Optimal Power Flow in Hybrid AC/DC Microgrid using ANN for Cost minimization

[1]Pagidela Yamuna and [2]Visali N
[1,2]Department of Electrical and Electronics Engineering, JNTUA College of Engineering, Ananthapuramu, India.
[1]yamuna.pagidela@gmail.com, [2]nvisali.eee@jntua.ac.in

Correspondence should be addressed to Pagidela Yamuna : yamuna.pagidela@gmail.com.

Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202404039
Received 01 September 2023; Revised from 25 December 2023; Accepted 15 February 2024.
Available online 05 April 2024.

Abstract – Currently, this work lays the groundwork for sophisticated control methods and decision support systems in hybrid microgrid operations by providing insightful information about integrating artificial intelligence for improved microgrid control. In this work, a neural network (NN) method is proposed for power flow analysis in an IEEE 12-bus-based Hybrid AC/DC Microgrid. The study optimizes power dispatch, minimizes expenses, and minimizes losses in both AC and DC components. Simulation is carried out using MATLAB software and the results are presented and analysed. The accuracy of the NN's predictions of active power flows is demonstrated by training it on historical data and validating it on real-time observations. Regression plots comparing anticipated and real values demonstrate the effectiveness of NN-based analysis in reaching the ideal power distribution.

Keywords – Optimal Power Flow, Cost Analysis, Hybrid AC/DC Microgrid, IEEE 12 Bus System, Neural Network Controller.

I. INTRODUCTION

Now-a-days,Hybrid AC/DC microgrids—which combine energy storage and renewable generation—are becoming more and more popular for local decentralised power systems [1][2]. For these linked AC and DC networks to operate in a secure and cost-effective manner, effective coordination and dispatch are required [3][4]. However, typical approaches have obstacles in optimising due to diverse dynamics and variability from renewable resources [5][6]. In such intricate microgrids, optimal power flow (OPF) is essential for figuring out effective setpoints to reduce expenses [7][8]. Conventional deterministic OPF formulations are insufficient to handle uncertainty because of the occasional fluctuations [9][10]. Although research on using artificial neural networks (ANN) for optimal power flow (OPF) in hybrid AC/DC systems is limited, ANNs are a promising advanced control technology [11][12].

By suggesting an ANN-based controller to solve the OPF problem in a hybrid microgrid test case, the main goal of this work is to close this gap. The foundation of the platform is the modification of the extensively studied IEEE 12 bus system to include a DC component linked via an interlinking AC/DC converter [13][14]. The ANN design produces the best scheduled dispatches by processing load and renewables forecasts. A range of OPF goals and constraints on equity and inequality are developed, taking practical limitations, costs, and losses into account [15–17]. The capacity of the integrated ANN control scheme to produce high-quality, cost-effective solutions in the face of variable is evaluated compared. Thus, this study offers a fresh use of clever methods to improve hybrid microgrid control and optimisation in the future. Additionally, it creates an adaptable simulation setup for testing new technologies using benchmark instances [18][19].

However, deterministic steady state conditions, forecast accuracy, and centralised control capabilities are all predicated on limiting assumptions in traditional OPF formulations. In an attempt to improve OPF methods, distributed multi-agent systems and the incorporation of uncertainty information have been investigated. Nonetheless, the majority of methods concentrate mostly on AC systems, with little research done on DC and hybrid AC/DC microgrids, which can offer more operational flexibility. To enable stochastic optimisation, recent publications have examined intelligent optimisation techniques such as artificial neural networks (ANN). However, there is room for major increase in the scarce implementation of hybrid AC/DC grids. This paper describes the problem statement, test system specifics, ANN control design, results analysis, conclusions and future study directions.

II. LITERATURE REVIEW

The early research has focused on hybrid microgrid control schemes. A multi-agent reinforcement learning framework for optimal steady-state control was presented by Nateghi et al. [15], demonstrating the promise of AI-based control in hybrid microgrid environments. Similar to this, Shen et al. [16] highlighted the significance of stability in the control strategy by proposing a hybrid AC/DC microgrid control method with a voltage feedback loop and a coordinated controller based on a differential algebra equation. Differential evolution and coordinated control have been investigated as efficient ways to maximise the performance of hybrid AC/DC microgrids. Li et al. [17] provided evidence of the effectiveness of evolutionary algorithms in attaining optimisation through the application of coordinated control with differential evolution and self-adaptive policies. In the meantime, Khooban et al.[18] introduced cutting-edge techniques for reaching peak performance in their novel approach to load frequency regulation in shipboard microgrids.

The use of neural network-based techniques has grown in popularity for hybrid microgrid energy management systems. Gupta et al. [19-20] demonstrated the ability of machine learning to optimise energy distribution in microgrid configurations by implementing an artificial neural network (ANN)-based energy management system. By utilising neural networks to provide an adaptive method for dynamic control, Soltani et al.[21] demonstrated how flexible these systems are under different circumstances. Pedrasa and Spooner[22] surveyed the field of microgrid control techniques and offered a thorough synopsis of current approaches for managing microgrid generation and storage when the island is in operation. By presenting a microgrid energy management system based on the rolling horizon technique and highlighting the significance of anticipatory control for improved performance, Palma-Behnke et al.[23] advanced this understanding. Research on energy management and optimal power flow in microgrids has yielded important findings. Jiang et al. [24] discussed energy management in stand-alone and grid-connected modes and provided strategic insights on the best possible power flow. A stochastic-predictive energy management system for isolated microgrids was proposed by Olivares et al. [25-27] in order to handle the uncertainties related to renewable energy sources.

