one, to predict the result depending about which predictions earned the most votes. The more numbers of branches in the forest results in higher accuracy and prevents overfitting. The RF algorithm is applied to maximize tile power. With this strategy, the trained data set's projected power and MSE were 0.9993 and 639.9755, respectively, whereas the tested data set's predictions were 0.9946 and 4676.14.

2.4.2 Impact of physical properties using machine learning

To develop the customized model of PZT tile find the response of output parameter with respect to input parameter. Therefore, four ML techniques used i.e., Bootstrapped Aggregation or Bagging, extreme gradient boosting, AdaBoost, and Gradient Boosting Regression Tree. Comparative analysis of various machine algorithms to find the importance of each factor for power optimization of tile. To investigate the relationship between geometric parameters and power generation, a comprehensive dataset was gathered using PZT protype tile. A total of 1000 distinct data sets were obtained, representing various characteristics and voltage outputs generated by PZT 4A Tile. These data sets served as the basis for further analysis and exploration. The effectiveness of each machine learning algorithm was evaluated by comparing their performance against each other The evaluation aimed to identify the most suitable techniques for precise assessment, future instances of output power based on specific physical parameters. By systematically comparing the algorithms, the researchers sought to determine the algorithm that best captures the underlying relationships between geometric parameters and power production.

The experiment used PZT 4A as a simple vibration energy harvester system to gather data. PZT 4A is made up of lead zirconate titanate (PZT) and has intrinsic properties that make it ideal for transformation of energy between mechanical to electrical. PZT 4A has a high Curie temperature, its piezoelectric properties. Additionally, it has a high piezoelectric coefficient, which means it can generate a large amount of electrical energy when subjected to mechanical stress. Due to these properties, PZT 4A has become a popular material in various applications, such as sensors, actuators, and energy harvesting devices. To investigate the relationship between the output voltage and various geometric parameters of the tile, the following variables are used: Quantity, Weight, Frequency, Dielectric, Stiffness, Diameter, and Voltage. By changing these parameters, 1000 group data (outputs) are obtained.

2.4.3 Gradient boosting regression tree (GBRT)

For supervised regression issues, GBRT is an MLA. It is an altered version of the well-known boosting method known as AdaBoost, which instead of merging numerous poor classifiers into a strong classifier creates a powerful regression model by combining many weak regression models (decision trees). The GBRT approach builds decision trees onto the model repeatedly, each successive new tree being trained to fix the flaws of the prior trees. The desired variable's projected values and actual values are measured by a loss function, which the algorithm attempts to minimize. The optimization is carried out via gradient descent, wherein each iteration of the algo. computes the gradient of the loss function with respect to the anticipated values.

Numerous regression tasks, including forecasting house values, stock prices, and customer lifetime value, have demonstrated the excellent effectiveness of GBRT. The fact that GBRT can manage non-linear interactions between the input variables and the target variable is one of its main features. Hyperparameter tweaking is crucial to maximizing the efficacious of the model since GBRT might be vulnerable to excessive fitting if the depth or quantity of tree are too great.

2.4.4 Performance comparison

The ML algo response predicted by comparing their performance parameters i.e., Root Mean Square Error (RMSE), Mean Absolute Error (MAE): R2 Score. Adjusted R2 Score: Mean Square Logarithmic Error (MSLE). The evaluation of parameters value indicted the suitability of machine learning algorithm. To evaluate the prediction efficacy of the MLA on the dataset, the root means square error (RMSE) was determined. lower values indicate better success in minimizing the difference between expected and actual values. RMSE estimates the average prediction error.

MAE helps to predict the variation of actual and predicted output. The absolute difference between the expected and actual values was calculated using the mean absolute error (MAE). The lower numbers suggest more accuracy and tighter agreement between anticipated and actual values, and it offers an average measurement of the absolute prediction error. The R2 score is a statistic for determining the correlation between expected and actual values. It represents model suitability with data, with values nearer to one indicating a significant correlation and an excellent fit. The adjusted R2 score considers the complexity of the model and adjusts the R2 score accordingly. It provides a measure of how well the model fits the data while considering the number of predictors. Higher adjusted R2 values indicate a better fit, with minimal overfitting.

