



Enhancing Solar Energy Flow through the Integration of Intelligent Control Models: Analysis of the Diyala Distribution Network

Mohammed Saad Albayati*, Raghad Ali Mejeed

Department of Power and Electrical Machines Engineering, College of Engineering, University of Diyala, Diyala, Iraq

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ABSTRACT

The study investigates the integration of solar photovoltaic systems into the distribution networks of Iraq's Diyala Governorate to address energy-security and power-quality challenges. The objective of this study is to examine how these dispersed sources affect power flow efficiency and voltage stability. Careful planning and optimal sizing of renewable energy sources help lower electrical losses and strengthen the national grid's resilience, thereby guaranteeing that end-users receive safe and reliable electricity. Additionally, the algorithm showed great adaptability in handling weather and load fluctuations, facilitating the shift to more intelligent, stable, and resilient networks in areas with limited resources and demonstrating the solution's suitability for field deployment. The results demonstrated improved feeder-voltage performance after optimized PV allocation. At a total PV budget of 336 MW, the optimized allocation achieved a relative I₂ loss-index reduction of 62.37%, a minimum feeder voltage of 0.9551 p.u., and no voltage violations below 0.95 p.u. The reproducible ANN-P&O implementation achieved an MPPT efficiency of 97.14%, a mean three-phase THD of 1.16%, and a reference-settling time of 0.055 s.

*Corresponding Author Email: safaa88asd@gmail.com

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1. Introduction

Growing concern over carbon emissions has intensified the need for cleaner, more sustainable energy systems. Distributed renewable energy sources and microgrids can support this transition by reducing dependence on fossil fuels and improving local energy resilience [1]. In this context, this study addresses the technical challenges of integrating renewable generation into Diyala Governorate's conventional electricity distribution infrastructure. Previous studies showed that power-flow techniques, including backward/forward sweep methods, effectively evaluate distribution-network performance and maintain acceptable operating conditions.

The increasing penetration of photovoltaic (PV) generation in distribution networks has raised important concerns regarding voltage regulation, power losses, and network operating limits. Because PV output varies with solar irradiance and operating conditions, high penetration levels can affect feeder voltage profiles and power-flow behavior [2]. PV systems can be integrated at different scales, ranging from small residential installations to medium- and large-scale generation units connected through appropriate power-electronic interfaces and transformers. Large PV systems are typically connected to distribution or transmission networks through protection and switching equipment, whereas smaller systems are commonly integrated closer to consumer loads. Figure 1 illustrates a typical distribution-grid connection with PV units[3].

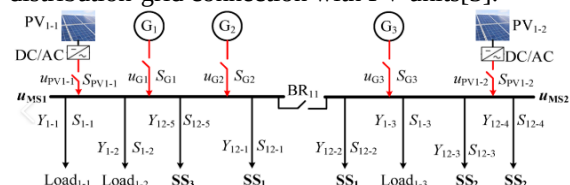


Figure 1. Bus connection diagram of a typical distribution grid network with PV units [3]

Typically installed in commercial buildings, medium-sized solar power plants range from 10 to 1000 kW. Larger units, up to hundreds of kilowatts, are set up similarly to large solar power systems, except for the inverter's rated capacity. The compact, often single-phase solar generator, which may produce up to 10 kilowatts, is fitted into a home that uses a lot of electricity. At this scale, the most common type doesn't need an inverter. Studies show that the distribution system has seen the greatest penetration of solar power into the electrical grid [1]. The global demand for clean and sustainable energy has

driven a significant increase in the integration of renewable energy sources into low-voltage distribution systems. As illustrated in Figures 1 and 2, PV solar power systems and wind energy are among the most widely adopted renewable energy technologies for mitigating carbon emissions [2].

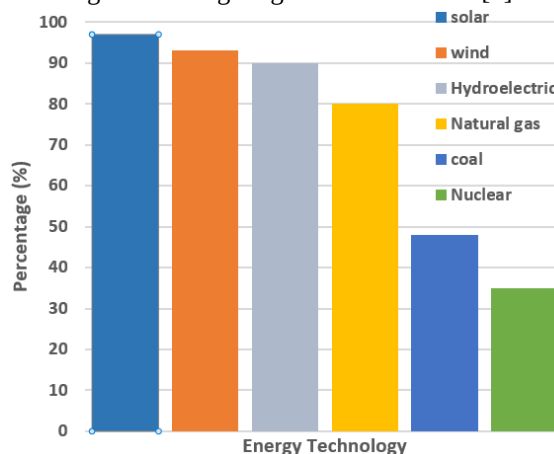


Figure 2. Comparison chart of the most popular renewable energy technologies [4]

Photovoltaic solar power systems are becoming increasingly prevalent in the distribution network every year, particularly in densely populated metropolitan regions where consumers are drawn to low installation costs and environmentally friendly energy sources. Every year, photovoltaic solar energy systems proliferate across the distribution network, especially in densely populated metropolitan regions. Eco-friendly energy solutions with comparatively inexpensive installation costs are being promoted to consumers [5]. Additionally, because the original network topology did not allow for bidirectional power flows, it becomes increasingly challenging to keep voltage levels within acceptable limits as the number of photovoltaic solar power producers linked to the distribution network increases. This is due to the fact that these solar generators rely on fluctuating weather. They might be included in medium- and small-sized distributed generating systems, as well as transmission and distribution networks [6].

Researchers have widely investigated PV hosting capacity and voltage regulation in distribution networks because high PV penetration can cause voltage rise, reverse power flow, feeder overloading, and other operational constraints [7]. Multi-objective hosting-capacity formulations, assessments of real low-voltage networks, topology-aware models, battery-assisted regulation, smart-inverter control, and power-index methods were used to quantify integration limits [8]. and increase permissible PV

Penetration [9]. The findings indicated that PV hosting capacity was strongly influenced by voltage limits, feeder loading, reverse power flow, and available control resources [10]. However, many approaches required detailed electrical models, controllable devices, or extensive network measurements [11].