Optimization modeling and power system applications have also been explored. Soroudi [28] provided a comprehensive guide to power system optimization modeling using GAMS, offering insights into modeling techniques applicable to hybrid microgrid configurations. Shah and Mithulananthan [29] conducted a review of optimal power flow literature, emphasizing the application of traditional and evolutionary methods in solving nonlinear power system problems.In the realm of microgrid integration and energy storage, Basu et al. [30] presented a review of microgrid concepts, underlining the importance of proper integration of diverse energy sources for enhanced performance. Additionally, Levron et al. [31-34] explored optimal power flow in microgrids with energy storage, shedding light on the intricate balance required for efficient operation.

In summary, the literature review highlights the diverse approaches and methodologies employed in the quest for optimal power flow in hybrid AC/DC microgrids with neural network control. The integration of control strategies, optimization techniques, and advanced technologies such as neural networks reflect a multidisciplinary effort to address the complexities inherent in modern hybrid microgrid systems [35-37].

III. MATHEMATICAL MODELLING

The mathematical models presented for optimal power flow in the IEEE 12-bus system and a hybrid AC/DC microgrid play a pivotal role in shaping the landscape of power system planning and operation.

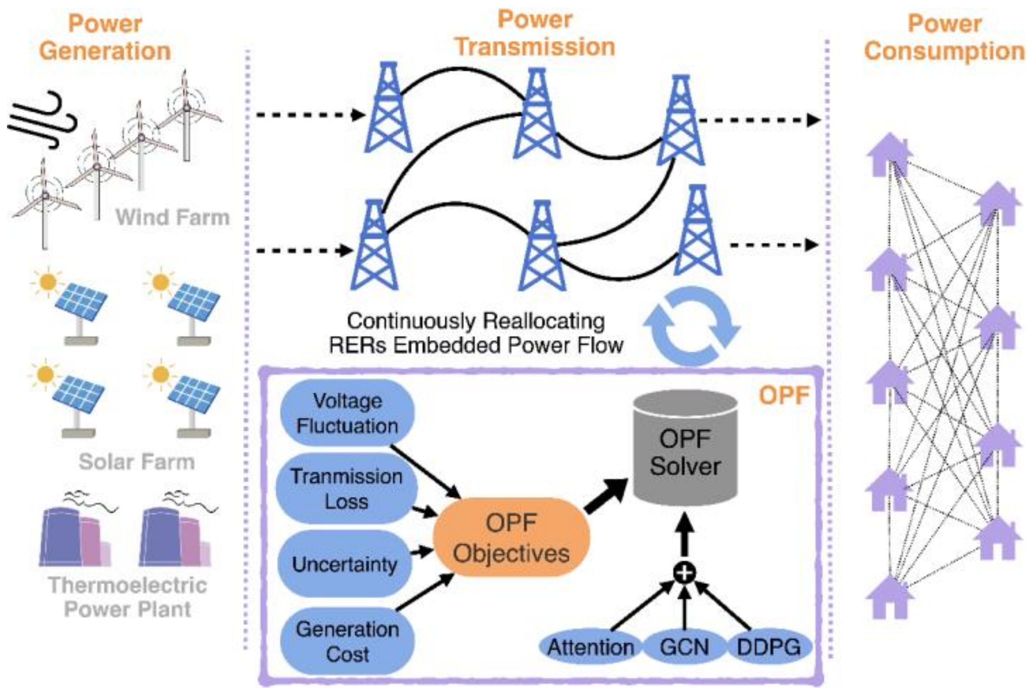

Fig 1. Representation of Optimal Power Flow

Fig 1 Show in Representation of Optimal Power Flow. These models, driven by a set of intricate equations, find extensive applications in enhancing operational efficiency, minimizing costs, and ensuring the seamless integration of renewable energy sources.

IEEE 12 Bus System

The IEEE 12-bus system is commonly used for power flow analysis, which involves determining the steady-state operating conditions of a power system. Now, The admittance matrix relates bus voltages and currents in the system. The elements Y_{ij}represent the admittance between buses i and j. The diagonal elements Y_{ii}represent the total admittance connected to bus i.

Let V_i = voltage magnitude at bus i
θ_i = voltage phase angle at bus i
P_i = Active Power at bus i
Q_i = Reactive Power at bus i

For each bus i, the bus admittance equations can be written as:

$$I_i = Y_{ii}V_i + \sum_{j=1}^{12} Y_{ij}(V_j < \theta_j - V_i < \theta_i) \tag{1}$$

Where, I_i – Complex Current Injected at bus i
Y_{ii} – Total admittance at bus i
Y_{ij} – Admittance at bus i and bus j

The optimal power flow equations, driven by nodal power balances, enable system operators to determine the optimal generator dispatch and power injections at each bus. This ensures the efficient utilization of available resources. The active power P_i and reactive power Q_i at each bus are related to the bus voltages and currents are:

$$P_i = \sum_{j=1}^{12} V_i V_j (G_{ij} \cos(\theta_i - \theta_j) + B_{ij} Sin(\theta_i - \theta_j)) \tag{2}$$

$$Q_i = \sum_{j=1}^{12} V_i V_j (G_{ij} \sin(\theta_i - \theta_j) - B_{ij} cos(\theta_i - \theta_j)) \tag{3}$$

Where, G_{ij} and B_{ij} are the real and imaginary parts of admittance Y_{ij}.

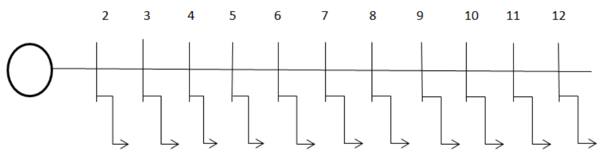

Fig 2. Single line diagram of IEEE 12 Bus System

Fig 2 Show in Single line diagram of IEEE 12 Bus System. The objective function seeks to minimize overall generation costs by incorporating cost coefficient for active and reactive power injection at each bus is

$$Minimize\ f(V, \theta, P, Q) = \sum_{i=1}^{12} (C_i^P . P_i^2 + C_i^Q . Q_i^2) \tag{4}$$

Where, C_i^P and C_i^Q are the cost Coefficients of active and reactive power injections at bus i.

