Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Optimizing Distributed Generation Placement In Distribution Systems: A Comparative Study Of AI, Machine Learning, And Deep Learning Algorithms

Dr. Harish S. Avchat[1], Amit B. Kasar[2], Dr. Prakash P. Rokade[3], Dr. Hafiz M. Shaikh[4], Dr. Pravin D. Gunaware[5], Dr.Divekar S. N , Dr. Sandip P. Gath[7]

156Assistant Professor, HSBPVT's Group of Institutions, Kashti, Maharashtra, India
2Assistant Professor, International Institute of Information Technology, Pune, Maharashtra, India
3Associate Professor, S. N. D. College of Engineering & Research Center, Yeola, Maharashtra, India
4Assistant Professor, VPKBIT, Baramati, Maharashtra, India
7Assistant Professor, Rajiv Gandhi College of Engineering, Ahmednagar, Maharashtra, India

Optimizing Distributed Generation (DG) placement in power distribution systems is crucial for minimizing power losses, enhancing voltage stability, and improving overall system efficiency. This study presents a comprehensive analysis and comparison of various Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) algorithms for optimizing DG placement and sizing in distribution networks. While traditional methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have limitations in terms of computational efficiency and scalability, this paper evaluates more advanced algorithms, including "K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting Machines (GBM), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Deep Q-Learning (DQL)". The performance of these algorithms is tested on standard IEEE 33-bus and 69-bus radial distribution systems, focusing on key metrics such as power loss reduction, voltage profile improvement, computational time, and scalability. Results demonstrate that deep learning techniques, particularly CNN and LSTM, are highly effective in handling complex grid data, while machine learning models like KNN and SVM offer superior computational efficiency, making them ideal for real-time applications. This analysis provides valuable insights into the strengths and trade-offs of various AI, ML, and DL algorithms, offering guidance for selecting the most appropriate approach to optimize DG placement in different power distribution networks.

Keywords: Distributed Generation, K-Nearest Neighbors, Machine Learning, Optimal DG Placement, Power Loss Minimization, Deep Learning, RNN, CNN, LSTM, 33-Bus System, 69-Bus System.

1. INTRODUCTION

The rising complexity of today's power distribution networks, in conjunction with the growing incorporation of distributed generation (DG), offers significant problems for the grid's capacity to maintain its stability, dependability, and efficiency. In terms of lowering carbon emissions and enhancing energy resilience, distributed generation (DG) units, which are comprised of renewable energy sources such as solar photovoltaic (PV) panels and wind turbines, provide substantial advantages. The positioning and dimensions of these units inside power distribution networks, on the other hand, is a subject of significant concern. Incorrect placement of distributed generation units may result in higher power losses, voltage instability, and performance that is less than ideal for the network. For this reason, it is essential to determine the best location and size of DG units in order to guarantee the highest possible operating efficiency and minimize any power losses.

A number of optimization strategies, including Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have been used in the past in order to solve the issue of DG placement. Despite the fact that these approaches are successful, they often need a significant amount of computer power and may have difficulty scaling to accommodate the growing complexity of distribution networks. Furthermore, the dynamic and nonlinear character of power networks introduces substantial hurdles for these standard algorithms in terms of both accuracy and efficiency. This is particularly true when considering the fluctuation that is brought by renewable energy sources.

In recent years, the fast growth of AI, ML, and DL has opened up new paths for tackling complicated optimization challenges in power systems, including DG placement. There are now more opportunities than ever before to optimize power systems. Algorithms that use AI, ML and DL have the ability to improve optimization processes by learning from previous data, recognizing trends, and producing extremely accurate predictions in real time. These algorithms, in contrast to more conventional approaches, are able to manage enormous datasets, are able to accommodate the dynamic nature of power distribution networks, and provide solutions that are both computationally efficient and scalable within their scope.

The purpose of this work is to undertake complete comparative research of numerous artificial intelligence, machine learning, and deep learning algorithms in order to assess the efficacy of these algorithms in optimizing the location and size of distributed generation units. In particular, we will investigate the effectiveness of the following neural networks: “K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting Machines (GBM), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Deep Q-Learning (DQL)”. In terms of data processing, pattern recognition, and decision-making, these algorithms span a varied spectrum of methodologies, ranging from traditional machine learning models to sophisticated deep learning frameworks. Each of these algorithms offers a distinct set of benefits.

