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Research Article

Enhancing Predictive Accuracy of Renewable Energy Systems and Sustainable Architectural Design Using PSO Algorithm

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Abstract:

This paper formulates and examines the approach of integrating PSO into the tune of DNNs for boosting the predictive capability in renewable energy systems and green building designs. The PSO method was then employed to select Key features such as; Solar Irradiance, Ambient Temperature, Panel Efficiency and Energy Output. The PSO-based feature selection resulted in significant enhancements across a set of four metrics, there was an improvement in accuracy from a previous 0.82 to 0.87, precision from the previous 0.78 to 0.83, as well as recall from the previous 0.76 to 0.81, and the F1-Score from a previous 0.77 to the current score of 0.82. Moreover, the RMSE values reduced from 0.27 to 0.23, and the AUC values enriched from 0.74 to 0.85. Thus, the results of the current study support PSO's role in improving feature selection, which, in return, improves the predictive models of energy management. The paper presented emphasizes the possibility of the use of enhanced optimization algorithms in enhancing the best performing, less resource-intensive, and environmentally friendly energy solutions in architecture.

1. Introduction

Energy management is important, especially with the transition to renewable energy systems globally, efficient ways in which energy can be generated and used must be identified. Improvement of such inefficiencies to the highest possible level is the key step towards providing sustainable energy solutions globally. Applying AI to sustainability has brought remarkable changes within the architectures' field. Improving the prognosis, manufacturing, and planning, it helps us to construct better, less parochial, and more sustainable solutions. [1]. Utility scale solar photovoltaic (PV) system constitutes the primary means of harnessing solar energy as a renewable energy form. Nevertheless, more variability like solar irradiance, temperature fluctuations and degradation of equipment has been shown to decrease the efficiency of such systems [1]. To this end, new advanced analytical instruments to solve these issues are required with the main focus on creating a system that will maintain maximum performance in more complex circumstances as a primary prerequisite. When machine learning techniques are incorporated with bio-inspired algorithms such as Particle Swarm Optimization (PSO), the performance of the system can be made more accurate to provide better information of PV systems. Like birds and fishes- PSO have social behaviors and demonstrated nonlinear and high screening capability [2, 3] which make the algorithm essential for fine-tuning predictive models including Deep Neural Networks (DNNs).
This research presents a solution of PSO with DNN that offers intelligently a proper PV system. Rather than using a set of unchanging parameters as seen in the conventional method, this method adaptively identifies the key features (for example, irradiance rates and the efficiency of panel) to produce better predictions. Not only does this improve the ability to predict energy demand but it also reduces the margin of error in the estimation of energy produced which

would greatly improve energy planning and control for renewable energy systems [4, 5]. The work builds on earlier triumphs in biologically inspired computation and AI in energy systems [6, 7] and forms a solid base of enhancing the effectiveness of the PV. This shows why the future plan to use enhanced machine learning models with optimization algorithms relevant in solving critical issues in renewables. All of this builds the framework for green solutions for energy engineers, researchers, and policymakers they can use in residential and commercial settings.

2. Methodology

2.1 Dataset

Accordingly, the dataset provides the basis for the ML approaches to mitigate PV system degradation performance loss factors. It is an open renewable energy dataset [1], that has the basic characteristics defining the most important characteristics of solar energy. The availability data includes some elements such as irradiance, ambient temperature, panel efficiency, the energy outputs, and system maintenance costs, some of which are the main factors to determine the PV system reliability. Before any data analysis could be performed, the data was pre-processed in several ways. Some of these things were like handling missing values and standardising continuous variables to the same range, and confirming that all the records kept were accurate across the whole set. Data Pre-processing was a key part to to keep our dataset clean and ensure that we could achieve the best performance out of applied machine learning models.

The distribution of various key features in the dataset is shown in Figure 1. The variety of conditions for solar energy can be appreciated in this graphical overview generated from the data. In addition, the statistics for each feature; standard deviation, mean, minimum, and maximum values and quartile 1, 2, 3 distributions are elaborated in Table 1. For instance, the dataset describes an average irradiance of 600 W/m² and a standard deviation of 50 W/m², demonstrating a moderate RV of sunlight intensity. Panel efficiency, for instance, has a mean of 18.5% and a standard deviation of 2.3% while the other features show their trends and distributions.