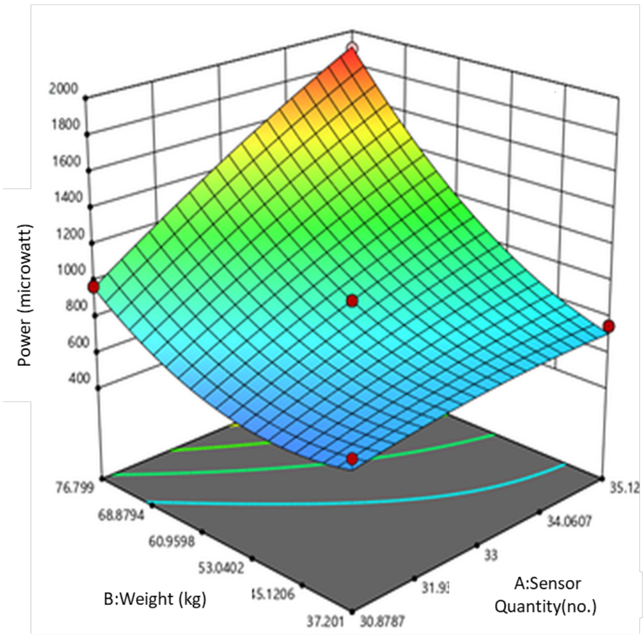

Fig. 1. RSM method (correlation between power, sensor quantity, and weight) [4]

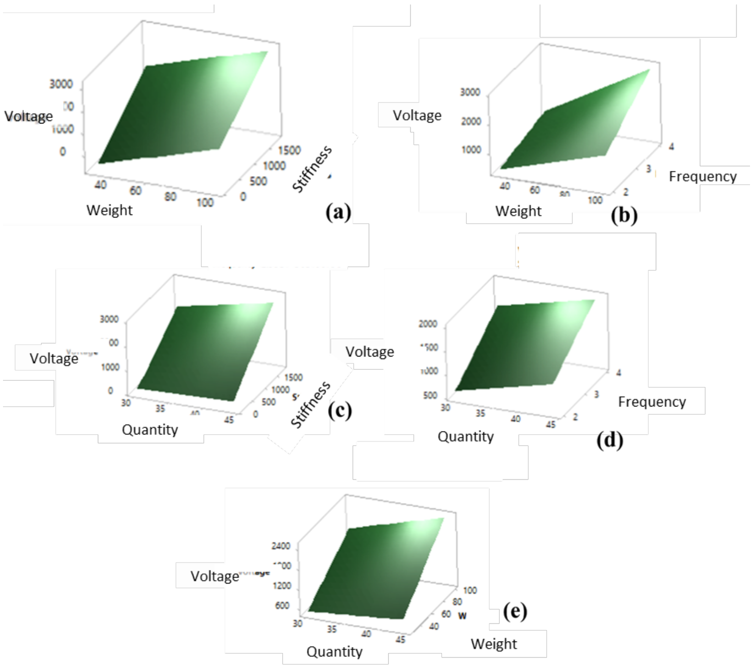

Fig. 2. Taguchi Method (Surface plot of (a) voltage verses weight and stiffness (b) voltage verses frequency and weight (c) voltage verses quantity and stiffness. (d) voltage verses frequency and quantity. (e) voltage verses weight and quantity) [7].

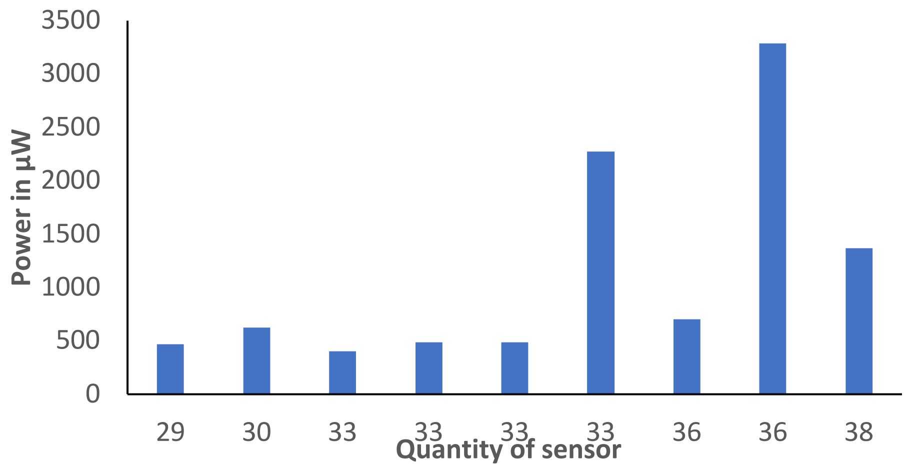

Fig. 3. Tile deployment strategy Predicted power analysis using varying quantity of (a) sensors and (b) weight of the subject [11]