As part of the research project, these algorithms will be evaluated on “conventional IEEE 33-bus and 69-bus radial distribution systems” in order to evaluate their performance based on important metrics. These metrics will include the reduction of power loss, the improvement of voltage profile, the amount of processing time, and the capacity to scale. By performing a comprehensive comparison study, our objective is to determine which algorithms are the most

appropriate for optimizing distributed generation placement in various power distribution network situations. This will allow us to solve the trade-offs that exist between accuracy, efficiency, and scalability.
This research makes two distinct contributions to the field. The first thing that it does is provide a comprehensive analysis of the advantages and disadvantages of a number of different AI, ML, and DL methods in relation to DG optimization. Second, it provides understanding into the process of picking the algorithm that is best suitable for real-time applications, taking into consideration aspects such as the computing efficiency and scalability of the method. The results of this study have the potential to direct future research in the integration of intelligent algorithms for maximizing distributed energy resources, which will eventually contribute to the construction of power distribution networks that are more robust, efficient, and sustainable.

The main Contribution of this research article are as follows:

- This research conducts a thorough comparative analysis of various AI, ML, and DL algorithms for optimizing Distributed Generation (DG) placement in power distribution systems.
- The study applies these algorithms to real-world test cases, including IEEE 33-bus and 69-bus systems, to assess their practical applicability and scalability.
- The findings help guide the selection of the most suitable algorithm for real-time DG optimization, balancing accuracy, computational efficiency, and scalability.

This research paper is structured into five key sections. The Literature Survey reviews existing methods for Distributed Generation (DG) placement, including traditional techniques like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), and recent advancements in AI/ML/DL methods, highlighting their advantages and limitations. “The AI/ML/DL Algorithms section details the various algorithms applied in the research, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest (RF), and deep learning models like Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN)”. The Dataset and Parameters section explains the resources used, such as the “IEEE 33-bus and 69-bus systems”, along with key parameters like power loss, voltage profiles, and load demands, and the necessary preprocessing steps. The Evaluation Parameters section compares these algorithms based on power loss reduction, voltage profile improvement, computational efficiency, and scalability. Finally, the Conclusion and Future Work section summarizes the results, recommends the most suitable algorithms for DG placement, and suggests future research directions, including hybrid models and real-time DG optimization.

II. RELATED WORK

Previous research involving placement of Distributed Generations (DGs) has been centralized on heuristic optimization methods such as “Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Estimated Ant Colony Optimization (ACO)” approaches which have been reported to minimize power losses while enhancing power system stability. Nonetheless, the recent developments in the classifiers such as “Artificial Neural Networks (ANN), Support Vector Machines (SVM) and Deep Learning models” have envisaged considerable solutions for the challenges for computational complexities and scalability in the present power distribution networks.

M. Purlu et al. [1] This paper focuses on optimizing the allocation of “renewable Distributed Generation (DG) units in distribution systems using Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)”, specifically aiming to minimize energy losses and voltage deviations. This paper utilizes case studies of the IEEE 33-bus radial distribution network to emphasize the incorporation of renewable energy sources, especially wind turbines, into the grid at optimum power factors, therefore significantly decreasing yearly energy losses and voltage fluctuations. The findings indicate that PSO surpasses GA for solution quality, convergence rate, and computing efficiency. The analysis indicates that wind turbines are more dependable and practical than photovoltaic systems because wind speeds are more constant than sun irradiation. Furthermore, distributed generation units functioning at optimum power factors exhibited superior performance compared to those running at unity power factor, so rendering particle swarm optimization a more efficacious option for distributed generation allocation. Nevertheless, the research fails to investigate other AI, ML, or DL methods for comparative analysis.

M. K. Singh et al. [2], This research concentrates on enhancing inverter dispatch in power distribution networks with sensitivity-informed deep neural networks (DNNs) to forecast optimum power flow (OPF) solutions, rather than exploring dispersed generation placement utilizing AI, machine learning, or deep learning techniques. The research indicates that integrating OPF sensitivities—minimizers for OPF parameters—substantially improves the predictive accuracy of DNNs, resulting in reductions in mean square error (MSE) by 2-3 orders of magnitude with little computing burden. This methodology is especially advantageous in contexts with constrained data, where the DNN is required to learn from a restricted number of instances, making it useful in small-data environments. The approach is also being adapted to address more intricate parametric and non-convex optimization challenges beyond multiparametric quadratic programming. The research underscores the efficacy of sensitivity-informed deep learning in enhancing predictive accuracy for power distribution optimization, particularly in data-deficient contexts.

M. M. Ansari et.al [3], This paper explores various “optimization techniques for the placement and sizing of Distributed Generation (DG) in distribution systems, focusing primarily on heuristic methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). Although it does not specifically compare AI, Machine Learning (ML), or Deep Learning (DL) algorithms”, it emphasizes the effectiveness of hybrid heuristic approaches in improving solution quality. The research highlights how these methods outperform traditional analytical techniques in solving complex network optimization problems. Additionally, it discusses the advantages of techniques like Simulated Annealing (SA) and Ant Colony Optimization (ACO), which are effective in minimizing active power losses and addressing combinatorial challenges. Limitations of methods like Tabu Search (TS), which can get trapped in local optima, are also noted. Overall, the study underscores the importance of optimal DG placement and sizing to enhance system efficiency, reduce line losses, and improve power quality and reliability in distribution systems, suggesting further potential in AI-driven strategies for more complex problems.