Constraints on voltage magnitudes, branch flow limits and generator limits ensure that the system operates within acceptable voltage profiles and adhere to physical and operational constraints.

$$V_{min} \leq V_i \leq V_{max} \tag{5}$$

$$P_i^2 + Q_i^2 \leq S_{i\,(\max)}^2 \tag{6}$$

$$P_{min} \leq P_i \leq P_{max} \tag{7}$$

$$Q_{min} \leq Q_i \leq Q_{max} \tag{8}$$

Ensuring Stable voltage profiles, power balance and adherence to equipment limits.

The complex power injections at bus i are:

$$S_i = P_i + jQ_i \tag{9}$$

$$S_i = V_i \sum_{j=1}^{12} V_j \,(Y_{ij}^*. e^{j\theta_{ij}} \tag{10}$$

Where, $Y_{ij}^* = G_{ij} - jB_{ij}$ and $\theta_{ij} = \theta_i - \theta_j$

Hybrid AC/DC Microgrid

The hybrid AC/DC microgrid model extends the analysis to accommodate both AC and DC components, allowing for effective integration and management of renewable energy sources.the active power for AC and DC components are given below:

$$P_i^{AC} = \sum_{j=1}^{12} V_i V_j (G_{ij} \cos(\theta_i - \theta_j) + B_{ij} Sin(\theta_i - \theta_j)) \tag{11}$$

$$P_i^{DC} = \sum_{j=1}^{12} V_i V_j G_{ij} \tag{12}$$

The reactive power for AC and DC components are given below:

$$Q_i^{AC} = \sum_{j=1}^{12} V_i V_j (G_{ij} \sin(\theta_i - \theta_j) - B_{ij} cos(\theta_i - \theta_j)) \tag{13}$$

$$Q_i^{DC} = \sum_{j=1}^{12} V_i V_j B_{ij} \tag{14}$$

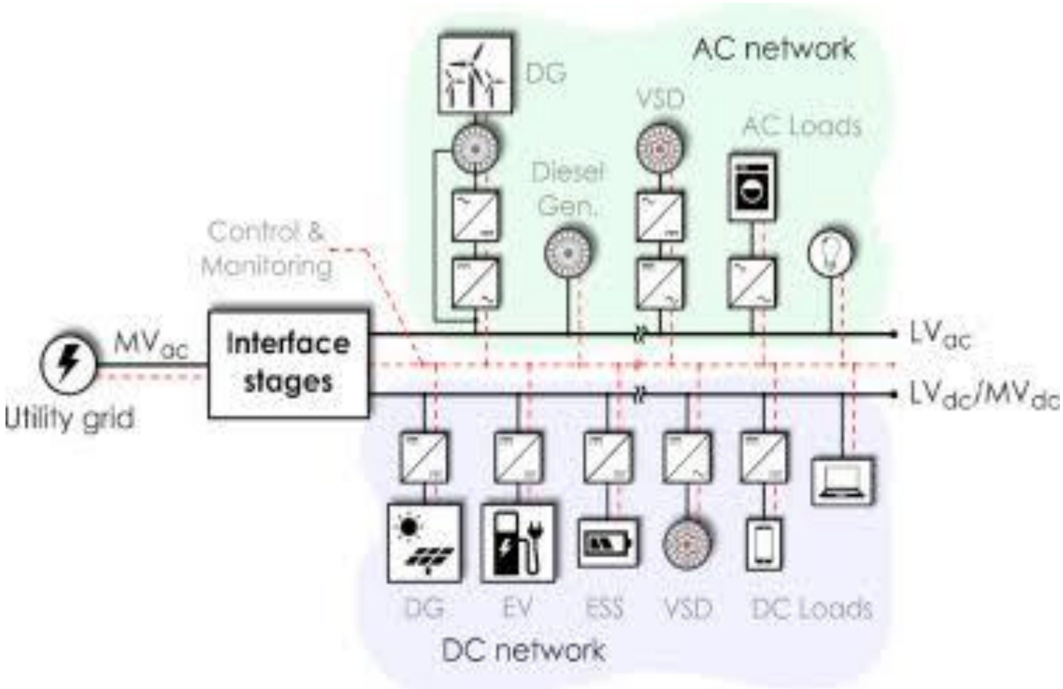

Fig 3. Hybrid AC/DC Microgrid

Fig 3 Show in Hybrid AC/DC microgrid. This model is essential for optimizing the operation of interconnected AC and DC systems, especially in scenarios where microgrids need to transition seamlessly from grid connected to islanded connected modes:

The complex power of AC and DC components are:

$$S_i^{AC} = P_i^{AC} + jQ_i^{AC} \tag{15}$$

$$S_i^{DC} = P_i^{DC} + jQ_i^{DC} \tag{16}$$

Therefore, It is efficient and secure operation during both modes. The models can be extended to incorporate ESS, allowing for the optimal utilization of batteries or other storage technologies in the microgrid. The power constraints of AC and DC components are:

$$P_i^{AC} \le P_{max}^{AC} \tag{17}$$

$$P_i^{DC} \leq P_{max}^{DC} \tag{18}$$

So, therefore, It is effective management of energy storage for balancing supply and demand

IV. PROPOSED METHODOLOGY

ANN Architecture

An artificial neural network model, both computationally and mathematically, simulates how the human brain works. To produce a single input value for the neurode, all of the weight-adjusted input values to a processing element are then combined using a vector to scalar function, such as summation, averaging, input maximum, or mode value. The computational module uses a transfer function to turn out its output (and subsequently the input signals for the next processing layer) after computing the input value. The input value of the neurode is altered by the transfer function. For this transformation, a sigmoid, hyperbolic tangent, or other nonlinear function is typically employed. The procedure is repeated across layers of processing units until the neural network generates a final output value, or vector of values.

