Artificial Intelligence-Based Smart Grid Optimization for Sustainable Power Distribution Systems

Aruna Mekala[1*], Dr. N. Lavanya[2], Dr. R. Madhana[3], Manoj Kumar Chaudhury[4], Pubali Mitra Paul[5], Prashant Kumar Tamrakar[6]

[1*]Assistant Professor, Department of Electrical Engineering Nalla Malla Reddy Engineering College, Hyderabad
Email ID: aruna.mekala@gmail.com
[2]Associate Professor, Department of Electrical Engineering, Nalla Malla Reddy Engineering College, Hyderabad
Email ID: drlavanyanannapaneni@gmail.com
[3]Assistant professor, Department of ELECTRICAL AND ELECTRONICS ENGINEERING, S.A. ENGINEERING COLLEGE, THIRUVERKADU, CHENNAI - 600 077, Tamilnadu.Email ID: drmadhanar@saec.ac.in
[4]Assistant Professor, Department of Electrical Engineering, IGIT Sarang, 759146, Odisha ORCID ID: 722-737-722-737, Email ID: mcelect05@gmail.com
[5]Assistant Professor, Department of ECE, Brainware University ORCID ID: 722-737-722-737X
Email ID: pubali.mitra.cu@gmail.com
[6]Assistant Professor, Department of Computer science and Engineering Rungta International skills university bhilai, 400023, Chhattisgarh ORCID ID: https://orcid.org/722-737-722-737 Email ID: Prashant.tamrakar35@gmail.com

HOW TO CITE:
Aruna Mekala , N. Lavanya, R. Madhana , Manoj Kumar Chaudhury , Pubali Mitra Paul , Prashant Kumar Tamrakar (2026). Artificial Intelligence-Based Smart Grid Optimization for Sustainable Power Distribution Systems. International Journal of Special Education, 41(16s), 722-737

COPYRIGHT STATEMENT:
Copyright: © 2026 Authors. Open access publication underthe terms and conditions of the Creative CommonsAttribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

ABSTRACT:
Distribution losses, voltage stability issues and difficulties in integrating renewable energy sources are still significant issues in today's power distribution systems. This study proposes a smart grid optimization framework for sustainable power distribution using the IEEE 33-bus radial distribution system (RDS) and artificial intelligence. Power-flow simulation and scenario generation were performed in MATLAB, and AI prediction and PV placement and sizing were done in Python. The 5120 scenarios were created by changing load multiplier, PV bus, PV size, and solar factor, all of which were generated in MATLAB. A Random Forest Regressor was trained to predict power loss, minimum voltage, voltage deviation and feasibility status. The trained model was then coupled with PSO to determine the best PV site and size. The AI-PSO solution has chosen Bus 7 (2000 kW PV) under a load multiplier of 0.70 and solar factor of 1.00. The active power loss obtained from MATLAB load flow is reduced from 94.9113 kW to 51.6514 kW, which is 45.5793% reduction. The minimum voltage improved from 0.940656 pu to 0.971389 pu. The optimized system also saved 378,956.74 kWh/year energy and 265.27 tons/year estimated CO_2 reduction.

Keywords: Artificial Intelligence; Smart Grid Optimization; PV Placement and Sizing; Sustainable Power Distribution

1. Introduction

The power distribution system is in the midst of a significant transformation, driven by rising demand for electricity, the integration of large-scale renewable energy sources, and the need for efficient and sustainable grid management. The conventional radial distribution network is a passive network and may suffer from high technical losses, poor voltage profiles and voltage instability, especially at the remote buses. Therefore, distributed generation has emerged as a valuable way of enhancing the performance of the distribution system, and its effectiveness is highly dependent on its location and size [1]. Solar PV generation can help to reduce feeder loading, help with local energy supply and improve voltage conditions; however if the PV is not placed in the right place or too much PV is installed, PV generation may not be effective in reducing losses, may cause voltage rise, reverse power flow and poor renewable utilization [2]. Recent studies have highlighted the need to take operational constraints, uncertainty and network performance into account when planning renewable distributed generation integration into distribution networks [3]. Many conventional methods have been used to integrate renewable DG, but they are based on analytical or optimization methods and involve repeated power-flow computations and can be computationally intensive in large scenario-based studies [4]. In this context, artificial intelligence is a promising tool to learn the behavior of the learning system from simulation data and to assist in fast decision making in energy systems [5]. Furthermore, adaptive control and intelligent distributed energy resource management are becoming more and more crucial to ensure voltage stability in modern distribution grids [6]. In this study, a smart grid optimization framework based on artificial intelligence for sustainable power distribution systems is proposed. The framework integrates IEEE 33-bus load-flow simulation in MATLAB, prediction using Random Forest in Python, PV placement and sizing using Particle Swarm Optimization, and validation of the optimized result in MATLAB.

The main objectives of this work are:

- To create a MATLAB-Python based framework for modelling, data generation, AI prediction and optimization of PV integration in IEEE 33-bus distribution system.
- To find the best position and size of PV by using AI based PSO to minimise power loss and improve voltage stability.
- To compare the optimized system with the existing one and estimate the energy savings and CO_2 reduction.

The key novelty of this manuscript is the integrated simulation-AI-optimization-validation workflow for efficient PV planning and sustainable operation of distribution systems..