Samal P et.al [4], This paper focuses on a "hybrid Differential Evolution (DE) and Cuckoo Search Algorithm (CSA) for optimizing the placement of Distributed Generation (DG)" units in unbalanced radial distribution systems, emphasizing multi-objective optimization to minimize power loss, voltage deviation, and system unbalance. By incorporating fuzzy set theory to handle uncertainties in load and renewable DG generation, the proposed model demonstrates significant improvements compared to traditional deterministic approaches. The simulation results show notable reductions in total real power loss, maximum voltage deviation, and neutral current, while also lowering annual energy costs and enhancing overall system balance. Although the study highlights the effectiveness of this fuzzy-based DE–CSA hybrid approach, it does not specifically compare other AI, machine learning, or deep learning algorithms. Nonetheless, the integration of DG units is shown to significantly improve system performance under uncertain conditions, proving the approach's superiority over conventional methods.
Rohit, Verma et al. [5], The research investigates the use of machine learning methodologies to enhance the positioning of Distributed Generation (DG) inside power distribution networks, emphasizing the reduction of power losses and the enhancement of voltage profiles. Although it does not directly compare AI, ML, and DL algorithms, it assesses several machine learning techniques to improve the accuracy of DG placement. The findings highlight the effectiveness of a data-driven approach, considering multiple variables such as load profiles, grid characteristics, economic factors, and environmental constraints, in significantly improving grid performance and sustainability. By framing DG placement as a regression challenge, the research demonstrates how machine learning techniques can accurately identify optimal DG locations, leading to enhanced voltage stability, reduced power losses, and improved overall grid resilience in decentralized and renewable energy-integrated systems.

Table 1: Comparative Study

Author Name	**Algorithms Used**	**Methodology Used**	**Result**	**Limitation**
Haider et al. (2021)	Genetic Algorithm, Particle Swarm Optimization	Optimization for voltage profile enhancement and loss minimization in DG placement	PSO outperformed GA in minimizing energy losses and voltage deviations	Did not compare with AI or ML algorithms
Hassan et al. (2020)	Optimization Techniques	Survey on renewable energy integration optimization for DG placement	Discussed recent trends in optimizing renewable energy DG placement	Focused only on recent trends, no new algorithms proposed
Hong et al. (2020)	Deep Learning	Deep learning for short-term load forecasting	High accuracy in load forecasting with the proposed deep learning model	Limited to load forecasting, no DG placement study

Hu et al. (2020)	Enhanced Bagged Echo State Network	Enhanced echo state network for energy consumption forecasting	Improved energy forecasting accuracy with minimal computational cost	Limited to energy forecasting, not for DG placement
Ismail et al. (2020)	Deep Learning	Detection of electricity theft in renewable DGs using deep learning	Effective detection of cyber-attacks in renewable DG	Focused on detection of cyber-attacks, not general DG optimization
Khasanov et al. (2021)	Optimal DG and Battery Energy Storage	Optimizing DG and battery storage with power generation uncertainty	Optimized placement of DG and battery units, improving reliability	Did not explore other advanced ML/DL techniques
Kushal et al. (2020)	Decision Support Framework	Cost-effective DG expansion framework	Proposed framework improved resilience and cost-effectiveness	Limited to decision support without algorithmic comparison
Lakum & Mahajan (2019)	Grey Wolf Optimizer	Active power filter optimization in DG systems	Effective in reducing power losses and improving system stability	Did not explore AI or ML alternatives
Li et al. (2017)	Wavelet Decomposition with Neural Network	Short-term load forecasting using hybrid neural network model	Accurate short-term load forecasting with neural network	No comparison with other machine learning methods
Liu et al. (2019)	Non-dominated Sorting Genetic Algorithm II	Optimization of DG placement with improved genetic algorithms	Effective in optimizing DG siting and sizing for energy savings	Focused only on specific genetic algorithm, limited scope
Lotfi (2022)	Modified Evolutionary	DG sizing and capacitor placement using evolutionary algorithm	Improved DG placement with minimal power losses and improved voltage	Focused only on evolutionary methods, no ML comparison