Researchers investigated optimal PV and distributed-generation placement and sizing to reduce network losses and improve voltage performance [12]. Researchers applied BitTorrent, Jellyfish Search, Grey Wolf, Osprey, teaching-learning optimization, clustering, and related planning methods to benchmark and real radial distribution systems [13-15]. These approaches generally showed that coordinated siting and sizing improved voltage profiles and reduced losses. However, many formulations depended on complete feeder parameters or combined PV with capacitors, DSTATCOMs, or storage, increasing modeling and infrastructure requirements [16].

Uncertainty- and reliability-aware distribution planning extended PV allocation beyond deterministic optimization [17]. Stochastic solar and load modeling, reliability-oriented planning, hybrid optimization, data-driven access limits, techno-economic planning, and coordinated DG-storage-network reconfiguration improved planning robustness [18-20]. These methods incorporated operating variability more explicitly but typically required uncertainty distributions, switching information, storage models, or additional network-control data that were not always available in data-limited distribution systems [21]. Researchers investigated intelligent voltage regulation for operational management of PV-rich distribution networks through smart-inverter control, physics-constrained neural networks, edge-based deep learning, and physics-informed LSTM models [22]. These methods improved voltage regulation and reduced violations under dynamic operating conditions [23]. However, they primarily focused on post-deployment control rather than distributing a predefined PV capacity among feeders [24].

Researchers developed intelligent MPPT control to improve PV energy extraction under irradiance variation and partial shading. ANN-assisted P&O, enhanced ANN models, hybrid ANN-based strategies, adaptive P&O, and broader hybrid MPPT methods improved convergence, tracking accuracy, and dynamic performance [25]. Because these techniques operated mainly at the converter level, they did not address

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feeder-level PV allocation or network-wide voltage and loss performance.

Feeder-level PV allocation therefore remains a distinct planning problem when the total available PV capacity is fixed, and detailed network information is limited. The present Diyala study addresses this problem by allocating fixed total PV budgets among feeders through constrained optimization, using the minimum-voltage criterion and relative loss reduction to evaluate the resulting network performance.

1.1 Radial Distribution Network Modeling without DGs

Without distributed generation, the fundamental model of a radial distribution network is as follows. In other words, electricity is delivered from the main feeder or substation to the loads through a single branching channel that links the source to every node in the network; there are no loops or local sources [5]. When solar or wind energy is added, this model can serve as a benchmark for evaluating the results. Because each load is fed from a single side, voltage steadily drops as we move away from the source, and losses are comparatively larger. Electrical engineering concepts and mathematical formulas model loads in a radial distribution network, including distribution transformers and transmission lines. The outline of the modeling procedure for each component is provided below. Thus, the active power entering the bus can be defined as follows [6]:

$$P_{in,j} = P_{L,j} + P_{out,j} + P_{loss,j} \quad (1)$$

Where denotes the active load at the bus, indicates the active power leaving the bus toward downstream buses, and represents the active power loss associated with the bus or its outgoing line.

Also, the reactive power entering the bus was expressed as follows [5, 6]:

$$Q_{in,j} = Q_{L,j} + Q_{out,j} + Q_{loss,j} \quad (2)$$

Whereas, represents the reactive load at bus, indicates the reactive power leaving the bus toward downstream buses, and denotes the reactive power loss associated with the bus or its outgoing line [26].

Furthermore, the active power loss on the line could be formulated using the equation below [27]:

$$P_{loss,ij} = R_{ij}I_{ij}^2 \quad (3)$$

In which, indicates the line resistance, and denotes the current magnitude in the line.

Next, the sending-end voltage at the bus might be presented as [28, 29]:

$$V_j = V_i - (R_{ij} + jX_{ij})I_{ij} \quad (4)$$

Where represents the receiving-end potential at the bus, indicates the line resistance between buses, denotes the line reactance between buses, and depicts the current flowing from the bus-to-bus line; where indicates the imaginary unit. Figure 3 shows the node-feeder structure representing the load distribution of the Diyala network [4, 5].

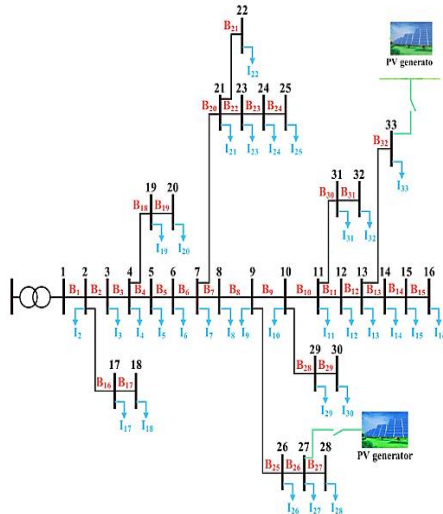


Figure 3. The node-feeder structure represents the load distribution of the Diyala network

Figure 3 shows how solar power system generation units are distributed across the Diyala network feeders. The designed solar power systems are distributed on high-load feeders to reduce losses and improve voltage. Figure 4 also shows the distribution line π -equivalent circuit [27].

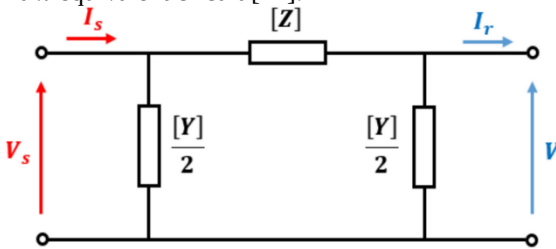


Figure 4. Demonstration of the distribution line π -equivalent circuit [30, 28]

Therefore, the transmitting terminal current (I_s) and sending terminal voltage (V_s) for the analogous circuit depicted in Figure 4 might be written in matrix form as follows [30, 31]:

$$\begin{bmatrix} V_s \\ I_s \end{bmatrix} = \begin{bmatrix} A_{vv} & A_{vi} \\ A_{iv} & A_{ii} \end{bmatrix} \begin{bmatrix} V_r \\ I_r \end{bmatrix} \quad (5)$$

Here, V_r and I_r denote the received voltage and current, respectively. It can be represented using the formula below:

$$\begin{cases} A_{vv} = 1 + \frac{ZY}{2} \\ A_{vi} = Z \\ A_{iv} = Y + (1 + \frac{ZY}{2}) \\ A_{ii} = 1 + \frac{ZY}{2} \end{cases} \quad (6)$$

Because of its capacitance, the branching element (Y) represents the distribution line's charging current. For short distribution lines, it is frequently disregarded, though. This assumption holds for the distribution network examined in this study. Consequently, the following matrix form may be used to express the transmitting-terminal potential (V_s) against the transmitting-terminal current (I_s) equation [28, 29]:

$$\begin{bmatrix} V_s \\ I_s \end{bmatrix} = \begin{bmatrix} 1 & Z \\ 0 & 1 \end{bmatrix} \begin{bmatrix} V_r \\ I_r \end{bmatrix} \quad (7)$$

Next, we will examine the two-winding transformer approximate equivalent circuit used to model distribution transformers. Using parallel and series components, this simple circuit design illustrates the transformer's main and secondary sides. Figure 5 shows the π -equivalent circuit diagram, where t denotes the turns ratio, and Z represents the transformer's equivalent leakage impedance.