2. Literature Review

The optimization of smart grid has been a key research area to enhance the efficiency, reliability and sustainability of modern distribution systems. Due to the high ratio of resistance to reactance and the long feeder structure, radial distribution networks often have high power losses and poor voltage profiles. The optimal allocation of distributed generation (DG) has thus been extensively investigated with regard to objectives, constraints, methods and algorithms [7]. In active distribution networks, planning of distributed generation is also coupled with flexibility resources like energy storage, which can further enhance the voltage regulation and the operational efficiency [8]. In radial distribution systems, the optimal placement of distributed energy resources is especially critical as it can result in higher losses or voltage limit violations if not placed properly [9]. The integration of solar PV has several advantages such as, support for local generation, reduction in grid dependency, reduction of feeder losses, and improvement of voltage profile. But, these benefits are highly site and size specific. Placement of multiple distributed generators in distribution networks has been proposed using hybrid optimization methods, which demonstrate that the technical performance can be improved more effectively through the optimized placement than through the arbitrary

placement of the distributed generators [10]. PV systems can also be coordinated with power-electronic support functions, like PV-STATCOM operation, for improving voltage stability and reactive power support [11]. Sensitivity-based methods have also been used to identify optimal locations of distributed energy resources, which decreases the search space for optimization algorithms [12]. In recent years, artificial intelligence has been helpful in the optimization of smart grid systems as the machine learning models can learn the behavior of the system from the data and can be used for quick decision making. The use of machine-learning based prediction techniques for distribution-system operation has already been demonstrated and highlights the usefulness of data-driven prediction in power systems [13]. Other more sophisticated learning techniques like graph neural networks have also been explored for optimal power flow estimation [14]. Furthermore, learning-based Volt/Var control has proven to be a promising approach to enhance the network operation and keep the voltage stable [15]. But there are many studies that are only concerned with direct optimization or prediction. Hence, an integrated framework that integrates simulation based dataset generation, AI prediction, PSO optimization, MATLAB validation, comparative analysis and sustainability evaluation is still useful for smart grid optimization using AI.

3. Methodology

The methodology presents a hybrid MATLAB–Python framework for AI-based smart grid optimization. MATLAB is used for IEEE 33-bus modeling, load-flow simulation, scenario generation, and final validation, while Python performs preprocessing, Random Forest prediction, and PSO optimization. The workflow identifies optimal PV placement and capacity to reduce losses, improve voltage stability, and support sustainable distribution operation.

3.1 Overall Research Framework

This study adopts a hybrid MATLAB–Python framework for artificial intelligence-based optimization of solar photovoltaic integration in a smart radial distribution system. MATLAB was used for distribution-system modeling, load-flow simulation, scenario generation, and final power-flow validation. Python was used for data preprocessing, machine learning model development, and particle swarm optimization. The proposed workflow combines simulation-based dataset generation, AI-assisted performance prediction, optimization-based decision-making, and MATLAB-based validation to determine an effective PV placement and sizing strategy for reducing power loss and improving voltage stability. As shown in Figure 1, MATLAB was used for power-flow simulation and dataset generation, whereas Python was used for data preprocessing, Random Forest model training, and PSO-based optimization. The optimized solution was then revalidated in MATLAB, followed by comparative and sustainability evaluation.

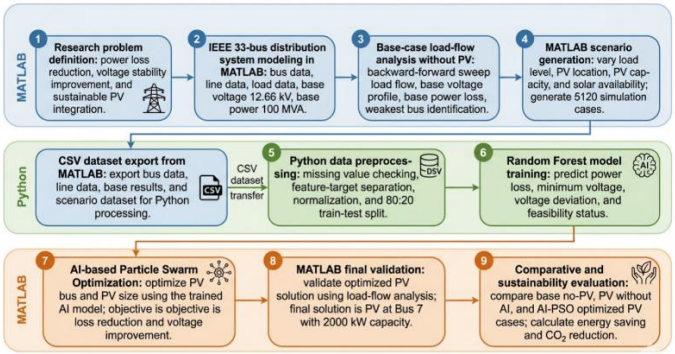

Figure 1. Proposed MATLAB–Python AI-PSO methodology for smart grid optimization and sustainable PV integration

3.2 Test System and Base-Case Analysis

The IEEE 33-bus radial distribution system was selected as the test network. The system consists of 33 buses and 32 active lines, with Bus 1 used as the slack bus. The base voltage and base power were set to 12.66 kV and 100 MVA, respectively. The total active and reactive loads of the network were 3715 kW and 2300 kvar. Solar PV installation was considered at candidate buses from Bus 2 to Bus 33.

A base-case load-flow analysis was first performed without PV integration and without AI-based optimization. The backward-forward sweep load-flow technique was used because of its suitability for radial distribution systems. The base case produced an active power loss of 202.6771 kW and a reactive power loss of 135.1409 kvar. The minimum voltage was 0.91309 pu at Bus 18, and the voltage deviation was 1.700944. Since the minimum voltage was lower than the allowable limit of 0.95 pu, the base case confirmed the need for optimized PV integration.

3.3 Simulation Variables and Scenario Generation

Various operating scenarios were created using MATLAB by changing the system loading condition, PV installation location, PV capacity, and solar generation availability. The system demand was modified based on the loading condition selected and the solar PV generation was modeled as an active power injection at the selected bus for each operating scenario. Then the backward-forward sweep load-flow method was carried out to determine the network losses, voltage profile characteristics and feasibility status.

Table 1. Input variables used for simulation and optimization

Parameter	Description	Range/Values	Function in the study
Load level	Represents variation in system demand	0.70, 0.85, 1.00, 1.15, 1.30	Operating condition
PV location	Candidate bus for solar PV connection	Bus 2 to Bus 33	Optimization decision
PV capacity	Rated solar PV size	250 to 2000 kW	Optimization decision
Solar availability	Fraction of available solar generation	0.25, 0.50, 0.75, 1.00	Renewable generation condition
Lower voltage limit	Minimum allowable bus voltage	0.95 pu	Operational constraint
Upper voltage limit	Maximum allowable bus voltage	1.05 pu	Operational constraint

This led to 5120 simulation cases. Load-flow analysis was carried out for each case, and the system response was recorded for further use in machine learning and optimization.

3.4 Data Preparation and Preprocessing

The results of simulation obtained from MATLAB were structured into a structured data set for the development of AI model. The chosen predictor variables were the level of system loading, PV location, PV capacity and the availability of PV generation. The response variables were the technical performance of the distribution network such as active power loss, minimum bus voltage, voltage deviation, and operational feasibility.

There were no missing data in the data set, which consisted of 5120 records. All cases converged to load-flow, which means that the generated set of

data was numerically valid. 421 of the simulated cases met the operating voltage requirements and 4699 did not meet the required feasibility condition. The dataset was preprocessed in Python, where missing values were identified, the data was split into predictor and response sets, the data was scaled using standard scaling, and the data was divided into training and testing sets. Using an 80:20 split, 4096 training samples and 1024 testing samples were obtained.