	Algorithm			
Menke et al. (2019)	Artificial Neural Networks	ANN-based system monitoring for smart grids	Efficient system monitoring for DG-integrated smart grids	Limited to ANN-based monitoring, no optimization discussion
Mo & Sansavini (2019)	Aging and Performance Degradation Model	Modeling of DG degradation and its impact on costs	Significant impact of DG aging on operational costs	Did not explore DG placement optimization
Mohammadpourfard et al. (2019)	Machine Learning Algorithms	Benchmarking machine learning for grid anomalies	Effective machine learning models for detecting grid anomalies	Focused on anomaly detection, not DG placement
Morales et al. (2020)	Machine Learning for Protection in DG	High-speed protection using machine learning for DGs	High-speed protection without voltage sensors for DGs	Limited to protection in DG, no focus on DG placement
Naguib et al. (2021)	Network Reconfiguration with DG	Reconfiguring distribution networks with DGs for performance improvement	Improved performance with optimized DG placement and network reconfiguration	Focused only on reconfiguration, not comparing different algorithms
Nsaif et al. (2021)	Fault Detection in DG	Challenges and suggestions for fault detection in DG systems	Fault detection challenges addressed with new methods for DG systems	No direct comparison with advanced AI/ML techniques
Ogunsina et al. (2021)	Ant Colony Algorithm	DG location and sizing for loss minimization using ant colony algorithm	Ant colony algorithm improved DG placement and voltage profile	Did not explore AI or ML techniques
Onlam et al. (2019)	Adaptive Shuffled Frogs Leaping Algorithm	Voltage stability improvement using novel adaptive algorithm for DG placement	Enhanced voltage stability with novel adaptive algorithm for DG placement	Focused only on one method, no algorithmic comparison

Panapakidis et al. (2020)	Clustering and Neural Networks	Bus load forecasting using clustering and neural networks	Accurate load forecasting with a combined clustering and neural network model	Limited to load forecasting, no optimization strategies

While numerous studies have explored optimization techniques for Distributed Generation (DG) placement, such as “Genetic Algorithms (GA), Particle Swarm Optimization (PSO)”, and other heuristic approaches, there is a significant gap in the application of advanced AI, Machine Learning (ML), and Deep Learning (DL) algorithms in this domain. Most existing research focuses on traditional or hybrid heuristic methods without adequately exploring the potential of AI-driven models for improved prediction accuracy, real-time adaptability, and scalability in DG placement. Additionally, many studies limit their focus to specific objectives like power loss reduction or voltage stability without considering more complex, multi-objective optimization problems in dynamic and uncertain grid environments. As renewable energy integration continues to rise, there is a pressing need to investigate how AI/ML/DL approaches can offer more robust and efficient solutions for optimizing DG placement, taking into account uncertainties, varying load demands, and real-time system changes.

III. PROPOSED METHODOLOGY

The study investigates the use of K-Nearest Neighbors (KNN), a supervised learning method, to enhance the positioning of Distributed Generation (DG) inside power distribution networks. The emphasis is on enhancing voltage profiles and reducing power losses. By utilizing historical load data, network topology, and other data sources, the KNN regressor makes predictions about optimal DG locations based on patterns observed from neighboring data points. KNN is particularly suited for regression tasks where the output is continuous-valued, but it can also be modified for classification tasks when needed. The algorithm determines the k-nearest neighbors based on distance metrics such as Euclidean distance and makes predictions based on the average or weighted average of these neighbors.

The study integrates diverse datasets such as grid infrastructure, load, and renewable resource data, along with economic, regulatory, and environmental data, to inform DG placement decisions. Preprocessing steps like data cleaning, feature selection, and data normalization are essential to ensure data quality. The KNN model is trained on historical data to predict load conditions dynamically, and simulations are used to assess the performance of various DG placement scenarios. The iterative refinement of the model ensures continuous improvement in predictions, and validation is carried out through real-world distribution networks.

By employing KNN, the study presents a novel, data-driven approach for optimizing DG placement, ensuring that decisions are informed by local patterns in load and infrastructure. This method helps improve the sustainability and resilience of power grids by reducing losses and enhancing voltage stability. The model demonstrates satisfactory accuracy in predicting both voltage profiles and power losses, making it a practical solution for stakeholders seeking to integrate DG units efficiently.