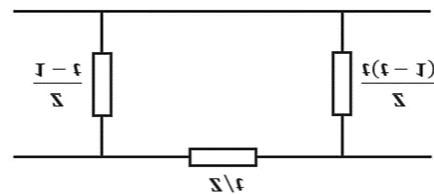


Figure 5. An illustration of a transformer with two sides

Additionally, real power (P) and reactive power (Q) elements are sometimes combined to depict the load model in a radial distribution network. Researchers may employ several load models, depending on the data needed for the investigation. The most common load model is the ZIP model, which includes three components: constant impedance load (Z), constant current load (I), and constant power load (P). The ZIP model 39 circuit architecture is shown in Figure 6. [32] [33]

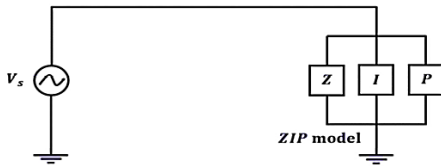


Figure 6. An illustration of a transformer with two windings using the π -equivalent model [34, 35]
The following is an analytical expression for a radial distribution network's ZIP load scheme:

$$P_z = P_0 + P_z \left(\frac{V}{V_0} \right)^2 \quad (8)$$

Also,

$$Q = Q_0 + Q_z \left(\frac{V}{V_0} \right)^2 \quad (9)$$

Whereas P_z denotes the load's constant impedance component and P_0 represents its constant power component. Q_0 represents the load's constant reactive power component. Also, Q_z indicates the load's constant reactive power component. Furthermore, V depicts the load's actual voltage magnitude. V_0 denotes the reference voltage magnitude. In a radial distribution network, these formulas show the connections between the load's power components, constant impedance, voltage magnitude, reactive power, and actual power.

1.2 Using DGs to Model Radial Distribution Networks

In this part, distributed generation sources like solar panels and wind turbines are included in the same radial network explanation. In this case, the network meets part of the local demand, reducing line current and lessening the burden on the primary source. Voltage improvement and loss reduction are typical outcomes, though they depend heavily on the DG's location, size, and operating style. Overvoltage or reverse flow might happen in some areas if the addition is poorly designed. The net active power demand at a bus might be expressed as [34, 35]:

$$P_j^{net} = P_{L,j} - P_{DG,j} \quad (10)$$

Here, represents the active load at the bus, and denotes the active power generated by DG at the bus. Also, the net reactive power demand at the bus can be formulated as follows [34, 35]:

$$Q_j^{net} = Q_{L,j} - Q_{DG,j} \quad (11)$$

Whereas, denotes the net reactive power demand at the bus, indicates the reactive load at the bus, and represents the reactive power generated by DG at the bus. Furthermore, the active power entering the bus can be as [36, 34, 35]:

$$P_{in,j} = P_{L,j} - P_{DG,j} + P_{out,j} + P_{loss,j} \quad (12)$$

Here, represents the active load at the bus; denotes the active power injected by DG at the bus; indicates the active power leaving the bus toward downstream buses; and depicts the active power loss associated with the bus or its outgoing line. Next, the active power loss on the line could be represented using the following equation [36, 35]:

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

where indicates the active power loss on the line, represents the line resistance, and denotes the line current magnitude. Lastly, the sending-end voltage at the bus might be expressed as follows [36, 35]:

$$V_j = V_i - (R_{ij} + jX_{ij})I_{ij} \quad (14)$$

Where, V_i represents the sending-end voltage at bus i , V_j denotes the receiving-end potential at bus j , R_{ij} indicates the line resistance between buses i with j , X_{ij} denotes the line reactance between buses i and j , also, I_{ij} depicts the current flowing from bus i to bus j , and j represents the imaginary unit.

Every distributed generation unit within the radial distribution network is required to be represented according to its unique properties. This involves simulating power-generating capabilities, such as wind turbine or solar PV models. DG models should include variables such as power-output variations, voltage-control capabilities, and responses to network conditions. Solar cell or PV array modeling depends on the diode arrangement. Because of its precision and practicality in many applications, the single-diode model is the most commonly used. Additionally, this technique replicates a solar cell using a single-diode model. An initial circuit design of the employed PV cells through N series and N shunt panel configurations is shown in Figure 7 [37, 38].

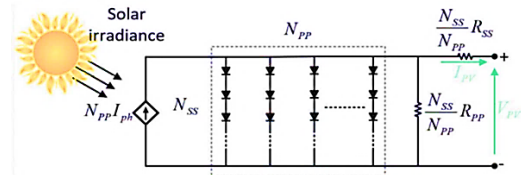


Figure 7. An early circuit design for the used photovoltaic array with N shunt and N series cell combinations [39, 36]

Additionally, the following equation might be utilized to characterize the fundamental current-voltage properties of a solar array. [39, 36]:

$$I_{PV} = N_{PP} I_{ph} \left[\exp \left(\frac{V_{PV} + R_{SS} I_{PV} \left(\frac{N_{SS}}{N_{PP}} \right)}{V_{TV} N_{SS}} \right) - 1 \right] - \frac{V_{PV} + R_{SS} I_{PV} \left(\frac{N_{SS}}{N_{PP}} \right)}{R_{PP} \left(\frac{N_{SS}}{N_{PP}} \right)} \quad (15)$$

In which,

$$I_D = I_0 \left[\exp \left(\frac{V_D}{V_{TV}} \right) - 1 \right] \quad (16)$$

Also,

$$V_{TV} = \frac{N_{CS} K T N_D}{Q} \quad (17)$$

The following variables represent the PV array's output current in these equations: I_{ph} is the current the solar cell generates from light. I_0 denotes the reverse saturation current. V_{PV} is the PV array's operating voltage, and N_D is the optimal diode factor. Q represents an electron's charge. R_{SS} also stands for series resistance. Panel shunt resistance is known as R_{PP} . V_{PV} denotes the terminal voltage. V_D denotes the diode voltage. N_{CS} is the number of cells linked in series in a solar module.