3.5 Random Forest-Based Performance Prediction

A multi-output prediction model, the Random Forest Regressor, was created to estimate the distribution-system performance under various loading and PV integration conditions. The model was taught to find the nonlinear relation between the operating and PV configuration parameters and the resulting grid performance indicators. The indicators predicted were active power loss, minimum voltage, voltage deviation, and feasibility condition.

Random Forest was chosen because it is well suited to engineering datasets that are structured, it can model nonlinear interactions between variables, and it is relatively accurate with few parameters to tune. The model was trained with 300 decision trees, and the random state was set to 42 for reproducability. The model was then used as the surrogate estimator in the optimization process and, as a result, the MATLAB load-flow simulation was not required to be repeated for each of the candidate PV solutions.

3.6 AI-Based Particle Swarm Optimization

Particle Swarm Optimization was used to determine the optimal PV location and capacity. The optimization process searched for the PV bus and PV size that minimized active power loss and voltage deviation while satisfying voltage constraints. The final optimization was conducted under a load level of 0.70 and full solar availability.

The PSO algorithm used 60 particles and 100 iterations. The inertia weight was set to 0.70, and the cognitive and social acceleration coefficients were both set to 1.50. During optimization, the trained Random Forest model predicted the performance of each candidate solution. A penalty was applied when a candidate solution violated the voltage limit. The final AI-PSO result selected Bus 7 as the optimal PV location with a PV capacity of 2000 kW. The predicted active power loss was 51.5996 kW, the predicted minimum voltage was 0.97029 pu, and the predicted solution was feasible.

3.7 MATLAB Validation and Comparative Analysis

The optimized solution from Python was again validated in MATLAB by performing backward-forward sweep load-flow analysis. The validated system was PV placement at Bus 7 with a capacity of 2000 kW and a load level of 0.70 and solar availability of 100%. MATLAB validation results were 51.6514 kW of active power loss, 0.971389 pu of minimum voltage and a feasible operating condition. This was to validate the technical feasibility and to meet the voltage constraints of the AI-PSO solution.

Then, a comparative analysis was performed on three cases, all operating under the same condition. The first case was the base system without PV. The second case was PV integration without AI optimization in which 1000 kW PV was installed at Bus 18. The third case was the PV system optimized by the AI-PSO with 2000 kW PV installed at Bus 7. Active power loss, minimum voltage, voltage deviation, renewable integration and feasibility status were taken into account.

3.8 Sustainability Evaluation

Power loss reduction, energy saving, voltage stability improvement, renewable integration and estimated CO_2 reduction were used to assess the sustainability performance of the optimized system. The active power loss of the AI-PSO optimized system was decreased from 94.9113 kW to 51.6514 kW as compared to the same-load no-PV case. This is equivalent to a reduction of 43.2599kW or 45.5793%.

The loss reduction was then multiplied by the operating time to determine the energy-saving benefit.

The optimized system, based on continuous daily operation, had an estimated daily energy saving of 1038.2377 kWh/day and a saving of 378,956.7422 kWh/year per year. The emission factor of 0.70 kg CO_2/kWh was used to calculate the estimated annual CO_2 reduction of 265.2697 tons/year. These outcomes illustrate the effectiveness of the proposed AI-PSO framework in optimizing the distribution network, ensuring stable voltage levels, facilitating renewable energy integration, and promoting sustainable power distribution.

4. Mathematical Model

The mathematical model formulates the distribution network, load variation, PV injection, load-flow calculation, power loss, voltage deviation, operational constraints, AI prediction, and PSO optimization. The IEEE 33-bus system is represented using bus voltages, branch currents, and line impedances. The objective function minimizes active power loss and voltage deviation while penalizing infeasible voltage conditions.

4.1 Distribution Network Representation

The IEEE 33-bus radial distribution network is modeled as a set of buses and distribution branches. Let N_b represent the total number of buses and N_l represent the total number of lines. In this study, the system contains $N_b = 33$ buses and $N_l = 32$ active lines. Bus 1 is considered the slack bus, while the remaining buses are treated as candidate buses for solar PV integration.

For a branch connected between bus i and bus j, the line impedance is represented as:

$$Z_{ij} = R_{ij} + jX_{ij} \quad (1)$$

where R_{ij} is the resistance, X_{ij} is the reactance, and j is the imaginary operator. The voltage at bus i is denoted by V_i, and the current flowing through the branch between buses i and j is denoted by I_{ij}.

The base impedance is calculated using the selected system base voltage and base power:

$$Z_{\text{base}} = \frac{V_{\text{base}}^2}{S_{\text{base}}} \quad (2)$$

where $V_{\text{base}} = 12.66$ kV and $S_{\text{base}} = 100$ MVA.

4.2 Load Model

The complex load demand at bus i is expressed as:

$$S_i = P_i + jQ_i \quad (3)$$

where P_i and Q_i are the active and reactive load demands at bus i, respectively. To represent different loading conditions, the base load is scaled using a load factor α. Therefore, the active and reactive load under a selected operating condition are defined as:

$$P_i^L = \alpha P_i \quad (4)$$

$$Q_i^L = \alpha Q_i \quad (5)$$

where P_i^L and Q_i^L are the adjusted active and reactive loads, and α is the load multiplier.

4.3 Solar PV Injection Model

Solar PV is modeled as an active power source connected at a selected bus. The actual PV output depends on the installed PV capacity and the solar availability factor. The PV active power injection is calculated as:

$$P^{PV} = S_{PV} \times \beta \quad (6)$$

where S_{PV} is the installed PV capacity in kW and β is the solar availability factor.

The net active power demand at the PV-connected bus is then calculated as:

$$P_i^{net} = P_i^L - P^{PV} \quad (7)$$

The reactive load remains unchanged because the PV unit is modeled as active-power injection only:

$$Q_i^{net} = Q_i^L \quad (8)$$

Thus, the net complex power at bus i is:

$$\boldsymbol{S_i^{net} = P_i^{net} + jQ_i^{net}} \quad (9)$$

4.4 Backward-Forward Sweep Load-Flow Model

The backward-forward sweep method is used to calculate bus voltages and branch currents

because the IEEE 33-bus system is radial. At each bus, the load current is calculated from the net complex power and bus voltage as:

$$I_i = \left(\frac{S_i^{net}}{V_i}\right)^* \quad (10)$$

where $(.)^*$denotes the complex conjugate.