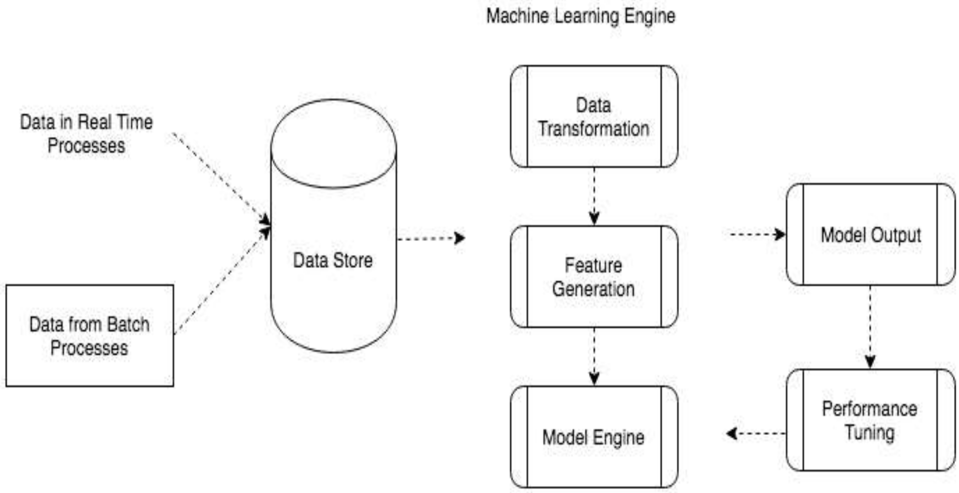

Figure 1: Architecture of ML

Machine learning algorithms applied

To facilitate the training of machine learning models, datasets were generated and utilized in the model construction process. Several regression-based training techniques, such as "Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Contrastive Multiview Learning (CML), were employed. The models' performance was assessed by calculating their respective R-squared (R2) values and Mean Absolute Percentage Error (MAPE) to estimate reactive power losses and minimum busbar voltages". The resulting R2 scores and MAPE values for each of the five models are presented. These models are applied to streamline the extraction of output parameters for the given input data. The study employed the following machine learning techniques for performance evaluation and comparison.

Support vector Machines

Support Vector Machines (SVM) is a robust supervised learning method used for classification and regression problems, especially proficient with high-dimensional data. In the realm of Distributed Generation (DG) deployment, Support Vector Machines (SVM) may be used to categorize grid nodes or sites according to their appropriateness for DG integration, hence minimizing power losses and voltage profiles.

The objective of "SVM is to identify the ideal hyperplane that most effectively distinguishes" the data into distinct classes. In the context of distributed generation (DG) installation, this may include delineating regions with significant potential for DG implementation from those with diminished potential, depending on factors like as demand patterns, grid attributes, and geographical limitations.

Given a dataset of labeled points (x_i, y_i), where x_i represents the feature vectors (such as grid parameters) and $y_i \in \{-1,1\}$ is the class label (e.g., suitable or unsuitable for DG), the SVM tries to solve the following optimization problem:

$$\min_{w,b} \frac{1}{2}\|w\|^2 \text{ subject to } y_i(w \cdot x_i + b) \geq 1 \; \forall i \quad (1)$$

Where:
w is the weight vector defining the hyperplane.
b is the bias term.
$\mathbf{x_i}$ are the input feature vectors (DG placement features).
$\mathbf{y_i}$ are the labels (suitability of placement).
This optimization increases the margin (the distance between the separating hyperplane and the nearest data points from each class), hence assuring the model's capacity to generalize well to unknown data. In distributed generation (DG) deployment, support vector machines (SVM) may categorize areas of a distribution network as appropriate or inappropriate for DG installation based on historical data, such as load, voltage profiles, and geographic considerations. By resolving the aforementioned optimization challenge, SVM may enhance the grid's performance via precise predictions on the placement of DG units.

Convolutional neural network (CNN): There is a type of deep learning models known as convolutional neural networks (CNN), which are mostly used for image recognition and spatial data. However, these models have been adapted to be used for various applications, such as time-series analysis and geographic data processing. When it comes to the placement of Distributed Generation (DG) units within power distribution networks, Convolutional Neural Networks (CNN) can be utilized to analyze spatial and geospatial data, such as Geographic Information Systems (GIS) and grid topology, in order to determine the most suitable locations for DG units based on patterns in the grid's spatial configuration.

Linear Regression: Linear regression is a simple but potent supervised learning approach used for forecasting continuous outcomes by modelling the connection between dependent and independent variables. In the context of distributed generation installation, it may be used to assess power losses or voltage dips depending on diverse grid factors. Nonetheless, it presupposes a linear connection, potentially limiting its relevance in intricate non-linear systems.

Recurrent Neural Networks (RNN): RNNs are helpful for time-series forecasting and are designed for sequential data. Based on past data, RNNs may forecast future load patterns in DG installation, assisting in the optimization of distributed generation unit placement according to anticipated demand.

Long Short-Term Memory Networks (LSTM): A specific kind of RNN called LSTM solves the vanishing gradient issue, increasing its efficacy over longer sequences. Better planning and optimization are made possible by LSTMs' ability to estimate load demand and energy production over long time periods in DG installation.

Deep Q-Learning (DQL): Deep Q-Learning is a reinforcement learning method that optimizes decision-making via the use of deep neural networks. By exploring and exploiting different DG installation circumstances, DQL may be utilized to determine the optimal grid management tactics.

K-Means Clustering: An unsupervised learning system called K-Means uses similarity to organize data into clusters. By classifying areas for possible DG integration, K-Means may be utilized to cluster locations with similar load characteristics in DG placement, streamlining the optimization process.