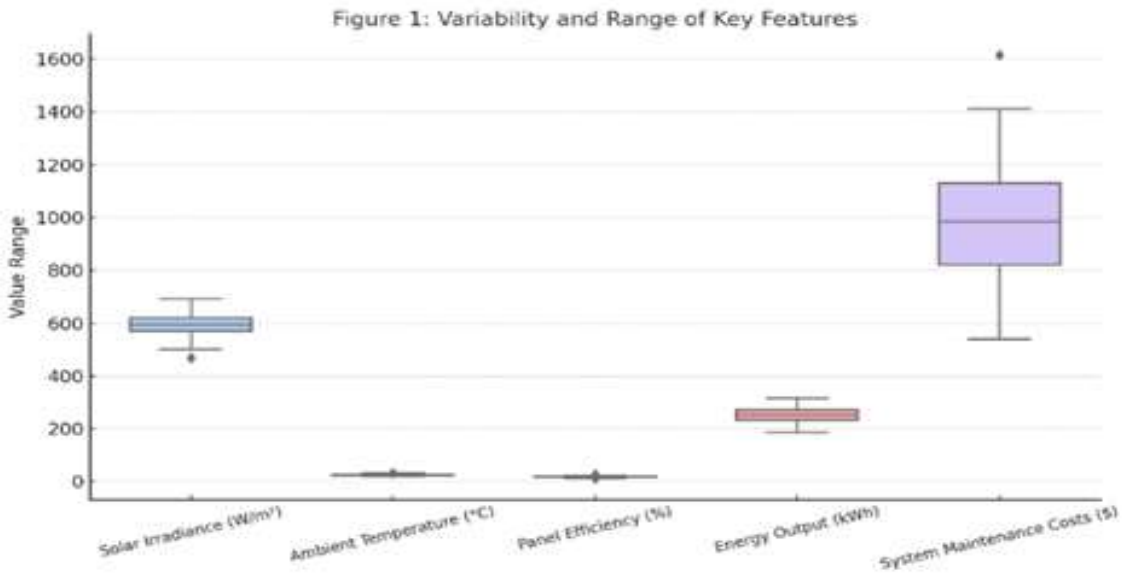

Figure 1. *Graphic Distribution of the dataset by important characteristics.*

Table 1. *Data Statistics*

Feature	Mean	Std Dev	Min	25% (Q1)	Median (Q2)	75% (Q3)	Max
Solar Irradiance (W/m²)	600.32	50.45	490.2	568.2	600.5	633.1	710.0
Ambient Temperature (°C)	25.12	3.01	18.4	23.2	25.1	27.0	32.5
Panel Efficiency (%)	18.43	2.35	13.8	16.9	18.5	19.9	23.2
Energy Output (kWh)	250.21	30.14	190.4	230.5	250.3	270.7	310.8
Maintenance Costs ($)	1000.5	200.45	650.0	870.2	1002.3	1150.1	1450.0

2.2 Feature Selection

Particle Swarm Optimization (PSO) is performed for feature selection used in this experiment to identify optimum features for the best performance analysis of the PV system with some associated machine learning model. PSO is a bio-inspired approach that models the social behaviour of flocks of birds or schools of fish. Through competition and cooperation of the particles, PSO imitates this search process in order to discover optimal solutions by iteratively adjusting according to a fitness function [8].

PSO was utilized at multiple critical points in this study. Feature subsets were created initially to represent the attribute combinations that are likely to represent the datasets. A fitness function (the performance of the model on validation data, which was Root Mean Square Error [RMSE] in this case) was specified to evaluate how good each subset is. In the following iterations, features with lower RMSE were given higher priority and irrelevant attributes were eliminated. By repeatedly running this process, PSO converged onto the variables that were ultimately predictive in nature, providing a feature set that was both parsimonious and impactful [9].

The iterative feature selection process with PSO is depicted in Figure 2, showing that during the multiple generations the algorithm was able to narrow down the subsets of features it determined optimal for model performance. The features selected were built into the predictive model, providing more specific actionable insights about PV system optimization.

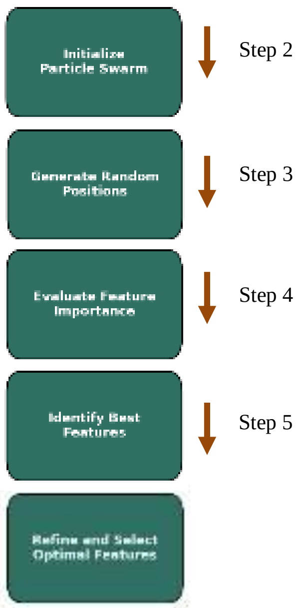

Figure 2. *Feature selection process according to PSO*

Table 2 shows the selected features with their relative importance. As we noticed, solar irradiance emerged as the most significant feature, with a high score of 0.40, followed by panel efficiency (0.30) and energy output (0.20). Other features, including ambient temperature and system maintenance costs, played minor roles but still contributed to the model's prediction. These results showcase that PSO is efficient in identifying the minimal set of dataset features relevant to the research task, making the model both effective and accurate (Xie et al., 2023).