During the backward sweep, branch currents are obtained by summing the downstream load currents. During the forward sweep, bus voltages are updated from the slack bus toward the terminal buses using:

$$V_j = V_i - Z_{ij} I_{ij} \quad (11)$$

The load-flow iteration continues until the voltage mismatch between two consecutive iterations satisfies:

$$\max | V^{k+1} - V^k | < \varepsilon \quad (12)$$

where k is the iteration number and ε is the convergence tolerance. In this study, the tolerance was set to 10^{-6}.

4.5 Power Loss and Voltage Deviation Model

The active and reactive power losses in the branch between buses $i$and $j$are calculated as:

$$P_{loss,ij} = | I_{ij} |^2 R_{ij} \quad (13)$$

$$Q_{loss,ij} = | I_{ij} |^2 X_{ij} \quad (14)$$

The total active power loss of the distribution system is obtained by summing the losses of all branches:

$$P_{loss,total} = \sum_{l=1}^{N_l} P_{loss,l} \quad (15)$$

Similarly, the total reactive power loss is calculated as:

$$Q_{loss,total} = \sum_{l=1}^{N_l} Q_{loss,l} \quad (16)$$

The voltage deviation index is used to evaluate the overall voltage profile of the system:

$$VDI = \sum_{i=1}^{N_b} | 1 - | V_i | | \quad (17)$$

A lower value of VDIindicates that the voltage profile is closer to the nominal value of 1.0 pu.

4.6 Operating Constraints

The bus voltage magnitude must remain within the acceptable operating range:

$$V_{\min} \leq | V_i | \leq V_{\max} \quad (18)$$

where:

$$V_{\min} = 0.95 \text{ pu} \quad (19)$$

$$V_{\max} = 1.05 \text{ pu} \quad (20)$$

A solution is considered feasible only when all bus voltages satisfy the specified voltage limits and the load-flow calculation converges successfully.

The PV location and size are also constrained as:

$$2 \leq B_{PV} \leq 33 \quad (21)$$

$$250 \leq S_{PV} \leq 2000 \quad (22)$$

where $B_{PV}$is the selected PV bus and $S_{PV}$is the installed PV capacity in kW.

4.7 AI-Based Prediction and Optimization Model

The artificial intelligence model is used to estimate distribution-system performance under different operating and PV integration conditions. The model input vector is defined as:

$$X = [\alpha,\ B_{PV},\ S_{PV},\ \beta] \quad (23)$$

where $\alpha$is the load multiplier, $B_{PV}$is the PV bus location, $S_{PV}$is the PV capacity, and $\beta$is the solar availability factor.

The model output vector is expressed as:

$$Y = [P_{loss,total},\ V_{\min},\ VDI,\ F_s] \quad (24)$$

where $P_{loss,total}$is the total active power loss, $V_{\min}$is the minimum bus voltage, $VDI$is the voltage deviation index, and $F_s$is the feasibility status.

The trained Random Forest model learns the nonlinear mapping:

$$f(X) \rightarrow Y \quad (25)$$

The optimization decision vector is defined as:

$$x = [B_{PV},\ S_{PV}] \quad (26)$$

The objective function minimizes active power loss and voltage deviation while penalizing voltage-limit violations:

$$F(x) = w_1 P_{loss,total} + w_2 VDI + P_v \quad (27)$$

where $w_1$and $w_2$are weighting coefficients, and $P_v$is the voltage penalty term:

$$P_v = \begin{cases} 0, & \text{if } V_{\min} \geq 0.95 \\ K(0.95 - V_{\min})^2, & \text{if } V_{\min} < 0.95 \end{cases} \quad (28)$$

where K is the penalty coefficient. This formulation encourages solutions with lower power loss, improved voltage profile, and feasible voltage operation.

4.8 Particle Swarm Optimization and Model Evaluation

Particle Swarm Optimization is used to search for the best PV location and capacity. Each particle represents one possible PV solution. The velocity of particle $i$at iteration $k+1$is updated as:

$$v_i^{k+1} = wv_i^k + c_1 r_1 (pbest_i - x_i^k) + c_2 r_2 (gbest - x_i^k) \quad (29)$$

The position of the particle is then updated as:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (30)$$

where $w$is the inertia weight, $c_1$is the cognitive coefficient, c_2 is the social coefficient, r_1 and r_2 are random numbers between 0 and 1, $pbest_i$is the best solution found by particle i, and $gbest$is the best solution found by the entire swarm.

The prediction accuracy of the AI model is evaluated using mean absolute error, root mean square error, and coefficient of determination. These metrics are defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (31)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (32)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad (33)$$

where $y_i$is the actual value, $\hat{y}_i$is the predicted value, $\bar{y}$is the mean of the actual values, and $n$is the number of samples. These metrics verify the suitability of the trained model before it is used for AI-based optimization.

5. Results

This section presents the simulation, artificial intelligence, optimization, validation, comparative, and sustainability results obtained from the proposed MATLAB–Python framework. The results are organized according to the developed workflow: base-case load-flow analysis, scenario generation, AI model training, AI-PSO optimization, MATLAB validation, comparative evaluation, and sustainability assessment.

5.1 Base-Case Load-Flow Result

The base-case load-flow analysis was performed on the IEEE 33-bus radial distribution system without PV integration and without AI-based optimization. This case was used to evaluate the original operating condition of the network before applying the proposed optimization framework. As shown in Table 2, the system had a total active load of 3715 kW and a total reactive load of 2300 kvar. The active power loss was 202.6771 kW, while the minimum voltage was 0.91309 pu at Bus 18.