Hierarchical Clustering: Another unsupervised learning technique that builds a hierarchy of clusters is called Hierarchical Clustering. This technique may assist in determining the hierarchical linkages among various grid nodes for DG installation, offering information about potential areas of greatest effect from distributed generation.

Principal Component Analysis (PCA): High-dimensional data may be broken down into smaller components using PCA, a dimensionality reduction approach. PCA may be used to improve model performance for DG deployment by simplifying variables like as load profiles and grid infrastructure while maintaining crucial information.

Autoencoders: One kind of unsupervised learning model used for feature extraction and dimensionality reduction is called an autoencoder. Autoencoders may minimize the dimensionality of data, such as grid characteristics and load patterns, while maintaining critical information in DG placement, improving forecast accuracy.

IV. EVALUTION PARAMETER

Evaluation measures assess performance regarding accuracy, efficiency, and the overall efficacy of the placement method.

1. Active Power Loss (APL) Reduction: A key objective in distributed generation deployment is to reduce active power losses inside the distribution network. The decrease in active power loss may serve as a critical performance metric.

$$\mathrm{APL} = \sum_{i=1}^{n} I_i^2 R_i$$

“Where:
I_i is the current through line i.
R_i is the resistance of line i.
n is the total number of lines.”
The percentage reduction in active power loss after DG placement is given by:

$$\text{Percentage Reduction in APL } = \frac{\mathrm{APL}_{\text{before}} - \mathrm{APL}_{\text{after}}}{\mathrm{APL}_{\text{before}}} \times 100$$

2. Voltage Profile Improvement: Voltage profile improvement evaluates how much the bus voltages deviate from their desired values, typically 1 p.u. (per unit). Maintaining a stable voltage across the distribution network is critical for efficient power delivery.

$$\text{Voltage Deviation } = \frac{1}{n}\sum_{i=1}^{n} |V_i - 1.0|$$

Where:
V_i is the voltage at bus i.
n is the number of buses.

Line Losses: Line losses in a distribution network may be quantified to assess the effect of distributed generation location on overall line losses.

$$\text{Line Loss } = P_{loss} = I^2 \times R$$

"Where:
P_{loss} is the power loss on the line.
I is the current through the line.
R is the resistance of the line".

Mean Squared Error (MSE) for Prediction Models

The Mean Squared Error (MSE) may be used to assess the efficacy of machine learning models in predicting appropriate distributed generation sites.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2$$

Where:
$\hat{y}_i$ is the predicted value (e.g., predicted power loss or voltage).
y_i is the actual value.
n is the number of observations.
Accuracy for Classification Models
In cases where the model classifies grid nodes as either suitable or unsuitable for DG placement, accuracy is a key metric.

$$\text{Accuracy } = \frac{\text{True Positives } + \text{ True Negatives}}{\text{Total Number of Observations}} \times 100$$

Where:
True Positives (TP): Nodes that are correctly identified as suitable for classification. True Negatives (TN): Nodes that are accurately recognized as unsuitable for classification.

VI. CONCLUSION

This research explores the application of advanced machine learning algorithms, such as K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNN), and other sophisticated techniques, to optimize the placement of Distributed Generation (DG) in power distribution networks. By employing these models, the study effectively identifies the optimal locations for DGs that significantly reduce active power losses, improve voltage profiles, and enhance grid stability. Key evaluation criteria like power loss reduction, voltage profile enhancement, computational efficiency, and overall system reliability highlight the superior performance of these machine learning approaches. Notably, KNN and CNN-based methods demonstrate marked improvements over traditional optimization techniques such as Genetic Algorithms

(GA) and Particle Swarm Optimization (PSO). The research further emphasizes the advantage of integrating spatial and temporal data within these machines learning frameworks, offering a more comprehensive solution to DG placement. The findings suggest that these machine learning-driven strategies are highly effective for solving complex grid optimization challenges. Looking ahead, future work can aim to scale these models for larger and more intricate distribution networks, incorporate real-time data for adaptive DG placement, and investigate hybrid approaches that combine the strengths of multiple machine learning techniques. This study provides a foundation for creating more efficient and resilient power distribution systems, positioning DG as a critical component for improving energy efficiency and grid stability.