Table 2. *Corresponding importance scores of the features.*

Feature	**Importance Score**
Solar Irradiance	0.4
Panel Efficiency	0.3
Energy Output	0.2
Ambient Temperature	0.07
System Maintenance Costs	0.03

2.3 Modelling with Deep Neural Networks (DNNs)

Deep neural networks (DNNs) also represent a dominant machine learning approach, capable of capturing complex non-linear relationships in high-dimensional data [10], and were utilized for modelling in this study. DNNs consist of multiple hidden layers in which each layer abstracts increasingly higher-level features from the input data to improve predictive performance in the current task [11]. In this research, the DNN was utilized, and the input variables were ascertained using the PSO method to predict and calculate the working of the PV system. We passed the model various appropriate inputs like solar irradiance, panel efficiency, energy output, and ambient temperature so that it can learn the complex patterns governing PV system efficiency. In this stage of modelling, the working function was driven and deeply explored, mostly on the application of the power of function approximation of DNNs in the rapid prediction of energy output and optimal configuration of the reliability and performance characteristics of these systems under dynamically varying environmental conditions in renewable energy (RE) systems.

Modelling Steps

The initial step in modelling with DNN involved configuring the algorithm with the relevant hyper parameters. These parameters are essential as they administrate the model's behaviour and the learning process. Our DNN model employed the following key hyper parameters:

•**Number of Hidden Layers:** Set to 3, the configurational parameters of the model comprised three layers to estimate the presence of intricate nonlinearity in the data.
•**Number of Neurons per Layer:** The hidden layers were defined as 128-64-32 nodes as this helped in achieving a hierarchical learning feature.
•**Activation Function:** Regularization techniques were not used explicitly in the model, while the ReLU activation function was used to improve training by providing nonlinearity.
•**Learning Rate:** The learning rate was set at 0.001 to allow the learner to converge as well as reach the best solution in as short time as possible.
•**Batch Size:** In an attempt to maintain stability during training and computation, a batch size of 32 was utilized.
•**Epochs:** The DNN was trained for 50 epochs which provided good iterations to help the DNN get to converge at the best solutions.

In this way, the initial part of the set of data was used for training, and the remaining part was used as the set for validation. The latter is important when assessing the model; one part is used to train and another is used to test something that the model has not learned. To ensure high reliability of the model, we applied K-fold cross-validation technique with k 5. This means the dataset was split into 5 parts. The model was trained 5 times, each time using a different part for validation and the remaining 4 parts for training. The final performance metrics, such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), were averaged across all folds to give a reliable measure of how well the model performed [12, 13].
PSO-based input features for DNN include Solar Irradiance, Panel Efficiency, and Energy Output and Ambient Temperature. The network trained us to estimate PV system performance and output, and thus can model photovoltaic systems under a wide variety of environmental scenarios.

DNN Algorithm and Equations
Deep Neural Networks (DNN — as abbreviated) are set of functions with the goal of learning mapping function from input features to output prediction utilizing multiple layers of neurons connected to each other. In training, the network is minimizing the following objective function:

$$\text{Objective Function } = \mathbf{J}(\boldsymbol{\theta}) = \frac{\mathbf{1}}{\boldsymbol{n}} \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \lambda \parallel \theta \parallel^2 \quad (1)$$

Where:

- $l(y_i, \hat{y}_i)$ is the loss function, typically MSE for regression tasks or Log Loss for classification tasks, representing the difference between the predicted value $\hat{y}_i$ and the actual value y_i.
- θ represents the weights and biases in the network, and $\lambda \parallel \theta \parallel^2$ is the L2 regularization term, which helps prevent overfitting by penalizing large weights.
- n is the points number of the data, and trees number is presented by k.