Table 2. Base-case load-flow results of the IEEE 33-bus system

Parameter	Value
Total active load	3715 kW
Total reactive load	2300 kvar
Active power loss	202.6771 kW
Reactive power loss	135.1409 kvar
Minimum voltage	0.91309 pu
Weakest bus	Bus 18
Voltage deviation	1.700944
Load-flow convergence	Successful

The base-case result confirms that the original distribution system suffers from high power loss and voltage violation. The minimum voltage of 0.91309 pu is below the lower voltage limit of 0.95 pu, which establishes the need for PV

integration and intelligent optimization. The base voltage profile is illustrated in Figure 2.

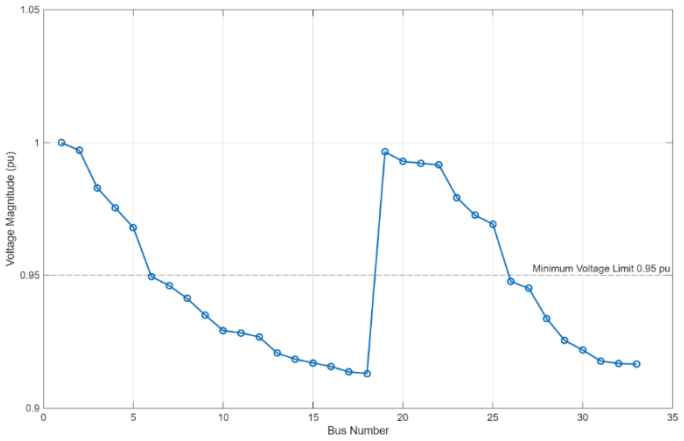

Figure 2. Base-case voltage profile of the IEEE 33-bus system

5.2 MATLAB Scenario Dataset Result

Using MATLAB, 5120 operating scenarios were generated by varying the load level, PV location, PV capacity and solar availability. Table 3 summarizes the results of the scenario generation. The simulation data set was numerically reliable, with all 5120 scenarios converging. Only 421 scenarios were feasible, however, 4699 scenarios did not satisfy the operating constraints.

Table 3. MATLAB scenario-generation summary

Parameter	Value
Total scenarios	5120
Converged scenarios	5120
Feasible scenarios	421
Infeasible scenarios	4699
Minimum scenario power loss	49.7458 kW
Best MATLAB PV bus	Bus 6
Best MATLAB PV size	1750 kW
Best load multiplier	0.70
Best solar factor	1.00

The optimum scenario obtained from MATLAB simulation was PV at Bus 6 with capacity of 1750 kW with load multiplier of 0.70 and solar factor of 1.00. In this situation, the minimum power loss was 49.7458 kW. The high number of infeasible cases shows that PV integration is not sufficient to ensure acceptable operation and optimization is needed for the selection of technically suitable PV placement and sizing.

5.3 AI Model Training Result

The dataset generated by MATLAB was used to train a Random Forest Regressor to predict the distribution-system performance. The model was tested by mean absolute error, root mean square error and coefficient of determination. The model had very high prediction accuracy for power loss, minimum voltage and voltage deviation as shown in Table 4.

Table 4. Random Forest model performance

Target indicator	MAE	RMSE	R^2
Total active power loss	2.0959	3.5126	0.9983
Minimum voltage	0.0005	0.0008	0.9985
Voltage deviation	0.0169	0.0274	0.9964
Feasibility status	0.0154	0.0746	0.9284
Overall average	0.5322	0.9039	0.9804

The feasible-status classification accuracy was 99.4141%, which showed that the model could be used to accurately classify feasible and infeasible operating cases. The high R^2 values show that the Random Forest model was able to learn the nonlinear relationship between loading condition, PV configuration and grid performance. The relationship between actual and predicted power loss is illustrated in Figure 3, which shows good correlation between the points, representing good predictive ability.

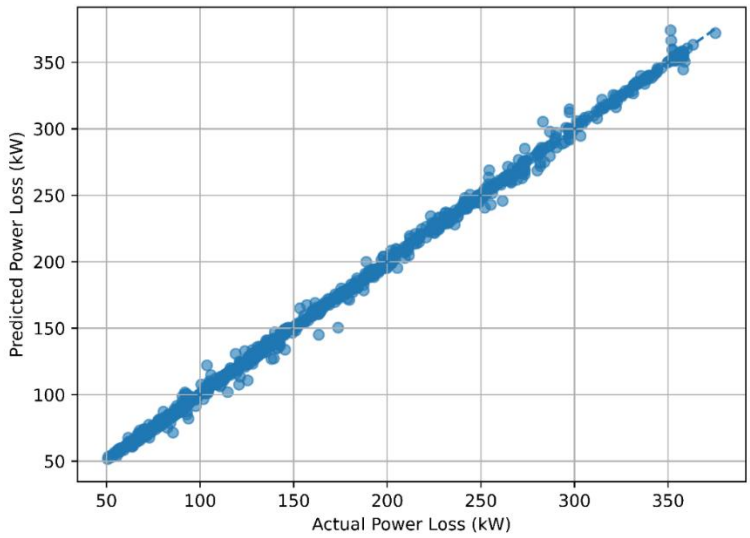

Figure 3. Actual versus predicted active power loss using the Random Forest model

The load level was the most important variable with an importance value of 0.8740, according to the feature-importance analysis. PV location, PV size and solar availability were assigned importance values of 0.0692, 0.0333 and 0.0235 respectively. This is in line with the behavior of the distribution system since the load demand has a significant impact on branch current, voltage drop and line losses.

5.4 AI-PSO Optimization and MATLAB Validation Result

The trained Random Forest model was used as a surrogate predictor for Particle Swarm Optimization. Optimization was performed for a load multiplier of 0.70 and solar factor of 1.00. Based on the AI-PSO algorithm, the best PV location was determined to be Bus 7 with a PV capacity of 2000 kW. Then, the optimized result was validated in MATLAB with backward-forward sweep load-flow analysis.

The results obtained from AI and validated by MATLAB are quite close as shown in Table 5. The value of the predicted active power loss was 51.5996 kW and the MATLAB validated active power loss was 51.6514 kW. The minimum voltage predicted was 0.97029 pu and the minimum voltage validated was 0.971389 pu.