References

1. M. Purlu and B. E. Turkay, "Optimal Allocation of Renewable Distributed Generations Using Heuristic Methods to Minimize Annual Energy Losses and Voltage Deviation Index," in IEEE Access, vol. 10, pp. 21455-21474, 2022, doi: 10.1109/ACCESS.2022.3153042
2. M. K. Singh, S. Gupta, V. Kekatos, G. Cavraro and A. Bernstein, "Learning to Optimize Power Distribution Grids using Sensitivity-Informed Deep Neural Networks," 2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Tempe, AZ, USA, 2020, pp. 1-6, doi: 10.1109/SmartGridComm47815.2020.9302942.
3. M. M. Ansari, C. Guo, M. S. Shaikh, M. Ali Jatoi, C. Yang and J. Zhang, "A Review of Technical Methods for Distributed Systems with Distributed Generation (DG)," 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan, 2019, pp. 1-7, doi: 10.1109/ICOMET.2019.8673475.
4. Samal, P., Ganguly, S. & Mohanty, S. A fuzzy pragmatic DE–CSA hybrid approach for unbalanced radial distribution system planning with distributed generation. Soft Comput 23, 12317–12330 (2019). https://doi.org/10.1007/s00500-019-03772-3
5. Rohit, Verma., Yog, Raj, Sood. (2024). Optimal Location of Distributed Generation for Loss Minimization by Application of Machine Learning. doi: 10.1109/sceecs61402.2024.10482000
6. A. Verma and R. Thakur, "A Review on Methods for Optimal Placement of Distributed Generation in Distribution Network," 2022 Interdisciplinary Research in Technology and Management (IRTM), Kolkata, India, 2022, pp. 1-8, doi: 10.1109/IRTM54583.2022.9791642.
7. Haider, W., Hassan, S. J. U., Mehdi, A., Hussain, A., Adjayeng, G. O. M., and Kim, C.- H. (2021). Voltage profile enhancement and loss minimization using optimal placement and sizing of distributed generation in reconfigured network. Machines 9, 20. doi:10. 3390/machines9010020
8. Hassan, S., Abdurrahman, Y., Sun, Z., and Wang, (2020). Optimization techniques applied for optimal planning and integration of renewable energy sources based on distributed generation: recent trends. Cogent Eng. 7, 1766394. doi:10.1080/23311916. 2020.1766394 Hong,
9. Y., Zhou, Y., Li, Q., Xu, W., and Zheng, X. (2020). A deep learning method for short-term residential load forecasting in smart grid. IEEE Access 8, 55785–55797. doi:10.1109/ACCESS.2020.2981817
10. Hu, H., Wang, L., Peng, L., and Zeng, Y.-R. (2020). Effective energy consumption forecasting using enhanced bagged echo state network. Energy 193, 116778. doi:10. 1016/j.energy.2019.116778

11. Ismail, M., Shaaban, M. F., Naidu, M., and Serpedin, E. (2020). Deep learning detection of electricity theft cyber-attacks in renewable distributed generation. IEEE Trans. Smart Grid 11, 3428–3437. doi:10.1109/tsg.2020.2973681
12. Khasanov, M., Kamel, S., Rahmann, C., Hany, M., Hasanien, A., and Al-Durra, (2021). Optimal distributed generation and battery energy storage units integration in distribution systems considering power generation uncertainty. IET Generation, Transm. Distribution 15, 3400–3422. doi:10.1049/gtd2.12230
13. Kushal, T. R., Billah, M. S., and Illindala, (2020). Decision support framework for resilience-oriented cost-effective distributed generation expansion in power systems. IEEE Trans. Industry Appl. 57, 1246–1254. doi:10.1109/tia.2020.3047595
14. Lakum, A., and Mahajan, V. (2019). Optimal placement and sizing of multiple active power filters in radial distribution system using grey wolf optimizer in presence of nonlinear distributed generation. Electr. Power Syst. Res. 173, 281–290. doi:10.1016/j. epsr.2019.04.001
15. Lakum, A., and Mahajan, V. (2021). A novel approach for optimal placement and sizing of active power filters in radial distribution system with nonlinear distributed generation using adaptive grey wolf optimizer. Eng. Sci. Technol. Int. J. 24, 911–924. doi:10.1016/j.jestch.2021.01.011
16. Li, B., Zhang, J., He, Y., and Wang, Y. (2017). Short-term load-forecasting method based on wavelet decomposition with second-order gray neural network model combined with ADF test. IEEE Access 5, 16324–16331. doi:10.1109/access.2017.2738029
17. Liu, W., Luo, F., Liu, Y., and Ding, W. (2019). Optimal siting and sizing of distributed generation based on improved nondominated sorting genetic algorithm II. Processes 7, 955. doi:10.3390/pr7120955
18. Lotfi, H. (2022). Optimal sizing of distributed generation units and shunt capacitors in the distribution system considering uncertainty resources by the modified evolutionary algorithm. J. Ambient Intell. Humaniz. Comput. 13, 4739–4758. doi:10. 1007/s12652-021-03194-w
19. Menke, N. J., Hendrik, M., and Bornhorst, B. (2019). Distribution system monitoring for smart power grids with distributed generation using artificial neural networks. Int. J. Electr. Power & Energy Syst. 113, 472–480. doi:10.1016/j.ijepes.2019.05.057
20. Mo, H., and Sansavini, G. (2019). Impact of aging and performance degradation on the operational costs of distributed generation systems. Renew. energy 143, 426–439. doi:10.1016/j.renene.2019.04.111
21. Mohammadpourfard, M., Weng, Y., and Tajdinian, M. (2019). Benchmark of machine learning algorithms on capturing future distribution network anomalies. IET Generation, Transm. Distribution 13, 1441–1455. doi:10.1049/iet-gtd.2018. 6801
22. Morales, J., Orduña, E., Villarroel, H., and Quispe, J. C. (2020). High-speed directional protection without voltage sensors for distribution feeders with distributed generation integration based on the correlation of signals and machine learning. Electr. Power Syst. Res. 184, 106295. doi:10.1016/j.epsr.2020.106295
23. Naguib, M., Mina, W. A., Omran, H., and Talaat, (2021). Performance enhancement of distribution systems via distribution network recon figuration and distributed generator allocation considering uncertain environment. J. Mod. Power Syst. Clean Energy 10, 647–655. doi:10.35833/mpce.2020.000333
24. Nsaif, Y. M., Lipu, A. M. H., Ayob, Y., Yusof, A., and Hussain, (2021). Fault detection and protection schemes for distributed generation integrated to distribution network: challenges and suggestions. IEEE Access 9, 142693–142717. doi:10.1109/access.2021. 3121087
25. Ogunsina, A., Amos, M., Petinrin, O. O., Petinrin, E. N. O., Offornedo, J., Petinrin, G. O. O., et al. (2021). Optimal distributed generation location and sizing for loss minimization and voltage