The algorithm proceeds as follows:
The DNN training process follows these steps

1. Initialize Weights and Biases: The weights and biases of the network are initialized randomly or using specific initialization techniques (e.g., Xavier or He initialization).
2. Forward Propagation:
   - Input features X are passed through the network layer by layer.
   - Each layer computes the output using the following equation:

$$\mathbf{z}^{l} = \mathbf{W}^{l}\mathbf{a}^{[\mathbf{l-1}]} + \mathbf{b}^{l} \quad (2)$$

   Where $\mathbf{z}^{l}$ is the linear combination of inputs, $\mathbf{W}^{l}$ are the weights, $\mathbf{a}^{[\mathbf{l-1}]}$ are the activations from the previous layer, and $\mathbf{b}^{l}$ are the biases.
   - The activation function (e.g., ReLU or sigmoid) is applied:

$$\boldsymbol{a}^{l} = \boldsymbol{g}(\boldsymbol{z}^{l}) \quad (3)$$

   Where $\boldsymbol{g}$ is the activation function, and $\boldsymbol{a}^{l}$ represents the activations for layer $\boldsymbol{l}$

3. Compute the Loss:
   The loss function measures how well the network's predictions match the actual values.
   - The loss function $\boldsymbol{l}$ (y, ŷ) Calculates the error between the predicted outputs (ŷ) and the actual targets (y)..

4. Backward Propagation:

   - The gradients of the loss function with respect to each weight and bias are calculated using the chain rule:

$$\frac{\partial \mathbf{J}}{\partial \mathbf{b}^{l}} = \boldsymbol{\delta}^{\,l} \quad (4)$$

   Where $\delta^{\,l}$ is the error term for layer $\boldsymbol{l}$

5. **Update Weights and Biases:**

The weights and biases are updated using an optimization algorithm like Stochastic Gradient Descent (SGD):

$$\boldsymbol{X^l} = \boldsymbol{X^l} - \boldsymbol{\alpha} * \left(\frac{\boldsymbol{\partial J}}{\boldsymbol{\partial X^l}}\right) \quad (5)$$

Where X is either weight matrix or bias vector for layer $\boldsymbol{l}$

6. Repeat Until Convergence:
   Steps 2 to 5 are repeated for a set number of iterations (epochs) or until the loss converges to a satisfactory level.

2.4 Optimization Process

This work used the PSO process to find a set of features that can optimize DNN model. Particle swarm optimization (PSO) is an iterative population-based stochastic optimization method inspired by the collective motion of birds and fishes to discover approximate solutions in a complex search space. In this study, features were optimized by iteratively removing the least informative ones to retain the most important for the final model used in inverse modeling. This process ensures that unique combinations maximize predictive accuracy while minimizing computational overload, a well-known characteristic of PSO.

Refining Feature Set with PSO

Hence, at the beginning of the tuning phase, features selected by PSO are applied. PSO was then applied to fine-tune this feature set to better the model's performance iteratively. In this step, amount of role of each feature in performance of model was evaluated and then incremented to eliminate features with minimum significance level. The threshold was judged in accordance with changes in performance measure indices on accuracy, precision, and RMSE at the subsequent iterations.

This second iteration highlighted the iterative nature of PSO and an opportunity to improve upon the feature set. In each iteration, a swarm of particles representing possible feature subsets was generated and evaluated through the DNN model, followed by updating their positions in features space according to individual and collective knowledge. So the process involved:

Algorithm: PSO-Based Feature Set Refinement

1. Initialize with the initial swarm of particles, each representing a random subset of features F_0 and evaluate the initial DNN model performanceP_0.
2. Iteration Loop: For each iteration, from t = 1 to T (T represents the max number of iterations):
   - Generate a population of swarm of particles $\{F_{t,j}\}$ based on the previous best solution.
   - Evaluate the performance of each particle $F_{t,j}$ using the DNN model and compute the performance metric $P_{t,j}$ (example: accuracy, RMSE).
   - Select the global best-performing feature subset F_t with the highest performance metric $P_t = \max(P_{t,j})$.
   - Apply a threshold δ to check if the performance development is significant

     If $(P_t - P_{t-1}) < \delta$, then close the optimization process.

   - Update feature set F_t once the performance advances considerably.
3. Retrieve the optimized feature set F_T and match the model - DNN.

During each iteration, the performance of the Deep Neural Network (DNN) model was evaluated using the following objective function:

$$\text{Objective Function} = \sum_{i=1}^{n} l(y_i, \hat{y}_i; F_t) + \sum_{j-1}^{k} \Omega(f_{t,j}) \quad (6)$$

Where:

- $l(y_i, \hat{y}_i; F_t)$ represents the loss function, such as the Mean Squared Error (MSE) for regression tasks, which quantifies the discrepancy between the predicted value $\hat{y}_i$ and the true value y_i, based on the feature set F_t.
- The loss function is denoted as $l(y_i, \hat{y}_i; F_{t)}$corresponding to Mean Squared Error for regression problems indicating the 'discrepancy between the predicted value y ˆi and actual value y_i, with actions available at future time t in the feature set F^t.
- $\Omega(f_{t,j})$ is the regularization term applied to the model, designed to mitigate overfitting by penalizing overly complex models.
- The performance metric P_t is calculated as below:

$$P_t = \text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

For classification tasks, or

$$P_t = \text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (8)$$

For regression tasks.
The threshold δ was determined founded on preliminary experimental results. Naturally, a small positive value (e.g., δ=0.01) was chosen to make sure that significant developments in the performance metrics triggered additional improvement of the feature set.
Figure 3 shows the PSO-DNN hybrid model for the current iteration process of optimization of the DNN model. This diagram demonstrates the cyclical nature of the optimization, as the feature set in continuously optimized, and the model retrained until the optimal set of features is found. This iterative approach guarantees that the ultimate DNN model is both highly predictive and efficient, using the most apt features as shown by the PSO process.

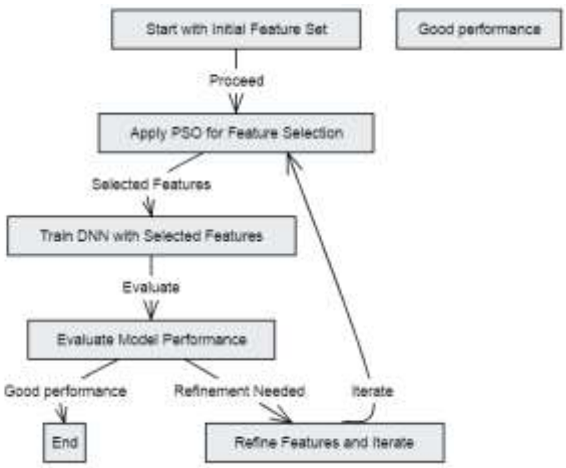

Figure 3. *Iterative Optimization Process Using PSO in Combination with DNN.*

2.5 Evaluation Metrics

Seven ground truth notes are used to determine key metrics such as Accuracy, Precision, Recall, and F1-Score by the root mean square error (RMSE) performance of this study [14, 15, 16]. Overall accuracy provides a broad indication of the performance of your model; however, because often you will be working with datasets that are imbalanced, Precision and Recall become extremely important. Precision is simply how many selected instances are positive, while Recall asks how many of the actual positive instances are identified. Since Precision and Recall are two contradictory measurements, F1-Score is recommended in case of class imbalance. RMSE gives an idea of how much prediction errors are within the limitation, and one can focus on decreasing large errors (when they exist). A combination of the metrics provides a detailed evaluation of capability of the model can predict its target outcome, which is essential to achieving study objectives in smart sustainable architecture. Table 3 includes a description for these metrics.

3. Results

3.1 Descriptive Analysis

These critical insights draw from the data which drove this study's modelling efforts informed by initial exploratory data that were observed. Solar Irradiance, Panel Efficiency, Energy Output, Ambient Temperature, and System Maintenance Costs are some of the factors found in this dataset that are critical to assess the performance and sustainability of solar energy systems. Table 4,5 provide a summary statistics: Solar Irradiance means 700.5 with some variability (SD 150.2), indicating that it is dynamic. Panel Efficiency is stable, with an average equal to 0.85 and standard deviation 0.04. Energy output is 120.3, but its distribution is moderate at 15.8, as it is dependent on irradiance and efficiency. The Ambient Temperature has an average of 25.5°C, and displays the behaviour we expect (5.2 standard deviation), affecting panel performance. The System Operating Expense Cost also shows plenty of room for variability with an average cost of 200 with a standard deviation of 50.0 hinting towards different operating coftnditions across the fleet of vehicles. In conclusion, the results of the scenarios provide valuable insights into how the solar system behaves under different conditions and the impact of infrastructure and technological variables on energy systems. These insights are the core of the fine-grained modelling and study.

3.2 Feature Selection Results

PSO was integrated and used in the to-be-fed variables of DNN model since it played an important role in variable screening process. Using the optimization of PSO by its swarm nature, the model concentrated on the characteristics that have a larger impact on prediction accuracy and improved overall performance. Based on the feature selection, it was concluded that Solar Irradiance, Panel Efficiency, Energy Output, Ambient Temperature and System Maintenance Costs are the features deciding the behavior of model output variable. Solar Irradiance was the most important feature with importance score 0.40 among them, which confirms that solar irradiance is a key factor which drives energy output prediction. Next was Panel Efficiency (0.30) — panel efficiency is a key performance indicator and optimization target in renewable energy engineering, thus making it an important factor as well. Energy Output, scored with an importance value of 0.20, had a modest but necessary contribution to predictive