Table 5. AI-PSO prediction and MATLAB validation result

Parameter	AI-PSO prediction	MATLAB validation
PV location	Bus 7	Bus 7
PV capacity	2000 kW	2000 kW
Load multiplier	0.70	0.70
Solar factor	1.00	1.00
Active power loss	51.5996 kW	51.6514 kW
Minimum voltage	0.97029 pu	0.971389 pu
Voltage deviation	0.494705	0.478326
Feasibility status	1	1

The prediction error was very small, with a power loss error of 0.0518 kW, minimum voltage error of 0.001099 pu, and voltage deviation error of −0.016379. This validates the accuracy of trained AI model to guide PSO search and the validity of the obtained solution when tested again using MATLAB load-flow analysis. The convergence behavior of the optimization is displayed in Figure 4.

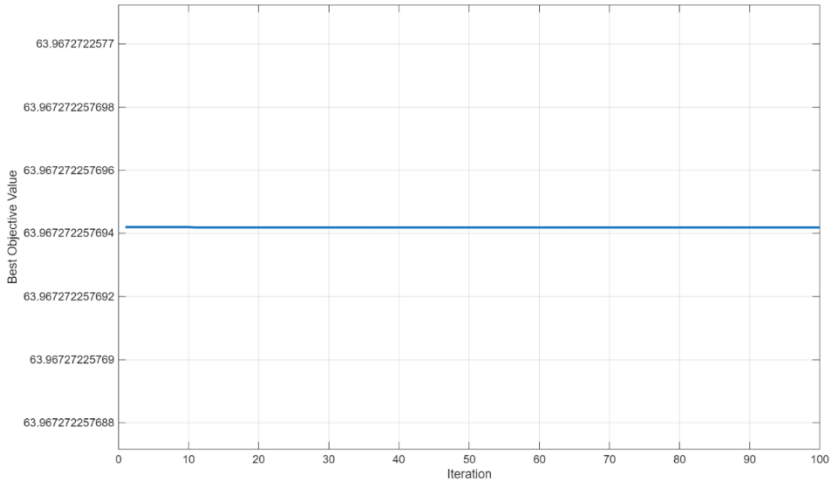

Figure 4. Optimization convergence curve of the AI-PSO process

5.5 Comparative Analysis of Operating Cases

A comparative analysis was performed under the same operating condition to evaluate the technical benefit of the AI-PSO optimized PV system. Three cases were compared: base system without PV, PV integration without AI optimization, and AI-PSO optimized PV integration. The results are presented in Table 6.

Table 6. Comparative performance of base, non-optimized PV, and AI-PSO optimized PV cases

Case	PV bus	PV size	Active power loss	Minimum voltage	Voltage deviation	Feasible
Base system without PV	0	0 kW	94.9113 kW	0.9407 pu	1.1632	No
PV without AI optimization	18	1000 kW	79.4196 kW	0.9570 pu	0.5405	Yes
AI-PSO optimized PV system	7	2000 kW	51.6514 kW	0.9714 pu	0.4783	Yes

The comparison shows that PV integration improves the performance of the distribution system, but AI-PSO optimization provides the best result. The base no-PV case was infeasible because its minimum voltage was below 0.95 pu. The non-optimized PV case improved the minimum voltage to 0.9570 pu and reduced power loss to 79.4196 kW. However, the AI-PSO optimized case further reduced the power loss to 51.6514 kW and improved the minimum voltage to 0.9714 pu. The power loss comparison is presented in Figure 5. The AI-PSO optimized system achieved the lowest active power loss among the three evaluated cases.

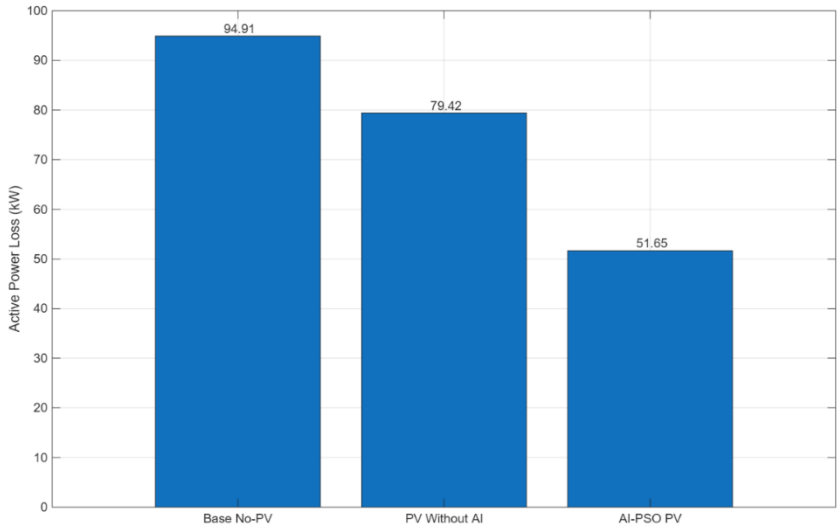

Figure 5. Active power loss comparison of the evaluated operating cases

The voltage profile comparison is presented in Figure 6. The base no-PV case falls below the 0.95 pu voltage limit, while both PV cases improve the voltage profile. The AI-PSO optimized case provides the highest minimum voltage and the most stable voltage profile.