Selection of ANN: The way they are designed allows them to capture complex relationships and patterns in data, making them valuable for a range of applications like pattern recognition, regression, and segmentation. **Fig 4** Show in Fitting neuralnetwork.

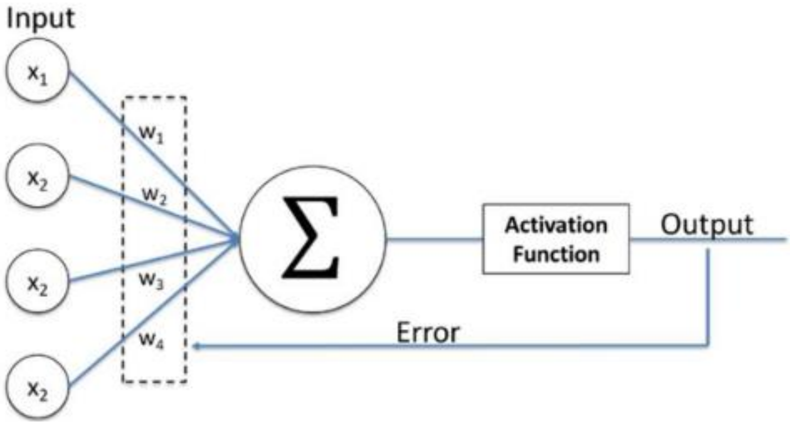

Fig 4. Fitting Neural Network

Training the ANN model: The process of training an Artificial Neural Network (ANN) involves making adjustments to the weights and biases of the network to minimize the difference between the expected and target outputs.

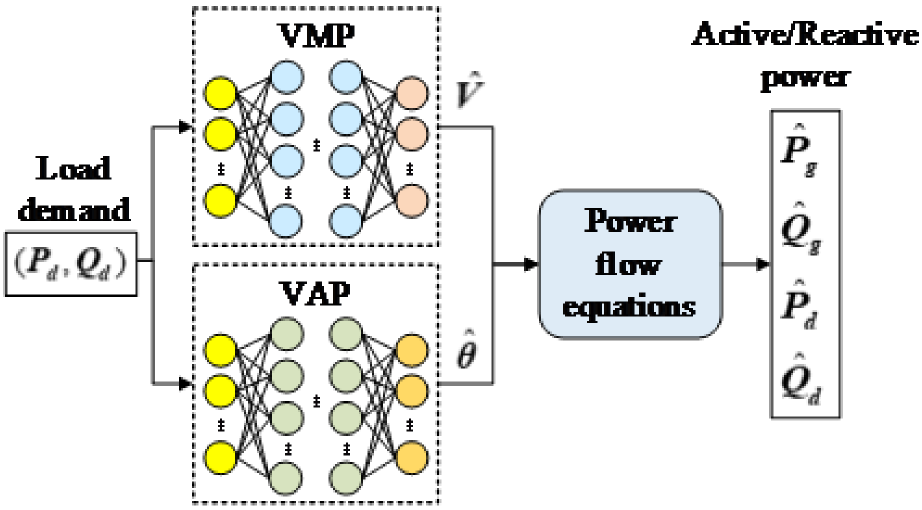

Fig 5. ANN Architecture

Optimization Algorithm

Usually, the target function is to minimise the overall cost of generating, including fuel expenses, while respecting limits such as voltage limits, power balance, and line flow restrictions. In comparison to other load flow methods, the Newton Raphson method offers a faster rate of convergence, making it the optimal choice for solving non-linear load flow equations. **Fig 6** Show in Flow Chart for NN-OPF.

Steps to design an algorithm:

Step 1: Initialization of System Data

- Define the cost coefficients (c_ac and c_dc), base MVA, bus data (bus matrix), and branch data (branch matrix) respectively.
- Admittance matrix (Ybus) construction: use the makeYbus function

Step 2: Neural Network Training

- Take the bus matrix and separate the real power demand (Pd) and reactive power demand (Qd).
- Initial voltage magnitudes (V) should be set to 1.
- Using Pd, Qd, and V as inputs, train a neural network (net) to predict voltage magnitudes (V).

Step 3: Optimal Power Flow

- Set voltage magnitudes (V) initially and continue iterating until convergence:
- Compute power flow utilising current V, Ybus, net, cost coefficients, Pd, and Qd.
- Adjust voltage magnitudes (V) in accordance with the power flow findings.

Step 4: Results Processing

- Use calcCost to determine the overall cost for both AC and DC power dispatch.
- Use calcLosses to determine power losses according to AC power dispatch, voltage magnitudes, and Ybus.

Step 5: Visualisations

- For analysis, plot the AC power dispatch (Pac) and DC power dispatch (Pdc).

Step 6: Validation and Testing

- Evaluate the system architecture by utilising diverse situations or datasets.
- Examine the neural network's resilience and the OPF solution's efficacy in varying circumstances.