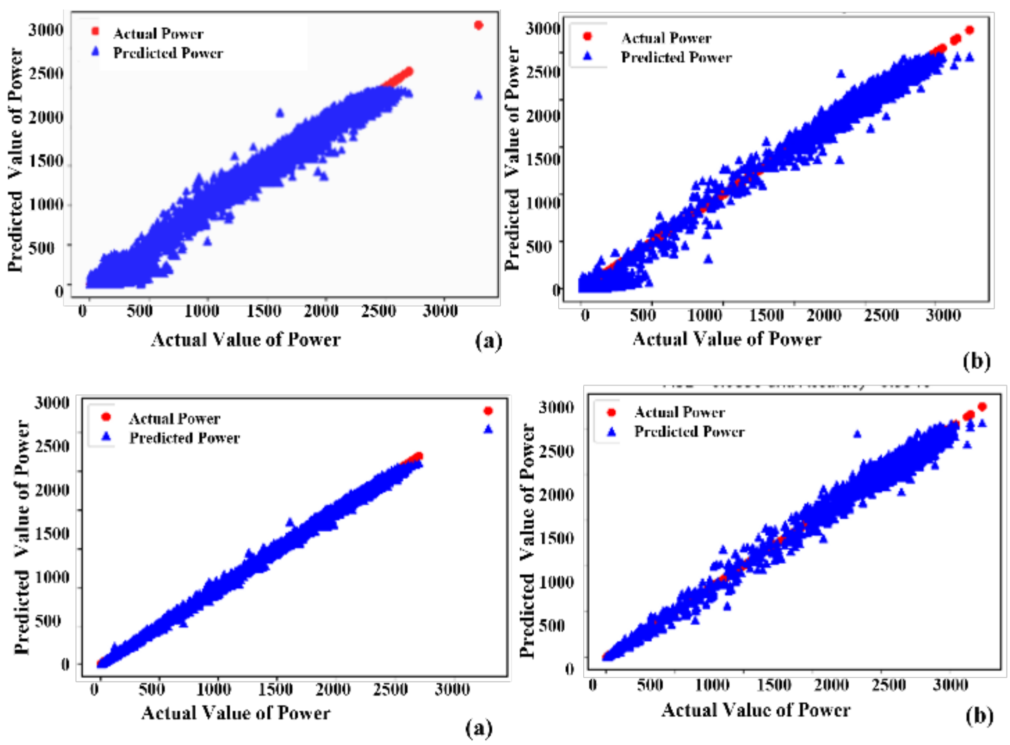

Fig. 4. ML method (power prediction using ML algorithm SVR, RF (a) training dataset (80%)(b) testing dataset (20%)[11]