1.3 Power Flow Problem Formulation

To determine the voltages, currents, and power losses in each branch, this section transforms the network into a computer problem. The balance between incoming power, outgoing power, and losses at each node typically forms the basis of the solution in radial networks. Because it shows how the voltage profile varies and how losses rise or fall based on the location of distributed generation, this formulation is crucial for evaluating the effects of integrating solar or wind energy. It also helps determine the DG's ideal size and placement. However, as distributed generators become more common, power flow may shift over time, potentially causing local congestion. The low-voltage distribution network's energy flow guidelines before, as well as after, distributed generators are integrated are shown in Figure 8 [39, 31].

To determine bus voltages, as well as the directions and quantities of currents flowing across the lines, we developed a load-balancing technique for the low-potential electric system. This method is based on two topology-derived matrices: the Branch Current-to-Bus Voltage (BCBV) matrix and the Bus Injection-to-Branch Current (BIBC) matrix. The technique is

applied to a simplified electrical system in Figure 9. The fundamental concept is to detect real power entries and the reactive and real power use of nodes using network data. We first assumed all node voltages were 1 per unit, except at the slack bus, where the voltage equals its nominal value.

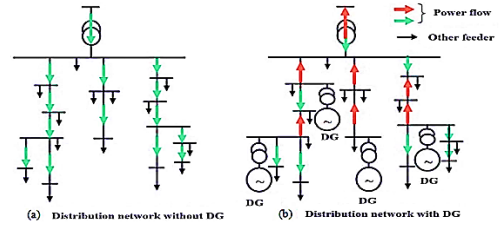


Figure 8. The integrated low-voltage distribution network's power flow directions before and after distributed generators [39, 40]

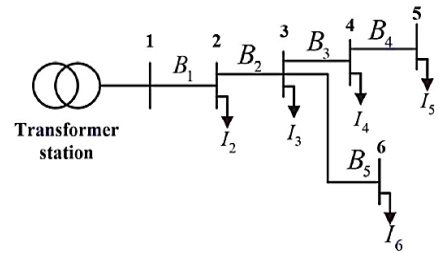


Figure 9. Testing the one-source substation in an LV radial distribution network [39, 40]

Additionally, the apparent power injection at node i used by the loads is provided by the following formula. [39-41]:

$$\bar{S}_i = P_i + jQ_i = \bar{V}_i * \bar{I}_i^* \quad (18)$$

Whereas, I and I_i^* denote the node-injected current conjugates i , and P_i and Q_i represent the load's active and reactive powers, respectively. The following expression represents the current injection at iteration k [30, 31]:

$$I_i^k = \left(\frac{\bar{S}_i}{V_i^k} \right)^* = \left(\frac{P_i + jQ_i}{V_i^k} \right)^* \quad (19)$$

Where is, I_i^k denotes the current injection at node i through the k -th repetition, $\bar{S}_i$ represents the complex energy injected at node i , V_i^k indicates the potential at node i through the k -th iteration, P_i depicts the active energy at node i , Q_i denotes the reactive power at node i , and $(\cdot)^*$ indicates the complex conjugate operator. Next, the current flowing along the line between can be written as a relation of the distinct currents in nodes as below.[39-41]:

$$\begin{cases} I_{36} = B_5 = I_6 \\ I_{45} = B_4 = I_5 \\ I_{34} = B_3 = I_5 + I_5 \\ I_{23} = B_2 = I_6 + I_5 + I_4 + I_3 \\ I_{12} = B_1 = I_6 + I_5 + I_4 + I_3 + I_2 \end{cases} \quad (20)$$

Thus, these relationships can later be represented in matrix form as follows.[28, 29]:

$$[B] = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \times [I] = [BIBC] \times [I] \quad (21)$$

Thus, $[B] = [B1 \ B2 \ B3 \ B4 \ B5]$ indicates the current-passing vector along the network's different lines; also, $[I] = [I2 \ I3 \ I4 \ I5 \ I6]^T$ represents the current vector inserted at the network nodes. Hence, the matrix form of the network of relations given in Eq. (20) can be rewritten as follows. [42]:

$$\begin{bmatrix} V_1 \\ V_1 \\ V_1 \\ V_1 \\ V_1 \end{bmatrix} - \begin{bmatrix} V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \end{bmatrix} = \begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 \\ Z_{12} & Z_{23} & 0 & 0 & 0 \\ Z_{12} & Z_{23} & 0 & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & Z_{45} & 0 \\ Z_{12} & Z_{23} & Z_{34} & 0 & Z_{36} \end{bmatrix} \times \begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \\ B_5 \end{bmatrix} \quad (22)$$

Also, Eq.(21) might be simplified such that[34, 35]:

$$[\Delta V] = [BCBV] \times [B] \quad (23)$$

Thus, by substituting Eq.(20 into Eq.(23), we can achieve the new formula :[34, 35]

$$[\Delta V] = [BCBV] \times [BICB] \times [I] \quad (24)$$

This procedure keeps going until the voltage profile difference between two consecutive iterations is less than a preset threshold:

$$[\Delta V^{K+1}] - [\Delta V^K] \leq \varepsilon \quad (25)$$

Whereas, ε denotes a pre-specified amount which indicates the convergence threshold.