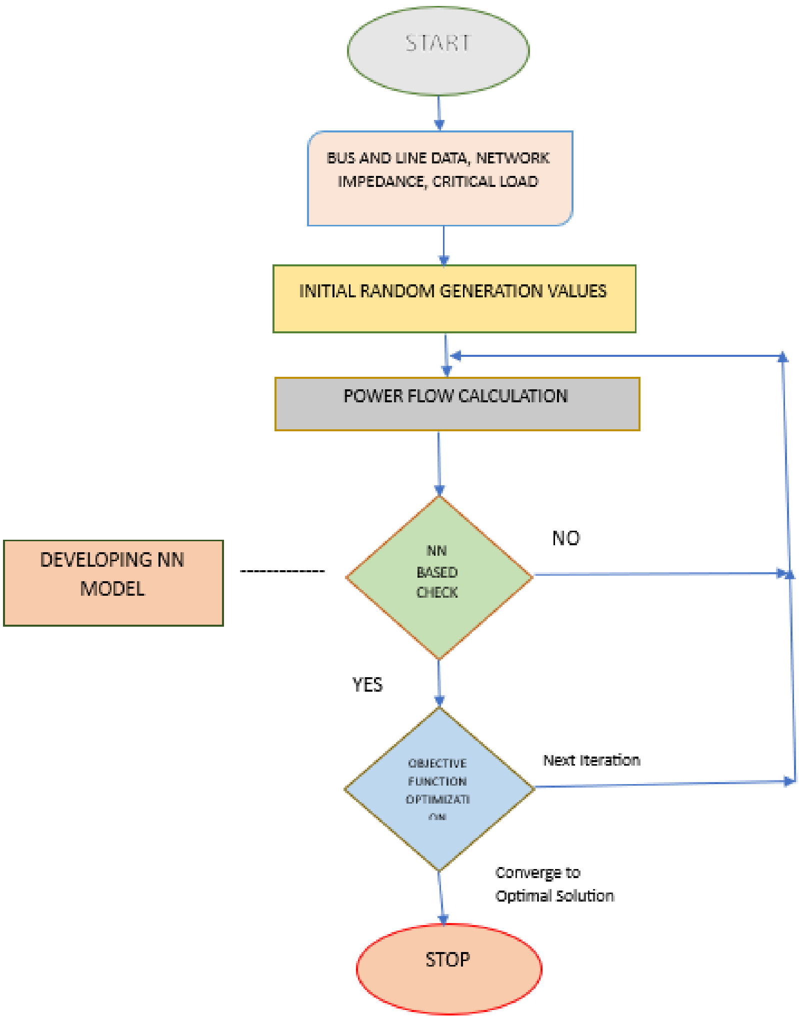

Fig 6. Flow Chart for NN-OPF

V. SIMULATION RESULTS

Power flow equations can be solved in a limited number of iterations thanks to the Newton Raphson technique, which has an iteration count that is independent of the number of buses taken into account. The collection of non-linear equations is converted into a set of linear equations by the Newton-Raphson method, which effectively approaches the original solution. Practically speaking, the most reliable power flow algorithm is the Newton Raphson approach. The method's drawback, though, is that each iteration requires solving the entire set of linear equations in addition to recalculating the terms of the Jacobian matrix.

A IEEE 12 bus system with 11 loads and 3 transformers has been chosen for analysis. A detailed description of the system is given below.

Table 1. System Configuration

System Details	
Buses	12
Generators	1
Loads	11
Shunts	0
Branches	12

The Bus data of the IEEE 14 bus system with Power generation and load details are given in **Table 2.**

Table 2. Bus Data

BUS DATA OF IEEE 12 BUS SYSTEM						
BUS NO	VOLT	ANGLE	GENERATION		LOAD	
	PU	DEG	P(MW)	Q(MVAR)	P(MW)	Q(MVAR)
1	1.02	0.05	350	100	-16.53	-
2	0.9944	-12.73	300	150	91.3	18.8
3	0.9891	-10.32	200	100	47.9	-3.8
4	0.9808	-8.776	150	90	7.6	1.7
5	0.9702	-14.29	120	80	11.1	7.6
6	0.9670	-13.37	100	50	-	-
7	0.9643	-13.38	100	0	-	-
8	0.9537	-14.91	100	0	29.8	16.7
9	0.9505	-15.09	90	0	8.9	5.9
10	0.9478	-15.07	80	0	6.2	1.7
11	0.9469	-15.16	70	0	13.6	5.9
12	0.9467	-16.03	60	0	14.8	4.9

Table 3. Load Data

From bus	To bus	Resistance (pu)	Reactance (pu)	Line Charging	Thermal Conductivity
1	2	0.02	0.06	0.03	150
1	4	0.05	0.20	0.04	150
2	3	0.06	0.17	0.02	80
3	4	0.01	0.04	0	0
4	5	0.02	0.06	0.01	100
4	6	0.06	0.18	0.02	100
6	7	0.0	0.1	0.0	0
6	8	0.0	0.1	0.0	0
6	9	0.0	0.1	0.0	0
9	10	0.01	0.03	0.1	50
9	11	0.0	0.0	0.0	0
9	12	0.0	0.0	0.0	0

Table 3 Show in Load Data. Regression analysis with supervised learning was chosen as the machine learning technique to train the neural network (NN) model on a substantial quantity of data for the power flow problem examined in this paper. The Data samples (power flow results) were gathered and AC power flow problems under various power system settings were solved using the MATLAB matpower module. The initial values of demand and voltage were adjusted to within ±10% of the baseline. There were at least 10,000 samples produced for every test power system. Three groups of the data were created: 10% for validation, 10% for testing, and 80% for training.

There are three hidden layers in the suggested NN model, as seen in **Fig 5**. It was selected to be the backpropagation activation function. In order to reduce the vanishing gradient issue during a NN model's training phase, it permits a little, non-zero constant gradient to slip through.