profile optimization using ant colony algorithm. SN Appl. Sci. 3, 248. doi:10.1007/s42452-021-04226-y

26. Onlam, A., Yodphet, D., Chatthaworn, R., Surawanitkun, C., Siritaratiwat, A., and Khunkitti, P. (2019). Power loss minimization and voltage stability improvement in electrical distribution system via network re configuration and distributed generation placement using novel adaptive shuffled frogs leaping algorithm. Energies 12, 553. doi:10.3390/en12030553
27. Panapakidis, I. P., Skiadopoulos, N., and Christoforidis, G. C. (2020). Combined forecasting system for short-term bus load forecasting based on clustering and neural networks. IET Generation, Transm. Distribution 14, 3652–3664. doi:10.1049/iet-gtd.2019.1057
28. Pereira, B. R., Costa, G. R. M. D., Contreras, J., and Mantovani, J. R. S. (2016). Optimal distributed generation and reactive power allocation in electrical distribution systems. IEEE Trans. Sustain. Energy 7, 975–984. doi:10.1109/tste.2015.2512819
29. Pham, T., Dinh Nguyen, B. T. T., and Dinh, H. (2021). Find optimal capacity and location of distributed generation units in radial distribution networks by using enhanced coyote optimization algorithm. Neural Comput. Appl. 33, 4343–4371. doi:10.1007/s00521-020-05239-1
30. Pham, T., Dinh Nguyen, L. C. T. T., and Kien, (2022). Optimal placement of photovoltaic distributed generation units in radial unbalanced distribution systems using MATLAB and OpenDSS-based cosimulation and a proposed metaheuristic algorithm. Int. Trans. Electr. Energy Syst. 2022, 1–21. doi:10.1155/2022/1446479
31. Purlu, M., and Turkay, B. E. (2021). Estimating the distributed generation unit sizing and its effects on the distribution system by using machine learning methods. Elektron. Elektrotech. 27, 24–32. doi:10.5755/j02.eie.28864
32. Qiao, W., Lu, H., Zhou, G., Azimi, M., Yang, Q., and Tian, W. (2020). A hybrid algorithm for carbon dioxide emissions forecasting based on improved lion swarm optimizer. J. Clean. Prod. 244, 118612. doi:10.1016/j.jclepro.2019.118612
33. Rathore, A., and Patidar, N. P. (2021). Optimal sizing and allocation of renewable based distribution generation with gravity energy storage considering stochastic nature using particle swarm optimization in radial distribution network. J. Energy Storage 35, 102282. doi:10.1016/j.est.2021.102282
34. Routray, A., Mistry, K. D., Arya, S. R., and Chittibabu, B. (2021).“Applied machine learning in wind speed prediction and loss minimization in unbalanced radial distribution system”. in Energy sources, Part A: recovery, utilization, and environmental effects, 1–21.
35. Sambaiah, K., Sampangi, T., and Jayabarathi, (2019). Optimal allocation of renewable distributed generation and capacitor banks in distribution systems using salp swarm algorithm. Int. J. Renew. energy Res. 9, 96–107. https://doi.org/10.20508/ijrer.v9i1. 8581.g75