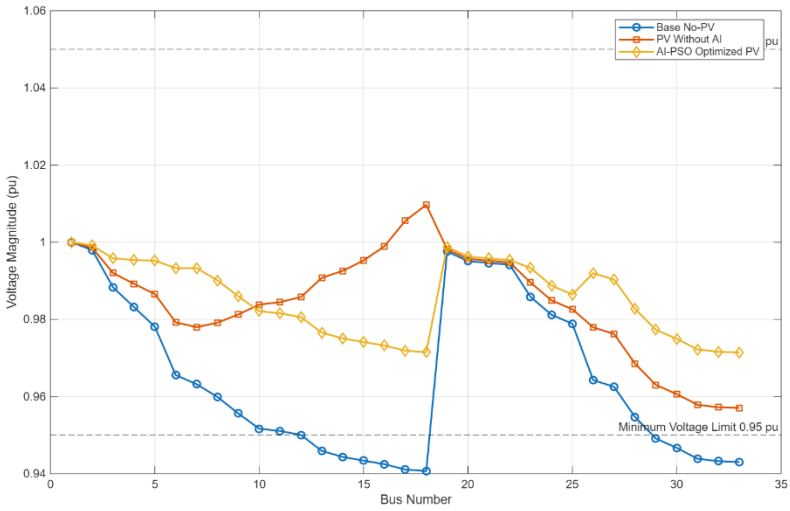

Figure 6. Voltage profile comparison of base, non-optimized PV, and AI-PSO optimized PV cases

Compared with the base no-PV case, the AI-PSO optimized system reduced active power loss by 43.2599 kW, corresponding to a 45.5793% reduction. Compared with the PV without AI case, the AI-PSO system reduced active power loss by 27.7682 kW, corresponding to a

34.9639% reduction. In addition, the minimum voltage improved by 0.030733 pu, and voltage deviation was reduced by 0.684836 compared with the base no-PV case.

5.6 Sustainability Result

The sustainability evaluation quantified the energy-saving and environmental benefits of the optimized PV system. As shown in Table 7, the AI-PSO optimized system produced a daily energy saving of 1038.2377 kWh/day and an annual energy saving of 378,956.7422 kWh/year compared with the base no-PV case. The estimated annual CO_2 reduction was 265.2697 tons/year.

Table 7. Sustainability performance of the AI-PSO optimized system

Sustainability indicator	Value
Power loss reduction compared with base no-PV case	43.2599 kW
Power loss reduction percentage	45.5793%
Daily energy saving	1038.2377 kWh/day
Monthly energy saving	31,147.1295 kWh/month
Annual energy saving	378,956.7422 kWh/year
Estimated annual CO_2 reduction	265.2697 tons/year
Estimated annual PV energy contribution	3,650,000 kWh/year
Renewable integration	76.9083%

The annual energy-saving comparison is shown in Figure 7. The optimized system achieved substantial annual energy savings compared with both the base no-PV case and the non-optimized PV case.

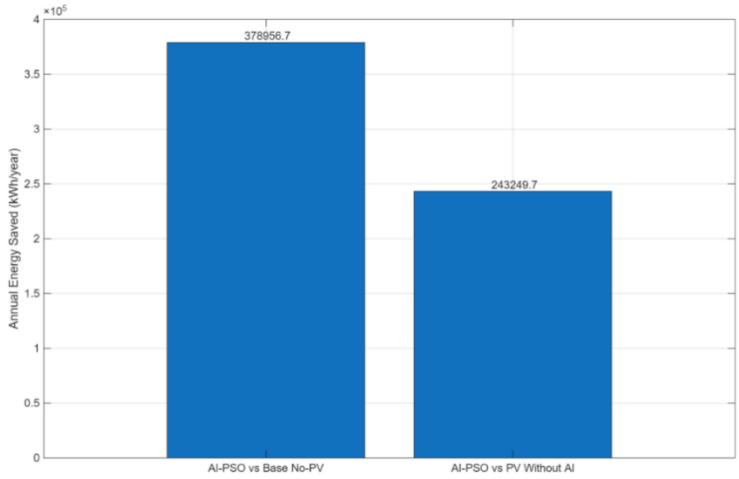

Figure 7. Annual energy-saving benefit of the AI-PSO optimized PV system

The results confirm that the proposed AI-PSO framework improves both the technical and sustainability performance of the distribution network. The optimized PV placement at Bus 7 with a capacity of 2000 kW reduced active power loss, improved voltage stability, increased renewable integration, reduced energy wastage, and produced measurable CO_2 reduction benefits.

Discussion

The results confirm that the proposed AI-PSO framework effectively improved the performance of the IEEE 33- bus radial distribution system. Among the evaluated cases, the AI-PSO optimized PV system achieved the lowest active power loss and the best voltage profile. Under the selected operating condition, power loss decreased from 94.9113 kW in the

base no-PV case to 51.6514 kW after optimization, showing that optimal PV placement and sizing can significantly reduce distribution losses. The voltage profile also improved, as the base no-PV case violated the 0.95 pu voltage limit with a minimum voltage of 0.940656 pu, while the AI-PSO case increased the minimum voltage to 0.971389 pu and maintained feasible operation.

The comparison with the non-optimized PV case further shows the value of intelligent optimization. Although PV without AI reduced power loss to 79.4196 kW and improved the minimum voltage to 0.9570 pu, the AI-PSO solution produced a lower loss of 51.6514 kW and a higher minimum voltage of 0.9714 pu. This confirms that PV integration alone is useful, but optimized sitting and sizing provide greater technical benefit. These findings agree with earlier DG placement studies, which reported that proper DG allocation improves loss reduction and voltage profile performance [16]. They also support the importance of correct access-point and capacity selection for distributed generation planning [17]. Compared with multi-objective DG optimization work, the present study adds AI-based surrogate prediction, PSO optimization, MATLAB validation, and sustainability evaluation in a single framework [18]. Earlier DG placement approaches also showed the value of optimized allocation, but the present work extends this through data-driven prediction and final validation [19]. The strong Random Forest prediction accuracy is consistent with learning-based power-system assessment studies [20], while the need for validation under wider operating conditions remains important for AI-based optimal power-flow methods [21].

The Random Forest model was reliable as a surrogate predictor, with R^2 values above 0.996 for active power loss, minimum voltage, and voltage deviation. The MATLAB validation error was also small, with only 0.0518 kW error in power loss and 0.001099 pu error in minimum voltage. The sustainability results are also significant, with annual energy savings of 378,956.7422 kWh/year and estimated CO_2 reduction of 265.2697 tons/year. Feature-importance results showed that load level was the dominant factor, which is reasonable because branch current, voltage drop, and line loss strongly depend on demand. PV location and size still contributed to voltage support and loss reduction.