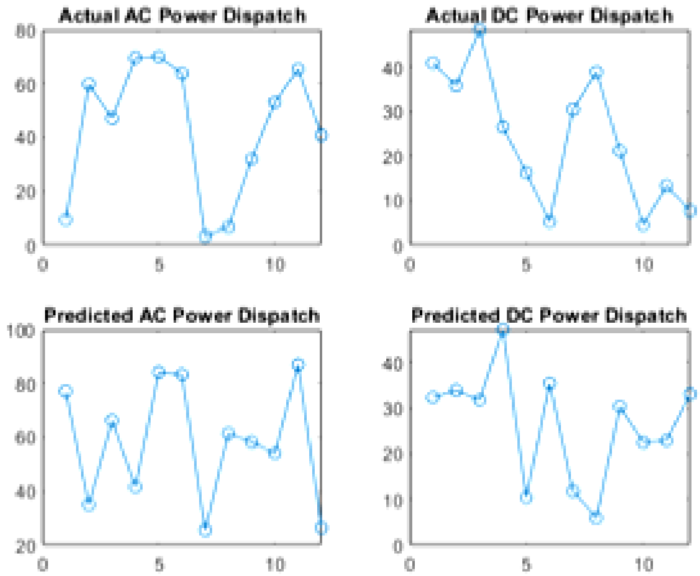

Fig 7. Optimal Power Dispatch for Actual and Predicted AC And DC Power

Using the modified OPF dispatch methods, the study's main objective was to create as closely as feasible the real system operations for a range of operating situations. In accordance with current operating rules, the ME dispatch method currently in use is based on an economical dispatch with some manual re-dispatching to remove thermal overloads. The OPF's recommended solutions were examined to make sure they adhered to established protocols.

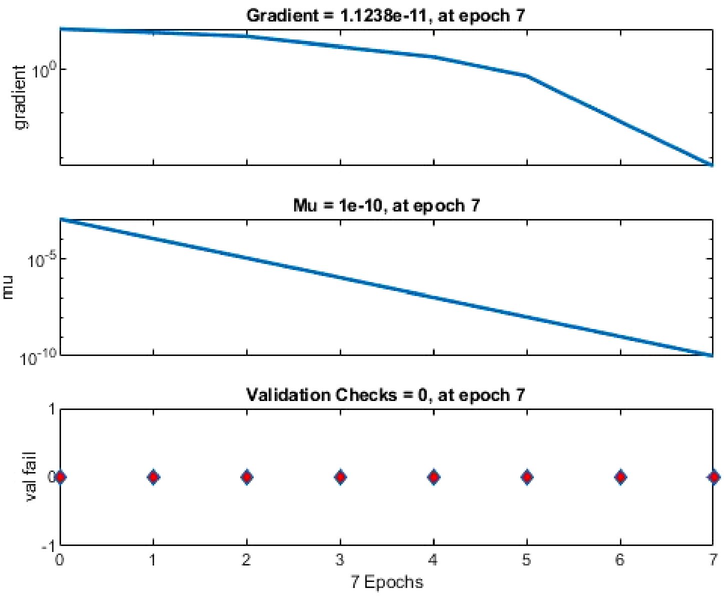

Fig 8. Plot Train State Output.

Under the identical operational conditions, a dispatch was produced using this approach. But in order to avoid making rash assumptions about how long the realized Mw savings would last, the advantages were not really translated into yearly dollar savings. Therefore, the study should demonstrate how to better define the system's operational boundaries using this OPF application.

The starting voltage magnitude, the total of the active and reactive power injections for each bus, and other variables are inputs for the suggested neural network model. Each bus's steady-state voltage magnitude and each branch's active power flow will be the output data used for training.

The min-max normalization technique is used to standardize the data before they are fed into the model to be trained. The lowest value for each data attribute is 0 and the largest value is 1.

The suggested NN model in **Fig 7** and **Fig 8** does a good job of reducing the MSE loss. After about 400 epochs, the training loss starts to rapidly decline and eventually reaches the plateau zone. Furthermore, the model performed a fantastic job of matching the output value to the anticipated 4 value. In **Fig 8**, the training error rate curve and the validation error rate curve were almost identical.

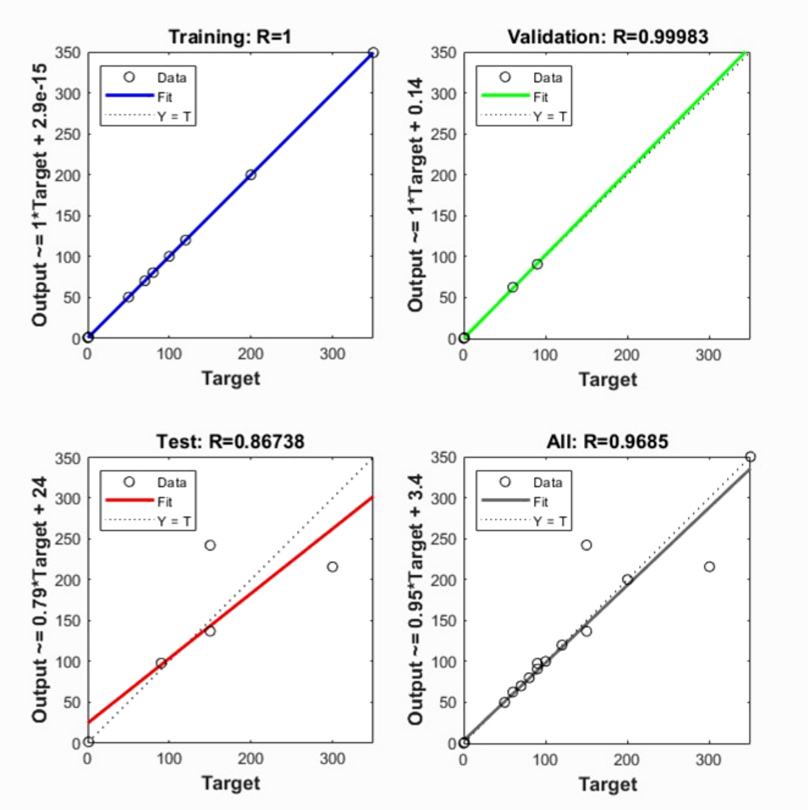

Fig 9. Regression Plots

Fig 9 Show in Regression Plots. The voltage magnitude at each bus is predicted by the suggested NN model for multiple systems with a high degree of accuracy; **Table I** illustrates the inaccuracy, which is approximately 0.5%. However, the NN model found it much easier to learn and anticipate the output values because almost all voltage magnitude values lie within the small range of 0.9 p.u. to 1.1 p.u.