Furthermore, this methodology calculates the transmission line active and reactive power losses in the radial distribution network. The distribution line's

active and reactive power losses can be written as follows: [34, 35]:

$$\begin{aligned} P_{ij} &= R_{ij} * |B_i|^2 \\ Q_{ij} &= Z_{ij} * |B_i|^2 \end{aligned} \quad (26)$$

Consequently, the distribution network's overall active and reactive losses may be shown as follows.[34, 35]:

$$P_{loss} = \sum_{i=1}^{N-1} \sum_{j=i+1}^N P_{ij} \quad (27)$$

$$Q_{loss} = \sum_{i=1}^{N-1} \sum_{j=i+1}^N Q_{ij} \quad (28)$$

Here, N stands for the total number of nodes. The power flow might be calculated using just one matrix, $[\Delta V/I]$, according to the mathematical description of the approach employed in this work. Equation (25) calculates this matrix. This indicates that this approach does not require the conductance matrix used in traditional techniques. For distribution networks, this method is therefore commonly more precise and efficient than traditional techniques. Its primary benefits also include substantially reduced computing time and simpler implementation. [34, 35] By incorporating renewable energy sources into Iraq's Diyala Governorate's distribution network, this project seeks to create reliable technological solutions to improve energy security and combat climate change. In particular, the study examines how distributed photovoltaic systems affect voltage stability and power-flow efficiency in low-voltage networks. To reduce electrical losses and improve voltage profiles, it also aims to identify optimal locations and solar power unit capacities. To improve maximum power point tracking efficiency, the study also seeks to apply hybrid intelligent control models. Additionally, it seeks to increase the national grid's resilience and guarantee that consumers receive dependable, safe electricity while adhering to standard regulations.

1.4 Study Gaps & Problem Statement

Previous studies did not adequately address feeder-level PV allocation under a fixed total PV capacity when detailed network information and monitoring infrastructure were limited. This limitation is particularly relevant to the Diyala distribution network, where recorded feeder-level load data are available but complete electrical and operational information is constrained. Accordingly, the present study focuses on constrained PV allocation across Diyala feeders to improve voltage performance and reduce the relative loss index under equal total PV budgets.

1.5 Novelty and Scientific Contribution

This study's novelty lies in applying a constrained Solar PV allocation strategy to recorded feeder-level data from the Diyala distribution network under fixed total PV budgets. Unlike the fixed-allocation benchmark, the proposed approach redistributes available PV capacity among feeders while maintaining the minimum voltage criterion. The study also compares fixed and optimized PV allocation under the same budget, showing improved feeder-voltage compliance and greater relative I2 loss-index reduction without increasing total installed PV capacity. In addition, the work integrates the feeder-level allocation analysis with the proposed P&O-ANN PV control framework to support efficient PV operation under varying irradiance and load conditions.

2. Materials and Methods

This section presents the methodology used to design the proposed electrical power distribution system to compensate for power shortages in the feeders of the Diyala distribution network using solar energy units. The authors implemented and simulated mathematical equations representing excessive loads and power shortages in the Diyala network feeders. The paper also described the programming steps required to design and implement the proposed compensation model. In addition, the authors presented the implementation procedure and the design parameters used to configure the simulation. Finally, the authors reviewed samples of the obtained data, including information on the Diyala distribution network stations, feeders, capacities, voltages, losses, and feeder loads.

2.1 The Proposed Model Structure

A MATLAB-based computational model was developed to represent the Diyala electricity distribution network and simulate the proposed power-distribution system. MATLAB provided the numerical and computational tools needed to implement the model, process feeder data, and evaluate key network performance indicators.

The proposed model was designed to support heavily loaded Diyala feeders by integrating dedicated solar PV units. The available PV capacity was distributed among the feeders using a constrained optimization strategy that considered feeder loading, voltage performance, and relative loss reduction. The model

was implemented in MATLAB using recorded data representing the Diyala distribution network. The PV units were assigned according to the selected total PV budgets while accounting for feeders' operating load conditions.

Figure 10 illustrates the main steps of the proposed methodology. The procedure begins by importing the recorded Diyala distribution-network dataset, followed by preprocessing and classifying the feeder data. The procedure then evaluates baseline feeder loading and loss indicators. After defining the total solar PV budget, the study applies constrained optimization to determine PV placement and allocation among feeders. The study then evaluates feeder voltages before and after PV integration and analyses and plots the resulting performance metrics. Figure 11 illustrates the distribution of solar PV generation units within the network structure. The PV units are allocated to selected feeders according to the proposed allocation strategy to reduce feeder loading, improve voltage performance, and reduce the relative network loss index.

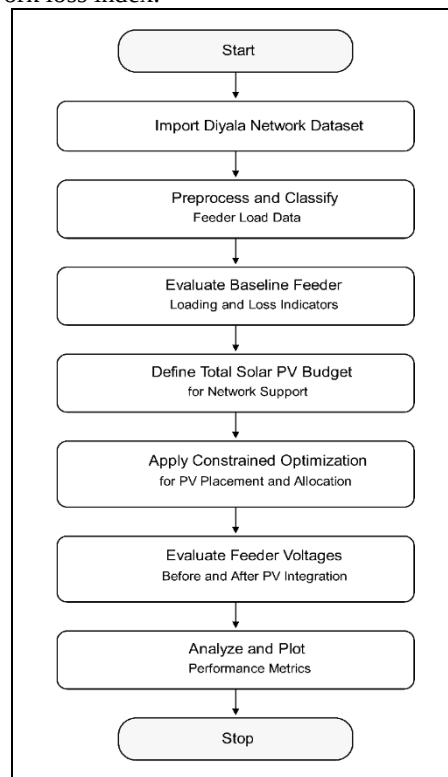


Figure 10. illustrates the flowchart of the methodology steps necessary to implement the proposed model

The optimal placement mechanism also selects PV units for feeders with higher loads or lower efforts in the Diyala network load distribution.