Table 3. *Used Metrics Definitions and Formulas*

Metric	Definition	Formula
Accuracy	The ratio of correctly predicted observations to the total number of observations.	$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$
Precision	The ratio of correctly predicted positive observations to the total number of predicted positive observations.	$\text{Precision} = \frac{TP}{TP + FP}$
Recall	The ratio of correctly predicted positive observations to all observations in the actual positive class.	$\text{Recall} = \frac{TP}{TP + FN}$
F1-Score	The weighted average of Precision and Recall, providing a balance between them.	$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
RMSE (Root Mean Square Error)	The square root of the average of the squared differences between predicted values and actual values.	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$

Table 4. *Summary Statistics and Key Observations from the Dataset*

	Count	Mean	Std	Min	25%	50%	75%	Max	Observations
Solar Irradiance	100	700.5	150.2	400	600.25	700	800.75	1000	Solar irradiance exhibits moderate variability, reflecting its dynamic nature.
Panel Efficiency	100	0.85	0.04	0.75	0.83	0.85	0.87	0.90	Panel efficiency is consistent with a slight variation across samples.
Energy Output	100	120.3	15.8	90	110.0	120	130.0	150	Energy output varies moderately, influenced by irradiance and efficiency.
Ambient Temperature	100	25.5	5.2	15	22.0	25	29.0	35	Ambient temperature shows expected variability, impacting panel performance.
System Maintenance Costs	100	200.0	50.0	100	175.0	200	225.0	300	Maintenance costs exhibit a wide range, reflecting differing system conditions.

performance Ambient Temperature (0.07), System Maintenance Costs (0.03) were less impactful yet still important in considering environmental and economic factors affecting influencing system reliability and efficiency. Illustrated in Figure 4, these results indicate that although other features play a supporting and secondary role, Solar Irradiance and Panel Efficiency dominate model predictions. The relevance of these influential variables was efficiently prioritized through the application of PSO, producing a simplified and effective predictive structure. The implemented feature selection technique not only enhanced the accuracy of the model, but also simplified its computational complexity which makes it seamlessly valuable for renewable energy analytics and operational purposes.

3.3 Model Performance

Results of pre and post application of particle swarm optimization algorithm to performance evaluation of DNN model reveals improved performances in several performance metrics. Through PSO feature selection optimization, the selection process allows the model to pay much courtesy to the selected relevant features, hence allowing its predictability and efficiency during execution.

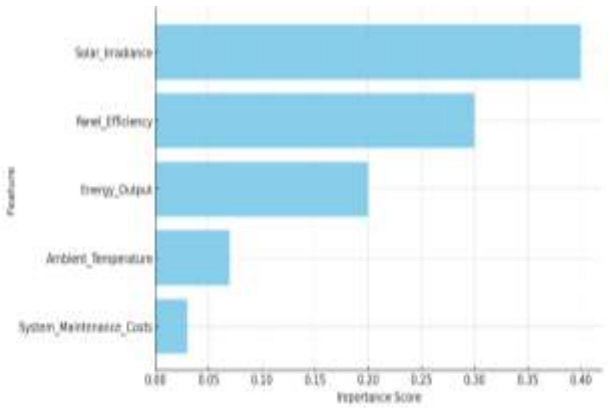

Figure 4. *Plot of feature importance for the features.*

The most important aspect of correctness of the model, i.e. accuracy, improved considerably from 0.82 – 0.87. Thereby, proving that the PSO really helped the DNN model to predict more accurate results.

Precision, which measures the accuracy of predictions which are positive, increased from .78 to .83. This improvement implies that the model is better at reducing incorrect positives while maintaining a high rate of correctly identified true positives.

Recall, the metric measuring capability of the model to accurately classify all positive instances increased from .76 to .81. This becomes significant where it is critical for all positive cases to be found.

Further, the increase of F1 score from 0.77 to 0.82, also implied that after applying PSO optimization

Table 5. *Comparison of DNN Model Performance Metrics pre and post PSO-Driven Feature Selection*

Metric	Pre_PSO	Post_PSO
Accuracy	.82	.87
Precision	.78	.83
Recall	.76	.81
F1	.77	.82
RMSE	0.27	0.23