VI. CONCLUSION

In this work, optimized power flow within a hybrid AC/DC microgrid is determined, showcasing the potential of neural networks in enhancing predictive capabilities. The findings contribute to the ongoing development of efficient and intelligent microgrid management systems. The optimized power distribution, cost reduction, and insights gained from the analysis underscore the significance of advanced control strategies in microgrid operations. Real power fluctuations and the voltage profile may point to areas that need improvement in terms of voltage and load requirements. Utilizing optimization techniques, loss optimization has been carried out, and the results show that a significant percentage of loss can be reduced with their assistance.

The suggested NN model illustrates possible benefits of machine learning in power systems. Because NN predictions are flexible, they can be incorporated into an optimization model to tackle the optimal power flow (OPF) problem for systems that have a number of renewable energy sources. The OPF calculation is made simpler and line flows can be directly calculated as part of the constraint using the NN model.

Data Availability

No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

Funding
No funding agency is associated with this research.

Competing Interests
There are no competing interests.

References
[1] "On certain integrals of Lipschitz-Hankel type involving products of bessel functions," Philosophical Transactions of the Royal Society of London. Series A, Mathematical and Physical Sciences, vol. 247, no. 935, pp. 529–551, Apr. 1955, doi: 10.1098/rsta.1955.0005.
[2] Venkataramana Ajjarapu,"Computational Techniques for Voltage Stability Assessment and Control E- Book—Library of Congress" Iowa State University, Department of Electrical and Computer Engineering. 1122 Coover Hall, Ames Iowa 50011, U.S.A. Control Number: 2006926216.
[3] Togiti, Varun, "Pattern Recognition of Power System Voltage Stability using Statistical and Algorithmic Methods" ,University of New Orleans Theses and Dissertations. (2012), 1488.
[4] B. Gao, G. K. Morison, and P. Kundur, "Voltage stability evaluation using modal analysis," IEEE Transactions on Power Systems, vol. 7, no. 4, pp. 1529–1542, 1992, doi: 10.1109/59.207377.
[5] P.-A. Lof, T. Smed, G. Andersson, and D. J. Hill, "Fast calculation of a voltage stability index," IEEE Transactions on Power Systems, vol. 7, no. 1, pp. 54–64, 1992, doi: 10.1109/59.141687.
[6] Lixin Bao, Zhenyu Huang, and Wilsun Xu, "Online voltage stability monitoring using var reserves," IEEE Transactions on Power Systems, vol. 18, no. 4, pp. 1461–1469, Nov. 2003, doi: 10.1109/tpwrs.2003.818706.
[7] Satish Joshi , "A Thesis on Voltage stability and contingency selection studies in electrical power system", Department of electrical engineering. Indian institute of technology Kanpur . December 1995.
[8] P. Kundur, T. Van Cutsem, V. Vittal 8.J. Paserba, V. Ajjarapu, G. Andersson, A. Bose, C. Canizares, N. Hatziargyriou, D. Hill, A. Stankovic, C. Taylor, "Power System Stability and Control McGraw",Hilll, 1994.
[9] "Definition and Classification of Power System Stability IEEE/CIGRE Joint Task Force on Stability Terms and Definitions," IEEE Transactions on Power Systems, vol. 19, no. 3, pp. 1387–1401, Aug. 2004, doi: 10.1109/tpwrs.2004.825981.
[10] L. A. Kraft and G. T. Heydt, "Adaptive Acceleration Factors for the Newton-Raphson Power Flow Study," Electric Machines & Power Systems, vol. 11, no. 4, pp. 337–346, Jan. 1986, doi: 10.1080/07313568608909188.
[11] S. Mehfuz and S. Kumar, "Two dimensional particle swarm optimization algorithm for load flow analysis," International Journal of Computational Intelligence Systems, vol. 7, no. 6, p. 1074, 2014, doi: 10.1080/18756891.2014.963973.
[12] K. Nohac, V. Sitar, and J. Veleba, "Load flow analysis in alternative tools using equations, physical and block diagrams," 2016 17th International Scientific Conference on Electric Power Engineering (EPE), May 2016, doi: 10.1109/epe.2016.7521747.
[13] D.K. Tanti Dharamjit, "Load Flow Analysis on IEEE 30 bus System", International Journal of Scientific and Research Publications, vol. 2, no. 11, November 2012.
[14] Deepinder Kaur Mander and Supreet Kaur Saini, "Load Flow Analysis: A Review", International Journal of Advanced Research in Electrical Electronics and Instrumentation Engineering, vol. 5, no. 3, March 2016.
[15] Deepinder Kaur Mander and GS Virdi, "Result Analysis on Load Flow by Using Newton Raphson Method", International Journal of Advanced Research in Electrical Electronics and Instrumentation Engineering, vol. 6, no. 7, July 2017.
[16] Vadimgadu Roja and M.S Sujatha, "A Review of Optimal DG Allocation in Distribution System for Loss Minimization", IOSR Journal of Electrical and Electronics Engineering, pp. 15-22.
[17] D. Shirmohammadi, H. W. Hong, A. Semlyen, and G. X. Luo, "A compensation-based power flow method for weakly meshed distribution and transmission networks," IEEE Transactions on Power Systems, vol. 3, no. 2, pp. 753–762, May 1988, doi: 10.1109/59.192932.
[18] G. X. Luo and A. Semlyen, "Efficient load flow for large weakly meshed networks," IEEE Transactions on Power Systems, vol. 5, no. 4, pp. 1309–1316, 1990, doi: 10.1109/59.99382.
[19] D. Rajicic and A. Dimitrovski, "A new method for handling PV nodes in backward/forward power flow for radial and weakly meshed networks," 2001 IEEE Porto Power Tech Proceedings (Cat. No.01EX502), doi: 10.1109/ptc.2001.964896.
[20] S. M. Moghaddas-Tafreshi and E. Mashhour, "Distributed generation modeling for power flow studies and a three-phase unbalanced power flow solution for radial distribution systems considering distributed generation," Electric Power Systems Research, vol. 79, no. 4, pp. 680–686, Apr. 2009, doi: 10.1016/j.epsr.2008.10.003.
[21] A. Augugliaro, L. Dusonchet, S. Favuzza, M. G. Ippolito, and E. R. Sanseverino, "A backward sweep method for power flow solution in distribution networks," International Journal of Electrical Power & Energy Systems, vol. 32, no. 4, pp. 271–280, May 2010, doi: 10.1016/j.ijepes.2009.09.007.
[22] A. Hamouda and K. Zehar, "Improved algorithm for radial distribution networks load flow solution," International Journal of Electrical Power & Energy Systems, vol. 33, no. 3, pp. 508–514, Mar. 2011, doi: 10.1016/j.ijepes.2010.11.004.
[23] M. M. Hamada, Mohamed. A. A. Wahab, and Nasser. G. A. Hemdan, "Simple and efficient method for steady-state voltage stability assessment of radial distribution systems," Electric Power Systems Research, vol. 80, no. 2, pp. 152–160, Feb. 2010, doi: 10.1016/j.epsr.2009.08.017.
[24] P. Mandal, T. Senjyu, N. Urasaki, A. Yona, T. Funabashi, and A. K. Srivastava, "Price Forecasting for Day-Ahead Electricity Market Using Recursive Neural Network," 2007 IEEE Power Engineering Society General Meeting, Jun. 2007, doi: 10.1109/pes.2007.385970.
[25] M. Tuo and X. Li, "Long-Term Recurrent Convolutional Network-based Inertia Estimation using Ambient Measurements," 2022 IEEE Industry Applications Society Annual Meeting (IAS), Oct. 2022, doi: 10.1109/ias54023.2022.9940112.
[26] L. Wu, J. Park, J. Choi, J. Cha, and K. Y. Lee, "A study on wind speed prediction using artificial neural network at Jeju Island in Korea," 2009 Transmission & Distribution Conference & Exposition: Asia and Pacific, Oct. 2009, doi: 10.1109/td-asia.2009.5356873.
[27] M. K. Thukral, "Solar Power Output Prediction Using Multilayered Feedforward Neural Network: A Case Study of Jaipur," 2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC), Dec. 2020, doi: 10.1109/isssc50941.2020.9358821.
[28] S. Huang, M. Yang, C. Zhang, J. Yun, Y. Gao, and P. Li, "A Control Strategy Based on Deep Reinforcement Learning Under the Combined Wind-Solar Storage System," 2020 IEEE 3rd Student Conference on Electrical Machines and Systems (SCEMS), Dec. 2020, doi: 10.1109/scems48876.2020.9352436.