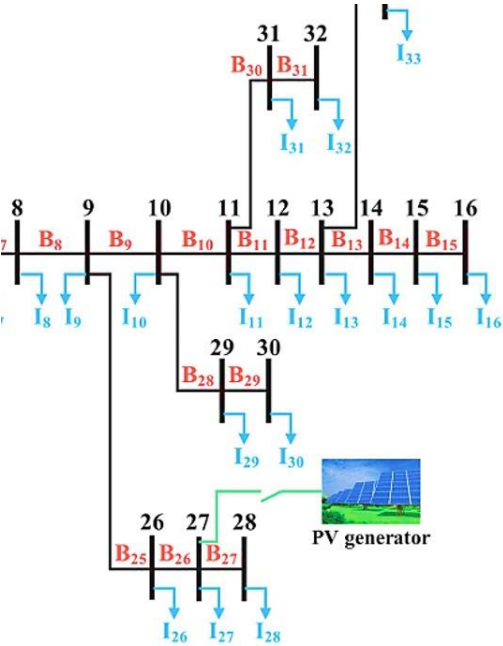


Figure 11. Optimal placement mechanism for choosing PV units based on feeders with higher loads or lower efforts in the Diyala network load distribution

2.2 Simulation Parameters and Assumptions

This section presents and adjusts the design specifications of the proposed system units. Table 1 summarizes the numerical methods and convergence criteria used in the MATLAB simulation to address the power flow issues.

Table 1. The employed computational assumptions and simulation algorithm details.

Parameter	Value / Configuration	Reference / Source
Simulation Environment	MATLAB (Custom scripts for matrix operations)	Section 2.1
Power Flow Method	Backward/Forward Sweep using BIBC and BCBV matrices	[2, 1]
Convergence Threshold ($\epsilon\epsilon$)	10–410–4 p.u.	Standard assumption for Eq. (24)
Dynamic Simulation Time Step	1 hour (for 24-hour evolution analysis)	Figure 15 Analysis

Line Charging Capacitance	Neglected (Assumed zero for short distribution lines)	Justified in Eq. (7) [28, 29]
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Table 2 also shows the specifications of the solar power generating models and the smart control units used to achieve optimal Maximum Power Point Tracking (MPPT) and ensure grid stability. Table 2. Design specifications of Diyala distribution network

Parameter	Value	Unit	Reference / Source
Total Substations	12	Stations	Official Dataset (Table 3)
Total Installed Capacity	2,139	MVA	Official Dataset (Table 3)
Total 33 kV Feeders	83	Feeders	Official Dataset (Table 3)
Maximum Network Load	1,164.2	MW	Official Dataset (Table 3)
Minimum Network Load	754.59	MW	Official Dataset (Table 3)
Average Total Load	~959.4	MW	Official Dataset (Table 3)
Base Voltage Level	33	kV	Network Topology [30, 31]

Table 3. Design settings of the photovoltaic (PV) system and hybrid control components

Parameter	Value / Configuration	Reference / Source
PV Cell Mathematical Model	Single-diode model	[39, 36]
MPPT Control Strategy	Hybrid P&O-ANN (Perturb & Observe - Artificial Neural Network)	Proposed Model (Table 4)
Target MPPT Efficiency	Achieved = 97.14%	Proposed Model (Table 4)

Maximum Total Harmonic Distortion (THD)	< 5% (Achieved: 1.16%)	IEEE Std 519 / Proposed Model
Voltage Stability Margin	± 2%	Proposed Model (Table 4)
Load Modeling Approach	ZIP Model (Constant Impedance, Current, and Power)	[34, 35]
Minimum Feeder Voltage Criterion	$V_{min} \geq 0.95$ p.u. (Achieved: 0.9551 p.u. at 336 MW)	Proposed Model (Figure 12)

Table 4 lists the smart artificial neural network (ANN) controller design specifications.

Table 4. Design settings and training components of the artificial neural network (ANN) controller

Class	Parameter / Setting	Value / Configuration	Rationale / Reference
Network Structure	Network Type	Feed-forward Back-propagation (FFBP)	Standard for non-linear function approximation in MPPT[39, 36].
	Input Layer Neurons	2	Represents environmental inputs: Solar Irradiance (GG in W/m²) and Cell Temperature (TT in °C).
	Hidden Layers	2 Hidden Layers	Captures complex non-linear I-V and P-V characteristics of the PV array.
	Neurons per Hidden Layer	10 (Layer 1), 8 (Layer 2)	Optimized via trial and error to balance learning capability and prevent overfitting.

	Output Layer Neurons	1	Represents the predicted optimal Duty Cycle (DD) or Reference Voltage (V_{ref}).
Transfer Functions	Hidden Layer(s)	tensing (Hyperbolic Tangent Sigmoid)	Maps inputs effectively to the non-linear regions of the PV curve.
	Output Layer	Purelin (Linear)	Allows the output to span the continuous required range (e.g., 0 to 1 for duty cycle).
Training Algorithm	Training Function	trainlm (Levenberg-Marquardt)	Provides the fastest convergence and lowest Mean Squared Error (MSE) for medium-sized datasets[40, 41].
	Performance Function	Mean Squared Error (MSE)	Standard metric for evaluating regression network accuracy.
	Data Division	70% Training, 15% Validation, 15% Testing	Ensures the model generalizes well to unseen weather conditions (Diyala climate data).
Training Hyperparameters	Maximum Epochs	1,000	Sufficient iterations for the network weights to converge to the global minimum.
	Learning Rate (η)	0.01	Prevents overshooting the minimum while ensuring steady weight updates.

	Moment um Coefficie nt	0.9	Accelerates convergence and helps the network escape shallow local minima.
	Validatio n Checks (max_fai l)	6	Implements early stopping to prevent overfitting if validation error increases.
	Target MSE (Goal)	$1 \times 100 - 41$ $\times 100 - 4$	Ensures high precision in predicting the maximum power point.

2.3 The Employed Dataset Analysis

In this study, readings from the Diyala Electric Distribution Network dataset were combined with standard data from the MATLAB toolbox to train and run the required tests to simulate the power-generating system that supplies network loads using solar cell sources. Additionally, official sources provided load readings and information for the Diyala distribution network in Excel files. Similarly, the primary dataset used to run the proposed MATLAB model simulation is the power processing unit dataset for the solar cell system.

To analyze the Diyala distribution network data, feeders must be represented as independent points in a radial model. Each feeder's actual load values in megawatts must be recorded, assuming an initial voltage that is near the nominal value (PU unit). Power-current relationships are then used to compute currents and losses, enabling identification of feeders that use the most energy and are most vulnerable to voltage dips. This research aims to accurately depict the network's performance before any enhancements and pinpoint vulnerabilities that need to be addressed, such as high loads, elevated losses, or voltage degradation.

3. Results and Discussion

The proposed model was implemented in MATLAB and evaluated under the defined simulation conditions. The following figures present the simulation results by the main stages of the proposed methodology.