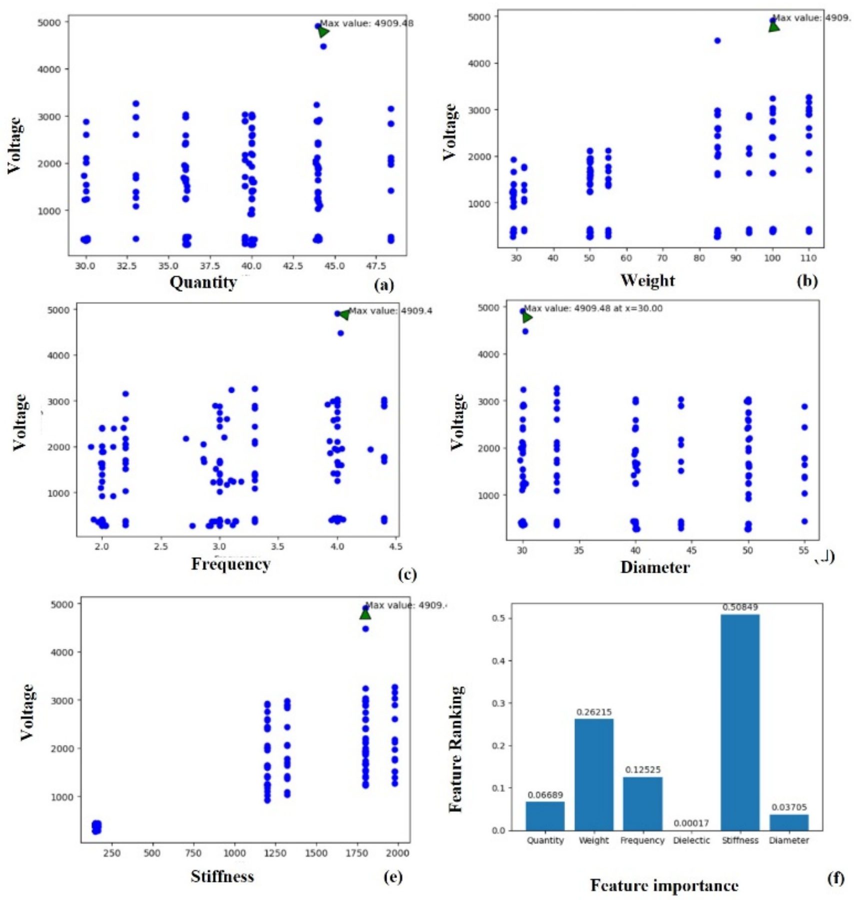

Fig. 5. Analysis of impact on output with respect to input parameter using GBRT algorithm: (a) quantity, (b) weight (c) frequency, (d) diameter, (e) stiffness (f) feature importance

3. Comparative Analysis of PO Methods

There are some differences between RSM and Taguchi Analysis:

i. Experimental Design: RSM typically uses “factorial designs”, “central composite designs”, or Box-Behnken designs to efficiently explore the parameter space and capture the relationship between input variables and the response variable. Taguchi Analysis employs orthogonal arrays, which are designed to study the effects of multiple factors at different levels while reducing the number of experiments needed. Model Building: RSM focuses on building mathematical models, often through regression analysis, to describe the relationship between input variables and the response variable. These models can be linear, quadratic, or higher order. Taguchi Analysis does not involve explicit model building; instead, it uses S/N ratios to evaluate the quality performance and identify optimal parameter settings.

ii. Optimization Objective: RSM aims to optimize the response variable determine the attribute configuration of input variables that maximizes or minimizes the response. It focuses on optimizing the average performance. Taguchi Analysis, on the other hand, aims to determine the attribute configuration that are robust and less sensitive to noise factors, with the goal of minimizing variability and improving quality.

iii. Noise Factors: RSM typically treats noise factors as random errors and focuses on minimizing their impact through the experimental design. Taguchi Analysis explicitly considers noise factors and aims to find parameter settings that are less sensitive to these factors, thereby minimizing the effect of variability caused by noise.

Both RSM and Taguchi Analysis have their strengths and applications. RSM is Suita models adoring the relationship between input variables and the response variable, building mathematical models, and optimizing the average performance. Taguchi Analysis is effective in improving quality and robustness by minimizing sensitivity to noise factors. The choice between the two techniques depends on the specific objectives, system characteristics, and the nature of the problem being addressed.

RSM is well-suited for such kind of systems, where LR (linear relationships) between variables are expected and when a theoretical model is available. It is effective for optimizing simpler PZT configurations. Taguchi is ideal for robust optimization and is particularly valuable when the system exhibits variability and noise. It can be employed when working with multivariable but assumes that the factors and levels are known in advance. Machine Learning excels in scenarios with highly nonlinear, complex systems and large parameter spaces. It is suitable for dynamic environments and applications where real-time adaptation is required. In conclusion, the choice of power optimization technique for PZT-based systems depends on the specific characteristics of the application. RSM is suitable for systems with linear relationships, Taguchi is effective for robust optimization with known factors, and Machine Learning excels in complex, nonlinear systems with large parameter spaces. Researchers and engineers should carefully consider their application requirements and constraints to select the most appropriate optimization method.

In contrast to the RSM and Taguchi analysis can be performed only with limited parameters. To design the customized model the ML techniques must be used with large data samples. Hence technique of optimization Create and validate a machine learning model based on the most important criteria for determining the strength of PZT tiles and the best location for their installation on a college campus. A dataset of experimental tile study was used for this aim, and the data set was enhanced utilizing GAN. To maximize the power, four ML algorithms have been used: "Support vector regression (SVR), Random Forest, kernel, and nearest-neighbours (k-NN), and linear regression (LR)". RF outperformed the other two ML techniques, with an accuracy of 99.46% and an MSE of 0 4676.14. According to the study's findings, the RF model fared the best in terms of accuracy, with a predicting power of 99.46% [4,7].