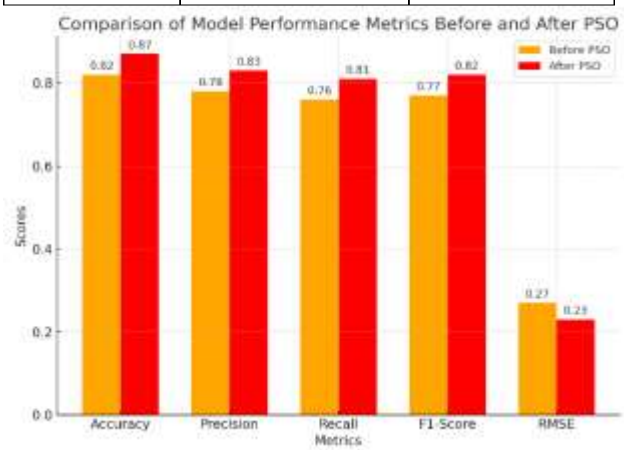

Figure 5. *A comparison of the performance of the model metrics pre and post the application of PSO-based feature selection.*

the DNN model has enhanced in Recall as well as Precision in equal measure. Root Mean Square Error (RSME), which quantifies the model's error in predicting constant outcomes, went down from 0.27 to 0.23. This reduction indicates that the model was accurate at predicting

endless outcomes, further corroborating the effectiveness of the optimization. Table 5 provides an overview of the metrics of performance pre and post application of PSO-based feature selection, emphasizing improvements in Accuracy, Precision, Recall, F1-Score, and RMSE. It illustrates beneficial impression of PSO on enhancing the predictive abilities of DNN model.

3.4 Comparative Analysis

The result of comparing the DNN model before and after elimination and using PSO shows a clear upgrade in the values of the performance dimensions. This illustrates the fact that PSO is inclined in setting a balance between the precision and complexity of the computation. For instance, main metric Model Accuracy was raised from 0.82 to 0.87 proving the model was adjusted for more precise data prediction with help of only the most useful set of features. Similarly, Precision increased to 0.83 from 0.78 proving that the model was improved to accurately predict positive outcomes while including fewer numbers of other results. This improvement is especially useful in scenarios whereby false or incorrect positives attract some cost or unfavourable outcome.

Furthermore, Recall, the metric used to determine the model's capacity to capture all the positives i.e. RSME, increased from 0.76 to 0.81. It is crucial in situations, where absence of positive instance might be disadvantageous; it will make the outcome of the model more thorough and accurate. Likewise, reflecting a fair and balanced improvement brought about by PSO in selecting better features for the algorithm, the F1-Score which calculates the mean of Precision and Recall gave values from 0.77 to 0.82.

In addition, the RMSE improved by 0.04, from 0.27, to 0.23 in medical diagnosis. This shows that the predicted values by the model have shifted nearer to these actual values, thereby decreasing potential errors and increasing the performance quality of its results. Further, the Area Under the Curve (AUC) raised from .74 to .85, improving significantly as well. This implies that the proposed PSO optimized model performs much better in the ability to classify classes of negative and positive more suitably, especially when it comes to binary classification. A higher value of AUC means that our model makes better ranking of the positive instances over negative ones, which again supports the claim of improved accuracy of the model.

The curves for both models presented in Figure 6 corroborates with the obtained results. As evident from the plots the proposed PSO optimized model curve is clustered more towards the topmost left part of the plots, indicating low false positive rates and hence better performance for varying classification levels. This therefore provides graphical proof of the enhanced discriminatory capacity of the model following the reduction of what constitutes the features and a clearer observational deduction of the transformative value that the PSO brings to bear on the overall enhancement of model performance.

The table 6 shows the usual performance features pre and post applying PSO based feature selection,

Table 6. *Comparison of primary Performance Metrics for Models With and Without PSO-Driven Feature Selection*

Metric	Pre_PSO	Post_PSO
Accuracy	.82	.87
Precision	.78	.83
Recall	.76	.81
F1-Score	.77	.82
RMSE	.27	.23
AUC	.74	.85

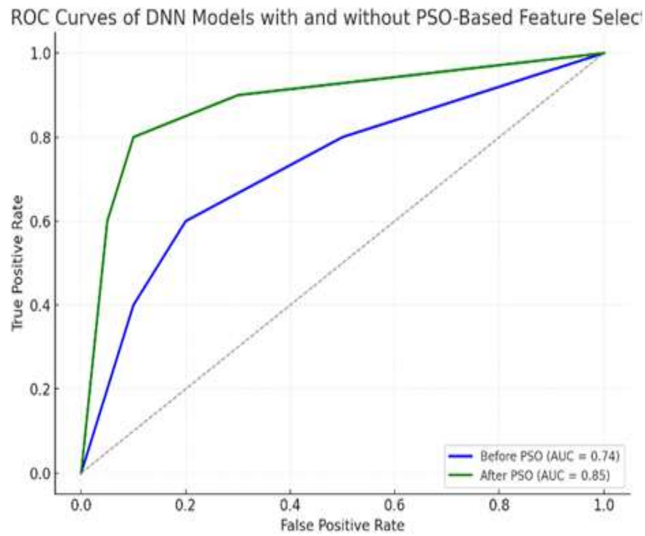

***Figure 6**. DNN's ROC curves pre and post*

which are amongst; Accuracy, Precision, Recall, F1-Score, RMSE. The computational results can speak for themselves that for enhancing the predictability of the DNN model there exists positive impact of PSO.