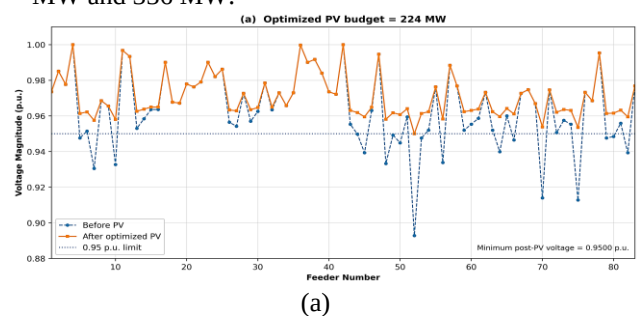
3.1 Simulation Results

We processed the recorded Diyala distribution-network data to identify the active feeders and extract their corresponding load values. We evaluated PV allocation under fixed total PV budgets. We applied a constrained optimization strategy to distribute the available PV capacity among the feeders while improving voltage performance and reducing the relative loss index. The following figures present the network performance before and after optimized solar PV allocation.

Figure 12 shows the feeder voltage profiles before and after optimized PV allocation for total PV budgets of 224 MW and 336 MW. Before integration, noticeable voltage drops were observed, particularly in heavily loaded feeders. After PV allocation, the voltage profile improved because local PV supplied part of the feeder demand. The minimum voltages were 0.9500 p.u. and 0.9551 p.u. for the 224 MW and 336 MW cases, respectively, with no feeders remaining below the 0.95 p.u. limit.

Figure 13 compares the fixed and constrained optimized PV-allocation strategies under identical total PV budgets. The relative I^2 loss-index reduction increased from 43.21% to 47.64% at 224 MW and from 56.08% to 62.37% at 336 MW. This improvement came from distributing the available PV capacity more effectively among the feeders without increasing total installed PV capacity.

Figure 14 compares the original feeder loads with the residual grid-supplied loads after constrained optimized PV allocation for total PV budgets of 224 MW and 336 MW.



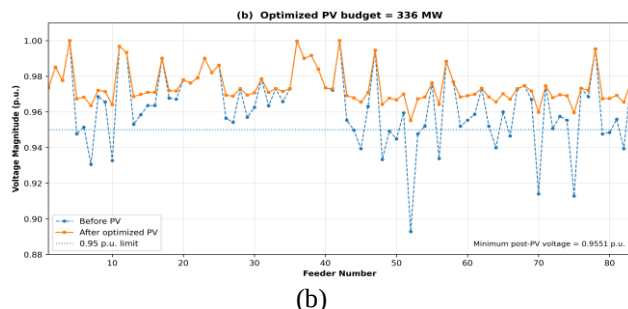


Figure 12. Voltage profiles before and after optimized PV allocation: (a) 224-MW and (b) 336-MW total PV budgets

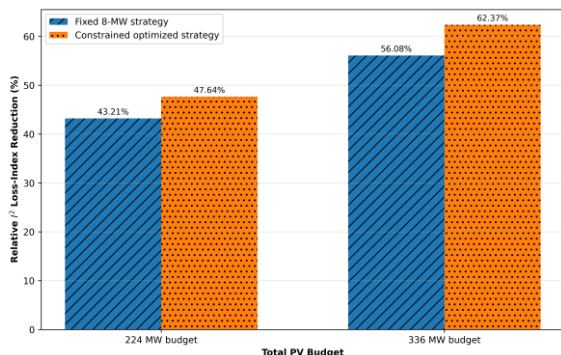


Figure 13: Same-budget comparison of fixed and optimized PV allocation

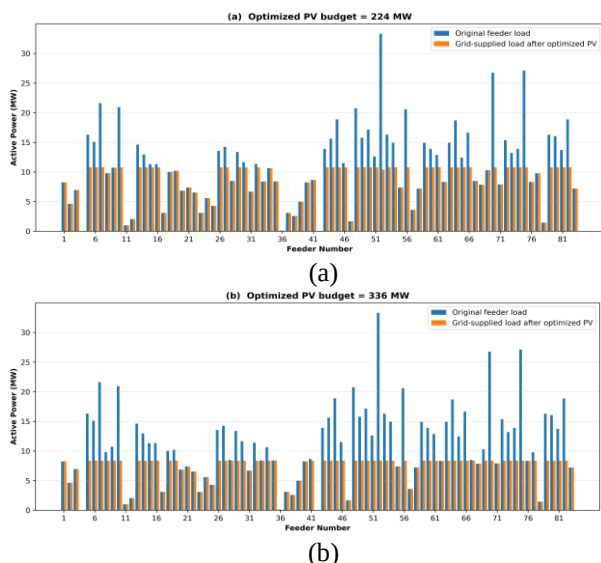


Figure 14. Feeder load and grid-supplied load after optimized PV allocation: (a) 224-MW and (b) 336-MW total PV budgets

Figure 14 illustrates the difference between the original feeder load and the residual grid-supplied load after optimized PV allocation. The grid-supplied

load decreased in feeders receiving PV support because PV units supplied part of the local demand. As a result, the main grid load decreased and the network's overall performance improved. Figure 15 shows the variation in PV generation and load demand over 24 hours.

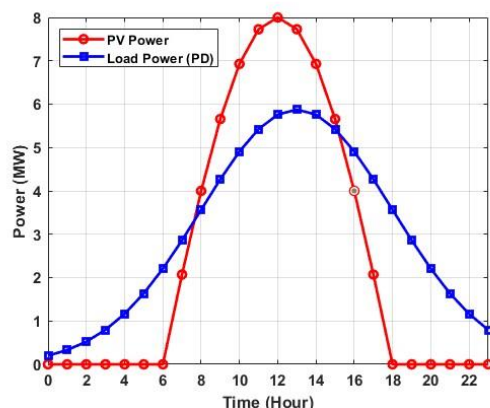


Figure 15. Evolution of PV and load power over 24 hours

Figure 15 depicts the relationship between solar energy production and load demand throughout the day. At peak hours, solar power surpasses the load, suggesting excess output that can be stored or fed to the grid. The load curve, by contrast, reflects the real demand period rather than the solar generation period and appears shorter and lower. In line with goals of increasing smart grid efficiency and lowering losses, this difference reflects an operational approach focused on optimizing renewable energy use and minimizing reliance on traditional energy sources.