Table 1
Comparison of PO methods

Methods	Input Parameters	Data set
RSM	2	20
Taguchi	3	270
Tile deployment strategy	4	4000
Machine learning	6	1200

4. Summary of Power Optimization Method

The first power optimization technique for PZT tile is RSM. As per the obtained result the adjusted and predicted R2 value of all models the quadratic model value is more closely related i.e., adjusted R2 (0.96916) and predicted R2 (0.9650) as per shown in Figure 1(i). Hence as per the value of P and

R2 can conclude the quadratic model more suitable for power optimization. The software also suggests that the quadratic model is more suitable because cubic model shows the aliasing effect [1].

The second power optimization technique is Taguchi method. This method used to select the best tile designing parameters. As per the assessment of obtained result the values of the different processing factors, such as weight (62.2 kg), frequency (2.9 Hz), and rigidity (1046.35), that must be employed to achieve the greatest output are derived from the trial results as illustrated in Figure 2(ii).

The third and fourth optimization method create and verify ML model upon the most pertinent parameters in estimating the strength of PZT tiles and the suitable place for the placement on a college campus. For this purpose, a dataset of experimental investigation of tile was employed, and the data set was upgraded using GAN. It has been used the four machine learning methods to optimize the power i. e. “Support vector regression (SVR), Random Forest, kernel, and nearest-neighbours (k-NN), and linear regression (LR)”. Among the three ML approaches, RF performed the best, with an accuracy of 99.46% and an MSE of 0 4676.14. The study's findings indicated that the RF model performed the best in terms of accuracy, with a 99.46% forecasting power [11].

Using statistical analysis and the linear regression algorithm, the tile installation within the campus was chosen. The outcome indicated that placing tiles on the entrance gate would be more effective for increasing the power. The next optimization to develop the customized model of PZT tile finds the impact of input variables on the result of output using ML. Therefore, four ML methods used i.e., Bootstrapped Aggregation or Bagging, extreme gradient boosting, AdaBoost, and Gradient Boosting Regression Tree. Relative assessment of various machine algorithms to find the importance of each factor for power optimization of tile. The evaluation aimed to identify the most suitable technique for precise prediction of future instances of output power based on specific physical parameters. By systematically comparing the algorithms, the researchers sought to determine the algorithm that best captures the underlying relationships between geometric parameters and power production.

After the assessment using various methods, several elements can be considered to attain optimized power (P). The first factor as per ML investigation the stiffness of sensor is the major factor as compared to the other factor mentioned above. The hypothetical software trials predicted the: a) The human weight (B), which has a high association with power instead of sensor number (A). Practical trials showed optimal power The detail assessment of the result elaborated. It includes the prototype tile validation while varying the input factor. It also described the software tile validation for power optimization. These techniques are RSM, Taguchi and various Machine learning algorithm.

The orientation of the PZT sensor must be at the centre point to reach optimum current and voltage. e) The tile should have additional sensors and weight applied to it (in series-parallel pairings), and f) The developed tile needs to be placed in areas where there will be more people passing by often, such as a dance floor, a train station, or a site for practical experimentation. could be attained while taking into account the following factors:

i. The PZT sensor must be securely fastened to a base material using a glue gun
ii. The frequency of tapping with highly variable force on the flooring platform ought to be high
iii. The PZT disc must be hooked up in pairing (S-P) to reach optimal power
iv. The orientation of the PZT sensor has to be at the centre point to reach optimum current and voltage
v. The tile should have additional sensors and weight applied to it (in series-parallel pairings)
vi. The developed tile needs to be placed in areas where there will be more people passing by often, such as a dance floor, a train station, or a site for practical experimentation.