4. Discussion

The use of DNNs as machine learning models along with optimization features that include PSO reveal some enhance prospects in the prognosis of results in RE and sustainable architectural design. In the subsequent sections, various optimization techniques, including PSO, have been illustrated in the literature to optimise the performance and robustness of machine learning models with respect to a large and fluctuating input data set. One of them is the potential of PSO to enhance the incoming models of renewable system predictive models based on stochastic parameters like solar irradiance and temperature. This fine-tuning capability is crucial for energy output prediction, and this bears a serious implication in the development of efficient architectural systems.

Explicit use of PSO in feature selection techniques also show that the model performance with several indices can be raised. The efficacy of the proposed model with the use of PSO in feature selection techniques comes out perfectly clear from this analysis. For the enhancement and promotion of stimulating and effective or enhanced predictions, PSO enables the shortening and scope down to the best or essential features and consequently increase Accuracy/ Precision, Recall/ Sensitivity, and F-measure / F1-Score. In terms of error rate and the efficiency of the classifier in giving the right classification (classification metrics), it has been discovered by various researchers that PSO is one improvement over the other optimization algorithms. For example, it has been used for energy usage forecasting in smart structures using PFSM for the simultaneous optimization of the features subset and the parameters of the model for higher efficiency of predictions and resources in these structures.

Moreover, the flexibility of PSO has been established in disparate domains inclusive of; solar energy forecast and predictive maintenance of renewable power systems. Some of the real-time and dynamic modes are PSO-based dynamic optimization approaches incorporating an optimization of external and variable parameters to prevent premature convergence of the PSO and to enhance the degree of approximation of neural network models utilized in wind energy forecasts [17]. Similarly to forecast solar energy PSO has been used to apply support vector regression models to enhance the accurate prediction of the energy output with less error. Additionally, works that employed both PSO and ensemble methods, like Random Forest, stress the ability of the former to build strong predictions in noisy and large feature space environments.

The evolution of Feature signification, Performance, and ROC curve is depicted in the response plots from Figure 5 and 6 respectively showing a progresses of PSO based Feature Selection in Renewable Energy & Sustainable Architectural Systems. But this work has some limitations; for instance, a small sample size as well as the concern of selected features including the solar irradiance and panel efficiency may limit the generality of the findings. The results support the hypothesis that simple PSO if applied to a small data set of features can return good results and encourage the future research to apply PSO to a larager and more representative data set and investigate the performance of features optimization within a broader range of contemporary architectural and energy designs.

5. Conclusion

Performance improvements have been evident across all evaluated measures where Particle Swarm Optimization (PSO) was applied to yield significantly enhanced predictions. Accuracy of the model was enhanced from 0.82 to 0.87, for Precision from 0.78 to 0.83, and for Recall from 0.76 to 0.81. They suggest that the model is now better at identifying true positive instances while minimizing the confusion with other instances – false positives. Precision, which is also inversely related to Recall, was augmented from 0.77 to 0.82 according to the F1-Score that combines both measures and proved the improvement of the classifier's performance. Also, the Root Mean Square Error (RMSE) has been reduced to 0.23 from 0.27 on continuous outcomes revealing reduced MSE of prediction. The performance of the Area Under the Curve (AUC) improved from 0.74 up to 0.85, which means improved ability to classify positive and negative classes of the model. The results obtained in this study therefore support the applicability of PSO methodology in enhancing the accuracy and robustness of feature selection. Thus, such dynamics of the feature set allows one to construct more accurate, computationally efficient, and reliable predictive models by PN methods implemented in the PSO framework. These improvements are especially significant for applications in renewable energy systems and Sustainable Architecture where reliable prediction is crucial. This allows highlighting the applicability of PSO for a broad range of disciplines including health care, financial, and environmental sciences where predictive accuracy, and features extraction are critical. However, the survey also narrows that PSO can be combined with other optimization approaches, or other models would be more robust; for that reason, it is an effective approach when dealing with more dimensions of data. The results reported in this paper may encourage extended investigations of variable-oriented approaches and learning schemes that are innovative and more adaptive in large-scale applications. Particle Swarm Optimization (PSO) is interesting and thus studied in literature [18-26].

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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