3.2 Results Discussion & Validation

The constrained feeder-level PV allocation improved network voltage performance under the evaluated fixed PV budgets. At 336 MW, the optimized allocation achieved a minimum feeder voltage of 0.9551 p.u., with no feeders below the 0.95 p.u. criterion, and increased the relative I^2 loss-index reduction from 56.08% for the fixed allocation benchmark to 62.37% for the constrained optimized allocation. The reproducible ANN-P&O implementation achieved an MPPT efficiency of 97.14%, a mean three-phase THD of 1.16%, and a reference-settling time of 0.055 s. The ANN also achieved a test R^2 of 0.99986 and a normalized test MSE of 3.53×10^{-5} . These results demonstrate consistent performance of the feeder-level allocation and intelligent PV-control components under the stated modeling assumptions.

Table 5. Summary of the achieved simulation outcomes

Metric	Achieved Value	Unit
Minimum Feeder Voltage at 336 MW	0.9551	p.u.
Mean Three-Phase THD	1.16	%
MPPT Efficiency	97.14	%
Relative I ² Loss-Index Reduction at 336 MW	62.37	%
Reference-Settling Time	0.055	s

Table 6. Validation & comparison with modern published articles

Study	Control Method	MPPT Efficiency	TH D	Grid/System Type
Proposed Model	P&O-ANN Hybrid	97.14%	1.16 %	Diyala LV Distribution Network
Usman Habib , et al. (2025) [31]	Hybrid Optimization	95.8%	~2.5 %	Iraqi Distribution on Grid
Tian, Z. et al. (2026) [41]	Super-Twisting Sliding Mode	~96.0 %	2.6 %	PV Grid-Connected System

By comparing the results with two recent studies published in peer-reviewed journals, the implemented model's accuracy was confirmed. The tracking efficiency of 97.14% and the harmonic distortion of 1.164% were within acceptable ranges compared with the reference research findings. This agreement increases confidence in the dependability of the mathematical model and the compensation procedure of the solar power units used by demonstrating the validity of the suggested algorithms and their applicability in real distribution networks with operational and climatic characteristics similar to the Diyala network.

4. Conclusions

The results confirmed the proposed framework's effectiveness in integrating solar PV units into the Diyala distribution network. Under the 336-MW optimized allocation, the minimum feeder voltage reached 0.9551 p.u., with no violations below the 0.95

p.u. criterion, while the relative I² loss-index reduction reached 62.37%. The reproducible ANN-P&O implementation achieved an MPPT efficiency of 97.14%, a mean three-phase THD of 1.16%, and a reference-settling time of 0.055 s. These findings demonstrate the potential of combining constrained feeder-level PV allocation with intelligent PV control under the stated modeling.

5. Limitations & Future Work

Several limitations of this study have been identified: (1) practical testing on a physical model is still required, since the model was validated only through software simulation. (2) The study focused only on solar cell systems; wind power systems and battery storage should be considered in future work. (3) The integration of weather forecasting models is recommended, as AI-based forecasting could improve the overall performance of the proposed system. (4) A comprehensive cost-benefit analysis is recommended for large-scale implementation, since the current economic analysis is limited. (5) It is also recommended to develop the model with real-time monitoring interfaces to support operators and engineers in practical applications. Future work should also consider combining wind energy with battery banks, conducting a comprehensive economic analysis, developing real-time monitoring interfaces, and implementing a physical prototype.

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Nomenclature

Symb ol / Abrev.	Description
ANN	Artificial Neural Network
B	Vector of currents flowing through the network lines
BCBV	Branch Current to Bus Voltage matrix

BIBC	Bus Injection to Branch Current matrix
DG	Distributed Generation
I	Vector of currents injected at the network nodes
I ₀	Reverse saturation current
I _{i*}	Conjugate of the current injected into node ii
I _{i(k)}	Current injection at node ii during the kk-th iteration
I _{ij}	Current magnitude in line ij
I _{ph}	Photocurrent generated from light
I _r	Receiving-end current
I _s	Sending-end current
j	Imaginary unit
K	Coefficient for adding solar power units
LV	Low Voltage
MPPT	Maximum Power Point Tracking
N	Total number of nodes
NCS	Number of series-connected cells in a PV module
ND	Diode ideal factor
P ₀	Constant power component of the load
PDG, i	Active power generated by DG at bus i
P _i	Active load at bus i
P _{i, loss}	Active power loss associated with bus i
P _{i, out}	Active power leaving bus i toward downstream buses
PZ	Constant impedance component of the load
PV	Photovoltaic
Q	Electron charge
Q ₀	Constant reactive power component of the load
QDG, i	Reactive power generated by DG at bus ii
Q _i	Reactive load at bus ii
Q _{i, loss}	Reactive power loss associated with bus ii
QZ	Constant impedance reactive component of the load
R _{pp}	Panel shunt resistance
R _{ss}	Series resistance
S _i	Apparent power injection at node ii
S _{i(k)}	Complex power injected at node ii at iteration kk
t	Transformer turns ratio
THD	Total Harmonic Distortion
V ₀	Reference voltage magnitude
VD	Diode voltage
V _i	Receiving-end voltage at bus ii
V _{i(k)}	Voltage at node ii at the kk-th iteration
VP	PV array operational (terminal) voltage

V _r	Receiving-end voltage
V _s	Sending-end voltage
X _{ij}	Line reactance between buses i and j
Y	Branching element (line charging admittance)
Z	Equivalent leakage impedance of the transformer
ε	Pre-specified convergence threshold

Data and Code Availability: The MATLAB and Python code, processed dataset, computational environment, and scripts used to reproduce the principal results of this study have been archived in a private Code Ocean Compute Capsule (<https://codeocean.com/capsule/9814916/tree>). The capsule reproduces the feeder-level PV-allocation, voltage-profile, and relative I² loss-index analyses, together with the ANN-P&O MPPT and inverter-performance calculations reported in this study. Access to the capsule is currently restricted to authorized users and will be made publicly available following acceptance and final publication of the manuscript.

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