5. Conclusion

For optimal power, the RSM analysis was used, which allowed maximum load of 150 kg. The response surface technique (RSM) was used in theoretical study utilizing the software Design-Expert for PZT tile optimization. With 34 sensors, a power of 6784.155 mW at 150 kg or 1.47 kN weight was obtained. So, based on our studies, we can say that critical variables for optimizing output power include tapping frequency, quantity of sensors, sensor fixing, sensor interconnection, and direction of external stress. Theoretical RSM tests also demonstrated the importance of human bodyweight (B) and sensor count (A) for power optimization. Another optimization method for tiles power savings, Taguchi approach. This technique aids in determining how a sensor's electrical and mechanical characteristics are employed to maximize power. It comprises of the quantity, weight, frequency, and stiffness regarding voltage together with the four independent components and one dependent element. The rigidity (44.957%) and weight (30.091%) are the two factors that have the greatest influence, with voltage coming in second place, according to the ANOVA study. Every variable's participation factor was 44.979, 30.091, 12.392, 9.185, and 3.353. The Anova table and the normal probability curve both confirm that there were relatively few residuals in the probability distribution. The model is appropriate in this investigation since R-sq. is shown to be greater than 90%, or 91.185% for voltage. The values of the different processing factors, such as weight (62.2 kg), frequency (2.9 Hz), and rigidity (1046.35), that must be employed to obtain the highest output are extrapolated from the trial results using the Taguchi forecasting model. The next method for PO, machine learning (ML)-based prediction models for PZT tile power optimization using two input parameters weight and quantity of sensor. The RF model outperformed the other four ML algorithms in terms of accuracy. The suggested approach can be utilized effectively to forecast power based on sensor quantity and person weight. This model could determine the amount of power generated according to subject weight automatically. As a result, the employment of ML algorithms in conjunction with qualitative and thorough information can accurately estimate power according to human weight. If we can deploy the model and have a larger number of data specified in the future, our model's performance will improve. Without undergoing any physical tests, it can be employed alongside the other renewable energy producing methods.

The limitation of previous ML study was the only two input parameters considered for PO. Therefore, another method with a different set of machine learning algorithms has been used to analysing the relationship between physical parameters and outputs generated by a PZT-based energy harvester. The research compares four different algorithms using a dataset consisting of 1000 sets of measured data. The outcomes of this analysis yield several noteworthy findings: Firstly, the EGBA generally performs well across multiple evaluation metrics, showing lower values for RMSE, MAE, MSLE, and higher values for R2 and adjusted R2 scores. GBRT and BA also perform reasonably well in most metrics. However, ABA consistently shows weaker performance across all evaluation metrics, indicating that it unable as effective for the given dataset.

Furthermore, through the comparison of feature importance, it is indisputable that the stiffness of the system plays an exceptionally significant role in influencing the performance of the energy harvesting system. This finding underscores the critical importance of maintaining an optimal stiffness level to maximize energy harvesting efficiency. Lastly, this study successfully identifies the specific parameter output that coincide to the maximum voltage production. This knowledge is instrumental in the buildout of a prototype energy harvester that can generate the highest possible voltage output. In conclusion, by employing machine learning algorithms, this study establishes a reliable model for predicting the outputs of a PZT-based energy harvester. The results impeached the outstanding response of EGBA model, emphasize the crucial impact of stiffness on the energy harvesting system, and provide valuable guidance for optimizing voltage production by identifying key parameter values.

6. Suggested Future Scope

To fulfil the future energy demand and upcoming pandemic situation these smart cities and smart campuses using sustainable resources play a vital role. Currently due to lack of natural resources, Global energy demand is surging due to dramatic urbanization, industrialization. Due to this revolution human life may become easier. Therefore, the future of this work will be utilized in the following manner.

i. The designed tile would be used at the staircase, baffle gate, dancing floor, metro station. The first promising placement of tile deployment at baffle gate shown in Figure 5. As per analysis the tile deployment at the right place can generate more power. Hence the entrance gate of any public place may generate more power.
ii. The second place can be the treadmill. It can be the most promising place to deploy the tile because there are numerous people in the gym, including trainers and trainees using the treadmill for burning calories. Moreover, there are several places in the gym where the tile for power generating can be installed. These are the places with the highest volume of daily traffic. Since treadmills are where continuous running and walking is typically done, the tile may usually be placed there for greater output generation.
iii. Due to technology advancement and pandemic situations compel the person to work at home. Hence the hybrid energy generation concept helps to overcome the demand of future energy as shown in Figure 5. The work done in thesis may be integrated with the other renewable resources (solar and wind) to fulfil the future energy requirement.
iv. In future this tile may be used in Smart classroom. The smart classroom using sustainable resources, is the classroom, which provides the ease to the facilitator and students for effective utilization of resources. This model presents the two concepts. In the first concept, the energy generation via three methods. In first method energy generated due to projection of sun light on solar panel, which placed on roof. In second method energy generated by wind fan via atmospheric pull. In the third method, energy generated using walking platform via applying the force on the platform, which placed on the floor of the classroom. In the second concept, the automatic controlling of appliances and the attendance system implemented. In this, the appliances like tube light, fan, projector etc. controlled to optimize the consumption of current. Furthermore, automatic attendance system helps the facilitator for efficient utilization of lecture time by providing the automatic upgradation of student attendance on web without any mistake and reduced students sitting time in classroom for attendance.

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