[29] S. M. Miraftabzadeh, F. Foiadelli, M. Longo, and M. Pasetti, "A Survey of Machine Learning Applications for Power System Analytics," 2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), Jun. 2019, doi: 10.1109/eeeic.2019.8783340.

[30] J. E. King, S. C. E. Jupe, and P. C. Taylor, "Network State-Based Algorithm Selection for Power Flow Management Using Machine Learning," IEEE Transactions on Power Systems, vol. 30, no. 5, pp. 2657–2664, Sep. 2015, doi: 10.1109/tpwrs.2014.2361792.

[31] W. A. Alsulami and R. S. Kumar, "Artificial neural network based load flow solution of Saudi national grid," 2017 Saudi Arabia Smart Grid (SASG), Dec. 2017, doi: 10.1109/sasg.2017.8356516.

[32] M. S. S. T. O. A. B. J. Duncan Glover, "Power System Analysis and Design", Cengage Learning, 2022.

[33] X. Li, A. S Korad, and P. Balasubramanian, "Sensitivity factors based transmission network topology control for violation relief," IET Generation, Transmission & Distribution, vol. 14, no. 17, pp. 3539–3547, Jul. 2020, doi: 10.1049/iet-gtd.2019.1196.

[34] R. Lukomski and K. Wilkosz, "Power system topology verification using artificial neural networks: maximum utilization of measurement data," 2003 IEEE Bologna Power Tech Conference Proceedings,, doi: 10.1109/ptc.2003.1304451.

[35] A. V. Ramesh and X. Li, "Spatio-Temporal Deep Learning-Assisted Reduced Security-Constrained Unit Commitment," IEEE Transactions on Power Systems, vol. 39, no. 2, pp. 4735–4746, Mar. 2024, doi: 10.1109/tpwrs.2023.3313430.

[36] A. Keyhani, A. Abur, and S. Hao, "Evaluation of power flow techniques for personal computers," IEEE Transactions on Power Systems, vol. 4, no. 2, pp. 817–826, May 1989, doi: 10.1109/59.193857.

[37] M. K. Thukral, "Solar Power Output Prediction Using Multilayered Feedforward Neural Network: A Case Study of Jaipur," 2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC), Dec. 2020, doi: 10.1109/isssc50941.2020.9358821.