Practically, the proposed framework can support distribution planning, PV hosting-capacity studies, voltage support, renewable planning, and smart grid decision-making. However, the study is limited by simulation-based data, a final comparison at load multiplier 0.70 and solar factor 1.00, active-power-only PV modeling, and single-PV optimization. Future research should include real field data, multi-PV placement, smart inverter reactive power control, battery storage, EV charging, demand response, uncertainty analysis, economic cost assessment, deep learning, reinforcement learning, cybersecurity, and real-time control.

Conclusion

This manuscript presented an artificial intelligence-based smart grid optimization framework for sustainable power distribution using the IEEE 33-bus radial distribution system. The proposed approach integrated MATLAB-based power-flow simulation and scenario generation with Python-based machine learning and Particle Swarm Optimization. A Random Forest model was trained to predict distribution-system performance, including active power loss, minimum voltage, voltage deviation, and feasibility status. The trained model was then used as a surrogate predictor within the AI-PSO optimization process to identify the optimal PV location and capacity. The AI-PSO optimizer selected Bus 7 with a PV capacity of 2000 kW as the final optimized solution under the selected operating condition. MATLAB validation confirmed the technical feasibility of this solution. The optimized system reduced active power loss from 94.9113 kW to 51.6514 kW, improved the minimum voltage from 0.940656 pu to 0.971389 pu, and reduced voltage deviation from 1.163162 to 0.478326. In

addition, the optimized system achieved an annual energy saving of 378,956.7422 kWh/year and an estimated CO_2 reduction of 265.2697 tons/year. These findings confirm that AI-based optimization can improve distribution efficiency, enhance voltage stability, support renewable energy integration, and promote sustainable power distribution.

References

A. R. Jordehi, "Allocation of distributed generation units in electric power systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 893–905, 2016.

P. Prakash and D. K. Khatod, "Optimal sizing and siting techniques for distributed generation in distribution systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 111–130, 2016.

R. H. Zubo, G. Mokryani, H. S. Rajamani, J. Aghaei, T. Niknam, and P. Pillai, "Operation and planning of distribution networks with integration of renewable distributed generators considering uncertainties: A review," *Renewable and Sustainable Energy Reviews*, vol. 72, pp. 1177–1198, 2017.

A. Ehsan and Q. Yang, "Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques," *Applied Energy*, vol. 210, pp. 44–59, 2018.

A. Mosavi, M. Salimi, S. Faizollahzadeh Ardabili, T. Rabczuk, S. Shamshirband, and A. R. Varkonyi-Koczy, "State of the art of machine learning models in energy systems, a systematic review," *Energies*, vol. 12, no. 7, Art. no. 1301, 2019.

D. Arnold, S. Saha, S. T. Ngo, C. Roberts, A. Scaglione, N. G. Johnson, S. Peisert, and D. Pinney, "Adaptive control of distributed energy resources for distribution grid voltage stability," *IEEE Transactions on Power Systems*, vol. 38, no. 1, pp. 129–141, 2022.

H. A. Pesaran, P. D. Huy, and V. K. Ramachandaramurthy, "A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms," *Renewable and Sustainable Energy Reviews*, vol. 75, pp. 293–312, 2017.

Y. Li, B. Feng, G. Li, J. Qi, D. Zhao, and Y. Mu, "Optimal distributed generation planning in active distribution networks considering integration of energy storage," *Applied Energy*, vol. 210, pp. 1073–1081, 2018.

I. A. Quadri, S. Bhowmick, and D. Joshi, "A comprehensive technique for optimal allocation of distributed energy resources in radial distribution systems," *Applied Energy*, vol. 211, pp. 1245–1260, 2018.

S. Kansal, V. Kumar, and B. Tyagi, "Hybrid approach for optimal placement of multiple DGs of multiple types in distribution networks," *International Journal of Electrical Power & Energy Systems*, vol. 75, pp. 226–235, 2016.

L. Luo, W. Gu, X. P. Zhang, G. Cao, W. Wang, G. Zhu, and Z. Wu, "Optimal siting and sizing of distributed generation in distribution systems with PV solar farm utilized as STATCOM (PV-STATCOM)," *Applied Energy*, vol. 210, pp. 1092–1100, 2018.

M. Gautam, N. Bhusal, M. Benidris, C. Singh, and J. Mitra, "A sensitivity-based approach for optimal siting of distributed energy resources," in *Proc. 2020 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2020, pp. 1–6.

H. Jiang, Y. Zhang, E. Muljadi, J. J. Zhang, and D. W. Gao, "A short-term and high-resolution distribution system load forecasting approach using support vector regression with hybrid parameters optimization," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3341–3350, 2018.

D. Owerko, F. Gama, and A. Ribeiro, "Optimal power flow using graph neural networks," in *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 5930–5934.

Z. Yuan, G. Cavraro, M. K. Singh, and J. Cortés, "Learning provably stable local Volt/Var controllers for efficient network operation," *IEEE Transactions on Power Systems*, vol. 39, no. 1, pp. 2066–2079, 2023.

M. Ilyas, S. M. Tanweer, and A. Rahman, "Optimal placement of distributed generation on radial distribution system for loss minimisation and improvement of voltage profile," *International Journal of Modern Engineering Research*, vol. 3, no. 4, pp. 2296–2312, 2013.

S. K. Injeti and N. P. Kumar, “A novel approach to identify optimal access point and capacity of multiple DGs in a small, medium and large scale radial distribution systems,” *International Journal of Electrical Power & Energy Systems*, vol. 45, no. 1, pp. 142–151, 2013.

S. Sultana and P. K. Roy, “Multi-objective quasi-oppositional teaching learning based optimization for optimal location of distributed generator in radial distribution systems,” *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 534–545, 2014.

S. Kansal, B. B. R. Sai, B. Tyagi, and V. Kumar, “Optimal placement of distributed generation in distribution networks,” *International Journal of Engineering, Science and Technology*, vol. 3, no. 3, pp. 47–55, 2011.

M. Sun, I. Konstantelos, and G. Strbac, “A deep learning-based feature extraction framework for system security assessment,” *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5007–5020, 2019.

A. Venzke, G. Qu, S. Low, and S. Chatzivasileiadis, “Learning optimal power flow: Worst-case guarantees for neural networks,” in *Proc. IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, 2020, pp. 1–7.